

Structure and Interpretation of Signals and Systems

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Contents

Preface	ix
1 Signals and Systems	1
1.1 Signals	2
1.2 Systems	27
1.3 Summary	42
Exercises	45
2 Defining Signals and Systems	49
2.1 Defining functions	50
2.2 Defining signals	66
2.3 Defining systems	68
2.4 Summary	82
Exercises	84
3 State Machines	93
3.1 Structure of state machines	94
3.2 Finite state machines	98
3.3 Nondeterministic state machines	107

3.4	Simulation relations	112
3.5	Summary	121
	Exercises	129
4	Composing State Machines	137
4.1	Synchrony	138
4.2	Side-by-side composition	139
4.3	Cascade composition	143
4.4	Product-form inputs and outputs	148
4.5	General feedforward composition	151
4.6	Hierarchical composition	154
4.7	Feedback	155
4.8	Summary	177
	Exercises	179
5	Linear Systems	187
5.1	Operation of an infinite state machine	189
5.2	Linear functions	192
5.3	The $[A, B, C, D]$ representation of a system	195
5.4	Continuous-time state-space models	218
5.5	Summary	219
	Exercises	227
6	Hybrid Systems	231
6.1	Mixed models	233
6.2	Modal models	235
6.3	Timed automata	240
6.4	More interesting dynamics	250
6.5	Supervisory control	260
6.6	Formal model	266

6.7	Summary	268
	Exercises	269
7	Frequency Domain	275
7.1	Frequency decomposition	277
7.2	Phase	283
7.3	Spatial frequency	284
7.4	Periodic and finite signals	285
7.5	Fourier series	289
7.6	Discrete-time signals	300
7.7	Summary	303
	Exercises	304
8	Frequency Response	311
8.1	LTI systems	313
8.2	Finding and using the frequency response	325
8.3	Determining the Fourier series coefficients	339
8.4	Frequency response and the Fourier series	340
8.5	Frequency response of composite systems	342
8.6	Summary	346
	Exercises	355
9	Filtering	363
9.1	Convolution	365
9.2	Frequency response and impulse response	378
9.3	Causality	382
9.4	Finite impulse response (FIR) filters	382
9.5	Infinite impulse response (IIR) filters	395
9.6	Implementation of filters	398
9.7	Summary	403

Exercises	406
10 The Four Fourier Transforms	413
10.1 Notation	414
10.2 The Fourier series (FS)	415
10.3 The discrete Fourier transform (DFT)	421
10.4 The discrete-Time Fourier transform (DTFT)	424
10.5 The continuous-time Fourier transform	428
10.6 Fourier transforms vs. Fourier series	434
10.7 Properties of Fourier transforms	444
10.8 Summary	458
Exercises	460
11 Sampling and Reconstruction	473
11.1 Sampling	474
11.2 Reconstruction	482
11.3 The Nyquist-Shannon sampling theorem	488
11.4 Summary	494
Exercises	495
12 Stability	499
12.1 Boundedness and stability	503
12.2 The Z transform	509
12.3 The Laplace transform	521
12.4 Summary	530
Exercises	532
13 Laplace and Z Transforms	537
13.1 Properties of the Z tranform	538
13.2 Frequency response and pole-zero plots	550
13.3 Properties of the Laplace transform	552

13.4 Frequency response and pole-zero plots	557
13.5 The inverse transforms	559
13.6 Steady state response	570
13.7 Linear difference and differential equations	573
13.8 State-space models	584
13.9 Summary	596
Exercises	603
14 Composition and Feedback Control	611
14.1 Cascade composition	613
14.2 Parallel composition	620
14.3 Feedback composition	626
14.4 PID controllers	639
14.5 Summary	647
Exercises	648
A Sets and Functions	655
A.1 Sets	656
A.2 Functions	677
A.3 Summary	680
Exercises	684
B Complex Numbers	689
B.1 Imaginary numbers	690
B.2 Arithmetic of imaginary numbers	691
B.3 Complex numbers	692
B.4 Arithmetic of complex numbers	693
B.5 Exponentials	694
B.6 Polar coordinates	696
Exercises	701

Bibliography	703
Notation Index	704
Index	708

Preface

Signals convey information. Systems transform signals. This book introduces the mathematical models used to design and understand both. It is intended for students interested in developing a deep understanding of how to digitally create and manipulate signals to measure and control the physical world and to enhance human experience and communication.

The discipline known as “signals and systems” is rooted in the intellectual tradition of electrical engineering (EE). This tradition, however, has evolved in unexpected ways. EE has lost its tight coupling with the “electrical.” So although many of the techniques introduced in this book were first developed to analyze circuits, today they are widely applied in information processing, system biology, mechanical engineering, finance, and many other disciplines.

This book approaches signals and systems from a computational point of view. A more traditional introduction to signals and systems would be biased towards the historic application, analysis and design of circuits. It would focus almost exclusively on linear time-invariant systems, and would develop continuous-time models first, with discrete-time models then treated as an advanced topic.

The approach in this book benefits students by showing from the start that the methods of signals and systems are applicable to software systems, and most interestingly, to systems

that mix computers with physical devices and processes, including mechanical control systems, biological systems, chemical processes, transportation systems, and financial systems. Such systems have become pervasive, and profoundly affect our daily lives.

The shift away from circuits implies some changes in the way the methodology of signals and systems is presented. While it is still true that a voltage that varies over time is a signal, so is a packet sequence on a network. This text defines *signals* to cover both. While it is still true that an RLC circuit is a system, so is a computer program for decoding Internet audio. This text defines *systems* to cover both. While for some systems the state is still captured adequately by variables in a differential equation, for many it is now the values in registers and memory of a computer. This text defines *state* to cover both.

The fundamental limits also change. Although we still face thermal noise and the speed of light, we are likely to encounter other limits—such as complexity, computability, chaos, and, most commonly, limits imposed by other human constructions—before we get to these. The limitations imposed, for example, when transporting voice signals over the Internet, are not primarily physical limitations. They are instead limitations arising from the design and implementation of the Internet, and from the fact that transporting voice was never one of the original intentions of the design. Similarly, computer-based audio systems face latency and jitter imposed by an operating system designed to time share scarce computing resources among data processing tasks. This text focuses on composition of systems so that the limits imposed by one system on another can be understood.

The mathematical basis for the discipline also changes with this new emphasis. The mathematical foundations of circuit analysis are calculus and differential equations. Although we still use calculus and differential equations, we frequently need discrete math, set theory, and mathematical logic. Whereas the mathematics of calculus and differential equations evolved to describe the physical world, the world we face as system designers often has nonphysical properties that are not such a good match for this mathematics. This text bases the entire study on a highly adaptable formalism rooted in elementary set theory.

Despite these fundamental changes in the medium with which we operate, the methodology of signals and systems remains robust and powerful. It is the methodology, not the medium, that defines the field.

The book is based on a course at Berkeley required of all majors in Electrical Engineering and Computer Sciences (EECS). The experience developing the course is reflected in certain distinguished features of this book. First, no background in electrical engineer-

ing or computer science is assumed. Readers should have some exposure to calculus, elementary set theory, series, first order linear differential equations, trigonometry, and elementary complex numbers. The appendices review set theory and complex numbers, so this background can be made up students.

Approach

This book is about mathematical modeling and analysis of signals and systems, applications of these methods, and the connection between mathematical models and computational realizations. We develop three themes. The first theme is the use of sets and functions as a universal language to describe diverse signals and systems. Signals—voice, images, bit sequences—are represented as functions with an appropriate domain and range. Systems are represented as functions whose domain and range are themselves sets of signals. Thus, for example, an Internet voice signal is represented as a function that maps voice-like signals into sequences of packets.

The second theme is that complex systems are constructed by connecting simpler subsystems in standard ways—cascade, parallel, feedback. The connections determine the behavior of the interconnected system from the behaviors of component subsystems. The connections place consistency requirements on the input and output signals of the systems being connected.

Our third theme is to relate the declarative view (mathematical, “what is”) with the imperative view (procedural, “how to”). That is, we associate mathematical analysis of systems with realizations of these systems. This is the heart of engineering. When electrical engineering was entirely about circuits, this was relatively easy, because it was the physics of the circuits that was being described by the mathematics. Today we have to somehow associate the mathematical analysis with very different realizations of the systems, most especially software. We do this association through the study of state machines, and through the consideration of many real-world signals, which, unlike their mathematical abstractions, have little discernable declarative structure. Speech signals, for instance, are far more interesting than sinusoids, and yet many signals and systems textbooks talk only about sinusoids.

Content

We begin in Chapter 1 by describing signals as functions, focusing on characterizing the domain and the range for familiar signals that humans perceive, such as sound, images, video, trajectories of vehicles, as well as signals typically used by machines to store or manipulate information, such as sequences of words or bits.

Systems, also introduced in Chapter 1, are described as functions, but now the domain and the range are themselves sets of signals. Systems can be connected to form a more complex system, and the function describing these more complex systems is a composition of functions describing the component systems.

Chapter 2 focuses on how to define the functions that we use to model both signals and systems. It distinguishes declarative definitions (assertions of what a signal or system is) from imperative ones (descriptions of how a signal is produced or processed by a system).

The imperative approach is further developed in Chapter 3 using the notion of state, the state transition function, and the output function, all in the context of finite state machines. In Chapter 4, state machines are composed in various ways (cascade, parallel, and feedback) to make more interesting systems. Applications to feedback control illustrate the power of the state machine model.

In Chapter 5, time-based systems are studied, first with discrete-time systems (which have simpler mathematics), and then with continuous-time systems. We introduce the notion of a state machine and define linear time-invariant (LTI) systems as state machines with linear state transition and output functions and zero initial state. The input-output behavior of these systems is fully characterized by their impulse response.

Chapter 7 introduces frequency decomposition of signals, Chapter 8 introduces frequency response of LTI systems, and Chapter 9 brings the two together by discussing filtering. The approach is to present frequency domain concepts as a complementary toolset, different from that of state machines, and much more powerful when applicable. Frequency decomposition of signals is motivated first using psychoacoustics, and gradually developed until all four Fourier transforms (the Fourier series, the Fourier transform, the discrete-time Fourier transform, and the discrete Fourier transform) have been described. We linger on the first of these, the Fourier series, since it is conceptually the easiest, and then more quickly present the others as generalizations of the Fourier series. LTI systems yield best to frequency-domain analysis because of the property that complex exponentials are eigenfunctions (the output is a scaled version of the input). Consequently, they are fully

characterized by their frequency response—the main reason that frequency domain methods are important in the analysis of filters and feedback control.

Chapter 10 covers classical Fourier transform material such as properties of the four Fourier transforms and transforms of basic signals. Chapter 11 applies frequency domain methods to a study of sampling and aliasing.

Chapters 12, 13 and 14 extend frequency domain techniques to include the Z transform and the Laplace transform. Applications in signal processing and feedback control illustrate the concepts and the utility of the techniques. Mathematically, the Z transform and the Laplace transform are introduced as extensions of the discrete-time and continuous-time Fourier transforms to signals on which Fourier transforms do not work, specifically signals that are not absolutely summable or integrable. Practically, the concern is for systems that are not stable and for systems that consume unbounded amounts of energy. These chapters extend the intuition of previous chapters to cover such systems.

The unified modeling approach in this text is rich enough to describe a wide range of signals and systems, including those based on discrete events and those based on signals in time, both continuous and discrete. The complementary tools of state machines and frequency domain methods permit analysis and implementation of concrete signals and systems. Hybrid systems and modal models offer systematic ways to combine these complementary toolsets. The framework and the tools of this text provide a foundation on which to build later courses on digital systems, embedded systems, communications, signal processing, hybrid systems, and control.

Pedagogical features

This book has a number of highlights that make it well suited as a textbook for an introductory course.

1. “Probing Further” sidebars briefly introduce the reader to interesting extensions of the subject, to applications, and to more advanced material. They serve to indicate directions in which the subject can be explored.
2. “Basics” sidebars offer readers with less mathematical background some basic tools and methods.

3. Appendix A reviews basic set theory and helps establish the notation used throughout the book.
4. Appendix B reviews complex variables, making it unnecessary for students to have much background in this area.
5. Key equations are boxed to emphasize their importance. They can serve as the places to pause in a quick reading. In the index, the page numbers where key terms are defined are shown in bold.
6. The exercises at the end of each chapter are annotated with the letters *E*, *T*, or *C* to distinguish those exercises that are mechanical (*E* for exercise) from those requiring a plan of attack (*T* for thought) and those that generally have more than one reasonable answer (*C* for conceptualization).

Notation

The notation in this text is unusual when compared to standard texts on signals and systems. We explain our reasons for this as follows:

Domains and ranges. It is common in signals and systems texts to use the form of the argument of a function to define its domain. For example, $x(n)$ is a discrete-time signal, while $x(t)$ is a continuous-time signal; $X(j\omega)$ is the continuous-time Fourier transform and $X(e^{j\omega})$ is the discrete-time Fourier transform. This leads to apparent nonsense like $x(n) = x(nT)$ to define sampling, or to confusion like $X(j\omega) \neq X(e^{j\omega})$ even when $j\omega = e^{j\omega}$.

We treat the domain of a function as part of its definition. Thus a discrete-time, real-valued signal is a function $x : \mathbb{Z} \rightarrow \mathbb{R}$, which maps integers to real numbers. Its discrete-time Fourier transform (DTFT) is a function $X : \mathbb{R} \rightarrow \mathbb{C}$, which maps real numbers into complex numbers. The DTFT is found using a function whose domain and range are sets of functions,

$$DTFT : [\mathbb{Z} \rightarrow \mathbb{R}] \rightarrow [\mathbb{R} \rightarrow \mathbb{C}].$$

This function maps functions of the form $x : \mathbb{Z} \rightarrow \mathbb{R}$ into functions of the form $X : \mathbb{R} \rightarrow \mathbb{C}$. The notation $[\mathbb{Z} \rightarrow \mathbb{R}]$ means the set of all functions mapping integers into real numbers. Then we can unambiguously write $X = DTFT(x)$.

Functions as values. Most texts call the expression $x(t)$ a function. A better interpretation is that $x(t)$ is an element in the range of the function x . The difficulty with the former interpretation becomes obvious when talking about systems. Many texts pay lip service to the notion that a system is a function by introducing a notation like $y(t) = T(x(t))$. This makes it seem that T acts on the value $x(t)$ rather than on the entire function x .

Our notation includes set of functions, allowing systems to be defined as functions with such sets as the domain and range. Continuous-time convolution, for example, becomes

$$\text{Convolution}: [\mathbb{R} \rightarrow \mathbb{R}] \times [\mathbb{R} \rightarrow \mathbb{R}] \rightarrow [\mathbb{R} \rightarrow \mathbb{R}].$$

We then introduce the notation $*$ as a shorthand,

$$y = x * h = \text{Convolution}(x, h),$$

and define the convolution function by

$$\forall t \in \mathbb{R}, \quad y(t) = (x * h)(t) = \int_{-\infty}^{\infty} x(\tau)y(t - \tau)d\tau.$$

Note the careful parenthesization. The more traditional notation, $y(t) = x(t) * h(t)$, would seem to imply that $y(t - T) = x(t - T) * h(t - T)$. But it is not so! Such notation undermines a student's confidence in algebra, since substitution of a value for t does not work!

A major advantage of our notation is that it easily extends beyond LTI systems to the sorts of systems that inevitably arise in any real world application, such as mixtures of discrete event and continuous-time systems.

Names of functions. We use long names for functions and variables when they have a concrete interpretation. Thus, instead of x we might use *Sound*. This follows a long-standing tradition in software, where readability is considerably improved by long names. By giving us a much richer set of names to use, this helps us avoid some of the preceding pitfalls. For example, to define sampling of an audio signal, we might write

$$\text{SampledSound} = \text{Sampler}_T(\text{Sound}).$$

It also helps bridge the gap between realizations of systems (which are often software) and their mathematical models. How to manage and understand this gap is a major theme of our approach.

How to use this book

At Berkeley, the first 11 chapters of this book are covered in a 15-week, one-semester course. Even though it leaves Laplace transforms, Z transforms, and feedback control systems to a follow-up course, it remains a fairly intense experience. Each week consists of three 50-minute lectures, a one-hour problem session, and one three-hour laboratory. The lectures and problem sessions are conducted by a faculty member while the laboratory is led by teaching assistants, who are usually graduate students, but are also often talented juniors or seniors.

We have developed laboratory components based on MATLAB and Simulink, and a separate set based on LabVIEW. In both cases, then lab content is closely coordinated with the lectures. The text does not offer a tutorial on LabVIEW, MATLAB, or Simulink, although the labs include enough material so that, combined with on-line help, they are sufficient. Some examples in the text and some exercises at the ends of the chapters depend on MathScript, the mathematical expression language used by both MATLAB and LabVIEW.

At Berkeley, this course is taken by all electrical engineering and computer science students, and is followed by a more traditional signals and systems course. That course covers the material in the last three chapters plus applications of frequency-domain methods to communications systems. The follow-up course is not taken by most computer science students. In a program that is more purely electrical and computer engineering than ours, a better approach might be to spend two quarters or two semesters on the material in this text, since the unity of notation and approach would be better than having two disjoint courses, the introductory one using a modern approach, and the follow-up course using a traditional one.

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curriculum. This took considerable courage, since the conceptual approach of the course was largely unproven.

Tom Henzinger probably had more intellectual influence over the approach than any other individual. The view of state machines, of composition of systems, and of hybrid systems owe a great deal to Tom. Gerard Berry also contributed a great deal to our way of presenting synchronous composition.

We were impressed by the approach of Harold Abelson and Gerald Jay Sussman, in *Structure and Interpretation of Computer Programs* (MIT Press, 1996), who confronted a similar transition in their discipline. The title of our book shows their influence. Jim McLellan, Ron Shafer, and Mark Yoder influenced this book through their pioneering departure from tradition in signals and systems, *DSP First—A Multimedia Approach* (Prentice-Hall, 1998). Ken Steiglitz greatly influenced the labs with his inspirational book, *A DSP Primer: With Applications to Digital Audio and Computer Music* (Addison-Wesley, 1996). Babak Ayazifar, with his visionary treatment of the course, has significantly influenced more recent versions of the book.

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Over several years, students at Berkeley have taken the course that provided the impetus for this book. They used successive versions of the book and the Web content. Their varied response to the course helped us define the structure of the book and the level of discussion. The course is taught with the help of undergraduate teaching assistants. Their comments helped shape the laboratory material.

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Signals and Systems

Contents

1.1 Signals	2
1.1.1 Audio signals	5
<i>Probing Further: Household electrical power</i>	11
1.1.2 Images	12
<i>Probing Further: Color and light</i>	15
1.1.3 Video signals	16
1.1.4 Signals representing physical attributes	17
1.1.5 Sequences	20
1.1.6 Discrete signals and sampling	22
1.2 Systems	27
1.2.1 Systems as functions	28
1.2.2 Telecommunications systems	29
<i>Probing Further: Wireless communication</i>	32
<i>Probing Further: LEO telephony</i>	33
1.2.3 Audio storage and retrieval	36
1.2.4 Modem negotiation	37
1.2.5 Feedback control systems	38
1.3 Summary	42
<i>Probing Further: Modems and Encrypted speech</i>	43
Exercises	45

1.1 Signals

Broadly speaking, a **signal** is a means to convey information. This printed page, for example, is a signal. So is the sound of someone reading the page aloud. In this text, a **system** is a process that generates signals or transforms signals. A person reading this book aloud, for example, is a system that converts the printed page signal into a sound signal. So is an electronic book reader for the blind. This book is about developing a deep enough understanding of signals and systems to be able to understand how such a book reader and many other systems work. We gain this understanding by dissecting the structure of signals, examining their interpretation, and developing systematic ways to analyze and synthesize them. Consider a few examples of signals and systems.

Example 1.1: A sound is a signal. A sequence of bits stored in a flash memory is also a signal. An MP3 player is a system that converts such a sequence of bits into high-quality stereo sound. A sequence of commands issued to a computer is also a signal. An **interactive voice response (IVR)** system converts spoken words into commands to a computer. IVR systems are commonly used today in call centers to efficiently handle high call volumes, for example in customer service centers.

Many mechanical machines produce sound as they operate. As they wear, the sound that they produce may change. Automated analysis of the sound that they produce can identify problems before the equipment fails. Such early detection is extremely valuable, particularly in safety-critical systems, such as jet engines or power-generation turbines. This book can help understand how to design systems for such automated detection.

Sound signals can also be converted to images. The famous iTunes visualizer is a beautiful example; it generates aesthetically pleasing colorful patterns on a screen that undulate synchronously with music. An **ultrasound imaging** system generates sounds with frequencies that are too high for humans to hear, and listens for their reflections. The sounds are reflected in materials where two distinct materials meet. These reflections can be used to safely construct images of a baby in a womb, for example, without exposing the baby to potentially harmful radiation.

Example 1.2: An image is a signal. A system that analyzes images, recognizing objects, faces, animals, etc., might form the heart of an Internet image search engine. A system that compares images might be used to enforce copyrights. In factory automation, it is common to use imaging systems to detect manufacturing defects. An image enhancement system might be used in a digital camera to, for example, automatically remove red eye, a bright reflection from the back of the retina that occurs when a camera flash is close to the camera lens.

Example 1.3: A computer program, which is a sequence of commands, is also a signal. **Malware**, short for malicious software, is software that surreptitiously performs undesired functions on your computer. A system that detects malware transforms the program signal into a simple yes or no answer. Either the program contains malware or it does not. Although they are far from perfect, such systems have gotten quite sophisticated, and they can often even detect obfuscated programs, programs that have been deliberately altered to attempt to hide their malicious intent.

Example 1.4: DNA molecules contain the genetic instructions used in the development and functioning of almost all known living organisms. A DNA molecule, therefore, is a signal, and a biological system uses the structure of the molecule to synthesize other molecules. The structure of a DNA molecule can be relatively simply represented as a sequence of one of four types of nucleotides denoted by the letters A, T, C, and G. A sequence of such letters, therefore, encodes the signal that the DNA molecule represents.

Example 1.5: Electromagnetic radiation can function as a signal. A radio broadcast system, for example, converts sound signals into electromagnetic radiation, which is then picked up by a radio antenna and converted back to sound. A television broadcast system converts images into sequences of bits, and then converts

the sequences of bits into radio signals. A TV receiver reverses these conversions. A radar system generates an electromagnetic signal, transmits it, listens for reflections, and then converts the reflections into images. Radar signals are routinely used in air traffic control systems, for example, and for collision avoidance systems in high-end cars.

One way to get a deeper understanding of a subject is to formalize it, to develop mathematical models. Such models admit manipulation with a level of confidence not achievable with less formal models. We know that if we follow the rules of mathematics, then a transformed model still relates strongly to the original model. There is a sense in which mathematical manipulation preserves “truth” in a way that is elusive with almost any other intellectual manipulation of a subject. We can leverage this truth-preservation to gain confidence in the design of a system, to extract hidden information from a signal, or simply to gain insight.

Mathematically, we model both signals and systems as functions. A **signal** is a function that maps a domain, often time or space, into a range, often a physical measure such as air pressure or light intensity. A system is a function that maps signals from its domain—its input signals—into signals in its range—its output signals. The domain and the range are both sets of signals; we call a set of signals a **signal space**. Thus, systems are functions whose domains and ranges are signal spaces.

We use the mathematical language of sets and functions to make our models unambiguous, precise, and manipulable. This language has its own notation and rules, which are reviewed in Appendix A. We begin to use this language in this chapter. Depending on the situation, we represent physical quantities such as time, voltage, current, light intensity, air pressure, or the content of a memory location by **variables** that range over appropriate sets. A variable has a name, such as n or *Intensity*, and a set of values that can be assigned to the variable.

Example 1.6: Time may be represented by a variable $n \in \mathbb{N}$, where \mathbb{N} represents the set of **natural numbers** $\{1, 2, 3, \dots\}$. We read the expression “ $n \in \mathbb{N}$ ” as “ n in the set of natural numbers,” and it means that n is a variable that can have any value in \mathbb{N} . For example, in **Unix time** or **POSIX time**, used by many computer systems to keep track of the date and time, the value of n represents the number of seconds that

have elapsed since midnight on January 1, 1970. The time at which we are writing this paragraph is $n = 1290876962$, a natural number.

Time may be represented many other ways. For example, the time of day may be represented as $h : m : s$, where $h \in \{0, 1, \dots, 23\}$ represents the hour, $m \in \{0, 1, \dots, 59\}$ represents the minute, and $s \in \{0, 1, \dots, 59\}$ represents the second. Mathematically, these three numbers form a three-tuple,

$$(h, m, s) \in \{0, 1, \dots, 23\} \times \{0, 1, \dots, 59\} \times \{0, 1, \dots, 59\},$$

where the \times operator forms the [Cartesian product](#) of sets.

In the study of physical systems, time is often represented by a variable $t \in \mathbb{R}_+$, where \mathbb{R}_+ is the set of non-negative real numbers, or $t \in \mathbb{R}$, the real numbers. In such a representation, the particular value $t = 0$ will typically have some meaning, representing for example the time at which a system first begins functioning. Such a model of time is often called **continuous time**, reflecting the fact that the set of real numbers is a **continuum**. (Technically, a continuum is ordered set that is dense, in the sense that between any two elements of the set there is another element, and for which every non-empty ordered subset that has an upper bound has a least upper bound. But this is more technical than we need for now.)

Example 1.7: The intensity of light reflected from a point on a page may be represented by a continuous variable $x \in [0, \text{MaxIntensity}]$, where $[0, \text{MaxIntensity}] \subset \mathbb{R}$ represents a range of real numbers from zero to *MaxIntensity*, where *MaxIntensity* is some maximum value of the intensity. The value $x = 0$ represents no reflected light, indicating that the point on the page is black, whereas *MaxIntensity* represents maximum reflected light, indicating that the point on the page is white.

1.1.1 Audio signals

Our ears are sensitive to sound, which physically is rapid variations in air pressure at a point in space. A particular sound can be represented as a function

$\text{Sound} : \text{Time} \rightarrow \text{Pressure}$
--

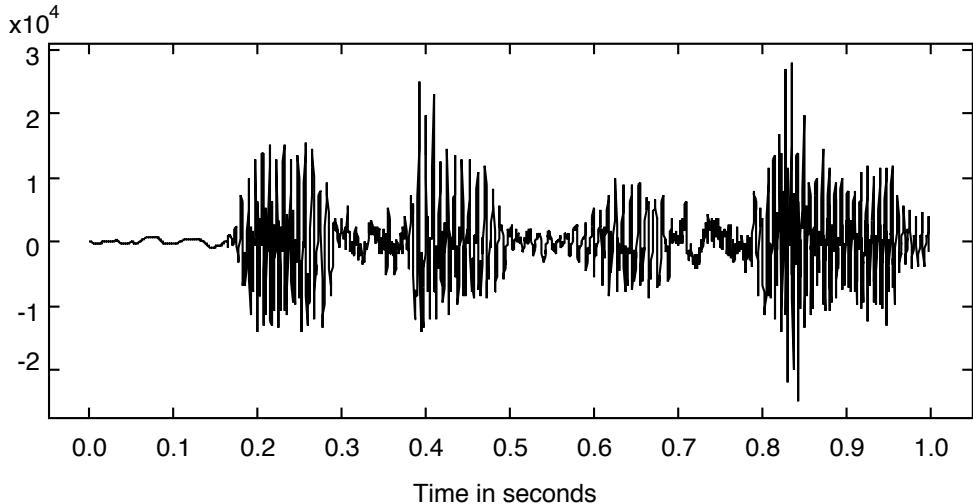


Figure 1.1: Waveform of a speech fragment.

where *Time* is the [domain](#) of the function, and *Pressure* is the [codomain](#).^{*} *Pressure* is a set consisting of possible values of air pressure, and *Time* is a set representing the time interval over which we wish to consider the signal.

Example 1.8: A one-second segment of a voice signal is a function of the form

$$\text{Voice}: [0, 1] \rightarrow \text{Pressure},$$

where $[0, 1] \subset \mathbb{R}$ represents one second of time. An example of such a function is plotted in Figure 1.1. The horizontal axis represents times $t \in [0, 1]$, and the vertical axis represents the values $\text{Voice}(t) \in \text{Pressure}$ for each $t \in [0, 1]$. Such a plot is often called a **waveform**.

The signal in Figure 1.1 varies over positive and negative values, averaging approximately zero. But air pressure cannot be negative, so the vertical axis does not directly represent air pressure. It is customary to normalize the representation of

^{*}For a review of the notation of sets and functions, see Appendix A.

sound by subtracting the ambient air pressure (which averages about 101,325 pascals, where one pascal (written Pa) equals one newton per square meter. Our ears, after all, are not sensitive to constant ambient air pressure (as we will see later, our ears are a [highpass](#) system). Thus, we take $\text{Pressure} = \mathbb{R}$, the real numbers, where negative pressure means a drop in pressure relative to ambient air pressure.

As plotted, the vertical axis in Figure 1.1 ranges from approximately $-32,768$ to $32,767$ (notice the annotation $\times 10^4$, which indicates that the values labeling the axis should be multiplied by 10,000). This is because the voice signal that is plotted is actually the internal representation in a computer of the voice signal, and each value of air pressure is represented by a 16-bit integer. Let us call the set of 16-bit integers $\text{Integers16} = \{-32768, \dots, 32767\}$. Then a more precise representation of the function would show that the codomain is Integers16 ,

$$\text{Voice}: [0, 1] \rightarrow \text{Integers16}.$$

When a computer plays back an audio signal, the audio hardware of the computer is responsible for converting members of the set Integers16 into air pressure. The actual air pressure at a human ear will depend on the audio hardware, its volume setting, the distance to the listener, and the acoustic properties of the media between the audio hardware and the listener.

The previous example models time as a continuum. However, a computer cannot directly handle such a continuum. In a computer, a sound is represented not as a continuous waveform, but rather as a list of numbers. Each number is called a **sample** of the signal. To get audio quality that is sufficient to make speech signals intelligible (voice-quality audio), 8,000 samples for every second of speech are generally sufficient. This is what is typically used for Internet voice signals. Voice transmission over the internet is called **voice over IP** or **VoIP**, where **IP** stands for Internet protocol. To get audio quality that is sufficient for music, 44,100 samples for every second of sound are typically used. This is the standard rate for compact discs (CDs), and it is the most commonly used rate for MP3 files and other music encoding formats. The tradeoff between sound quality and the number of samples per second is considered in Chapter 11.

Example 1.9: A close-up of a section of the speech waveform of Figure 1.1 is shown in Figure 1.2. That plot shows 100 samples. For emphasis, that plot shows

a dot for each sample rather than a continuous curve, with a stem connecting the dot to the horizontal axis. Such a plot is called a **stem plot**. Since there are 8,000 samples per second, the 100 points in figure 1.2 represent $100/8,000$ seconds, or 12.5 milliseconds of speech.

Such signals are said to be **discrete-time signals** because they are defined only at discrete points in time. A discrete-time one-second voice signal in a computer is a function

$$\boxed{\text{ComputerVoice}: \text{DiscreteTime} \rightarrow \text{Integers16},}$$

where $\text{DiscreteTime} = \{0, 1/8000, 2/8000, \dots, 7999/8000\}$ is the set of sampling times. By contrast, **continuous-time signals** are functions defined over a continuous interval of time (technically, a continuum in the set \mathbb{R}). The audio hardware of the computer is responsible for converting the *ComputerVoice* function into a function of the form *Sound*: $\text{Time} \rightarrow \text{Pressure}$. That hardware, which converts an input signal into a different output signal, is a system.

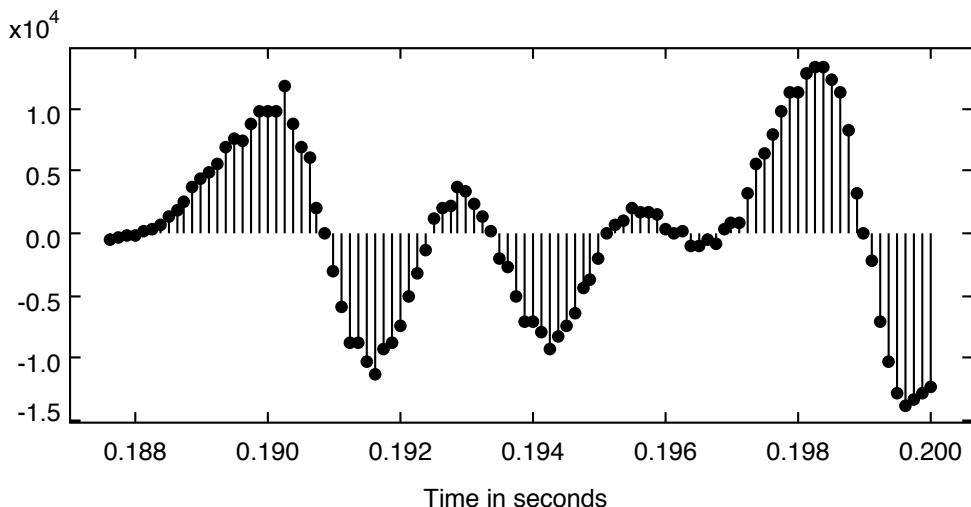


Figure 1.2: Discrete-time representation of a speech fragment.

The functions *Voice* and *ComputerVoice* of the previous examples are not easily defined by a mathematical expression that, given a value in the domain, provides a value in the codomain. We now consider an example where there is such an expression.

Example 1.10: The sound emitted by a precisely tuned and idealized 440 Hz tuning fork over the infinite time interval $\mathbb{R} = (-\infty, \infty)$ is the function

$$\text{PureTone}: \mathbb{R} \rightarrow \mathbb{R},$$

where the time-to-(normalized) pressure assignment is

$$\forall t \in \mathbb{R}, \quad \text{PureTone}(t) = P \sin(2\pi \times 440t).$$

(If the notation here is unfamiliar, see Appendix A.) Here, P is the **amplitude** of the sinusoidal signal *PureTone*. It is a real-valued constant. Figure 1.3 is a graph of a portion of this pure tone (showing only a subset of the domain, \mathbb{R}). In the figure, $P = 1$.

The number 440 in this example is the **frequency** of the sinusoidal signal shown in Figure 1.3, in units of **cycles per second** or **Hertz**, abbreviated **Hz**.[†] It simply asserts that the sinusoid completes 440 cycles per second. Alternatively, it completes one cycle in 1/440 seconds or about 2.3 milliseconds. The time to complete one cycle, 2.3 milliseconds, is called the **period**.

The *Voice* signal in Figure 1.1 is much more irregular than *PureTone* in Figure 1.3. An important theorem, which we will study in subsequent chapters, says that, despite its irregularity, a function like *Voice* is a sum of signals of the form of *PureTone*, but with different frequencies. A sum of two pure tones of frequencies, say 440 Hz and 660 Hz, is the function *SumOfTones*: $\mathbb{R} \rightarrow \mathbb{R}$ given by

$$\forall t \in \mathbb{R}, \quad \text{SumOfTones}(t) = P_1 \sin(2\pi \times 440t) + P_2 \sin(2\pi \times 660t)$$

Notice that summing two signals amounts to adding the values of their functions at each point in the domain. The two components are shown in Figure 1.4. At any point on

[†]The unit of frequency called Hertz is named after physicist Heinrich Rudolf Hertz (1857-94), for his research in electromagnetic waves.

the horizontal axis, the value of the sum is simply the addition of the values of the two components.

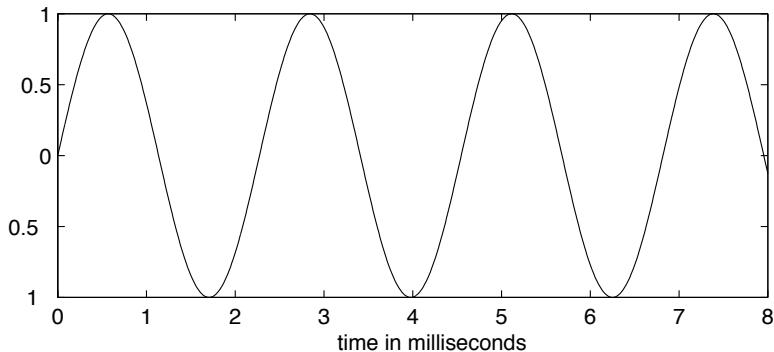


Figure 1.3: Portion of the graph of a pure tone with frequency 440 Hz.

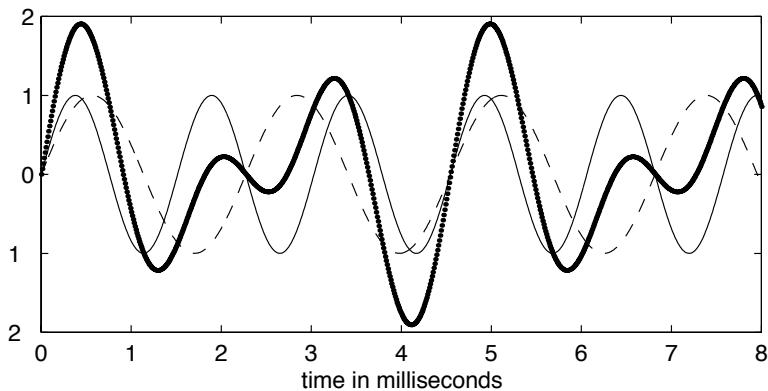


Figure 1.4: Sum of two pure tones (in bold), one at 440 Hz (dashed line) and the other at 660 Hz (solid line).

Probing Further: Household electrical power

In the U.S., household current is delivered on three wires, a **neutral wire** and two **hot wires**. The voltage between either hot wire and the neutral wire is around 110 to 120 volts, **RMS (root mean square**, the square root of the average of the voltage squared). The voltage between the two hot wires is around 220 to 240 volts, RMS. The higher voltage is used for appliances that need more power, such as air conditioners. The voltage between the hot wires and the neutral wire is sinusoidal with a frequency of 60 Hz. Thus, for one of the hot wires, it is a function $x: \mathbb{R} \rightarrow \mathbb{R}$ where the domain represents time and the range represents voltage, and

$$\forall t \in \mathbb{R}, \quad x(t) = 170 \cos(60 \times 2\pi t).$$

This 60 Hertz sinusoidal waveform completes one cycle in a period of $T = 1/60$ seconds. Why is the amplitude 170 volts, rather than 120? Because the 120 voltage is **RMS (root mean square)**. That is,

$$\text{voltage}_{\text{RMS}} = \sqrt{\frac{1}{T} \int_0^T x^2(t) dt} \text{ volts} = 120,$$

the square root of the average of the square of the voltage.

The voltage between the second hot wire and the neutral wire is a function $y: \mathbb{R} \rightarrow \mathbb{R}$ where

$$\forall t \in \mathbb{R}, \quad y(t) = -170 \cos(60 \times 2\pi t) = -x(t).$$

It is the negative of the other voltage at any time t . This sinusoidal signal is said to have a **phase shift** of 180 degrees, or π radians, compared to the first sinusoid. Equivalently, it is said to be 180 degrees **out of phase**. We can now see how to get the higher voltage for power-hungry appliances. We simply use the two hot wires rather than one hot wire and the neutral wire. The voltage between the two hot wires is the difference, a function $z: \mathbb{R} \rightarrow \mathbb{R}$ where

$$\forall t \in \mathbb{R}, \quad z(t) = x(t) - y(t) = 340 \cos(60 \times 2\pi t).$$

This corresponds to 240 volts RMS, as shown in figure 1.5.

Note that the neutral wire should not be confused with the ground wire in a three-prong plug. The ground wire is a safety feature to allow current to flow into the earth rather than through a person.

1.1.2 Images

If an image is a grayscale picture on a 11×8.5 inch sheet of paper, the picture is represented by a function

$$\text{Image}: [0, 11] \times [0, 8.5] \rightarrow [0, \text{MaxIntensity}], \quad (1.1)$$

where *MaxIntensity* is the maximum grayscale value (0 is black and *MaxIntensity* is white). The set $[0, 11] \times [0, 8.5]$ defines the space of the sheet of paper. More generally, a

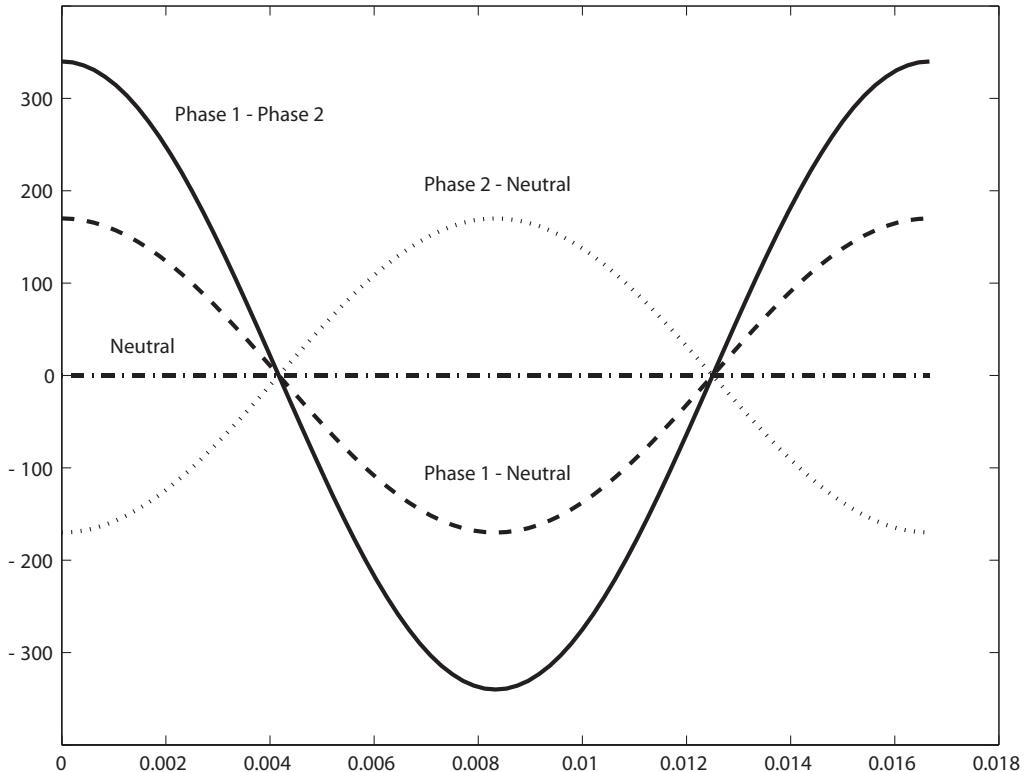


Figure 1.5: The voltages between the two hot wires and the neutral wire and between the two hot wires in household electrical power in the U.S.

grayscale image is a function

$$\boxed{\text{Image} : \text{VerticalSpace} \times \text{HorizontalSpace} \rightarrow \text{Intensity}},$$

where $\text{Intensity} = [0, \text{MaxIntensity}]$ is the intensity range from *black* to *white*. An example is shown in Figure 1.6.

For a color picture, the reflected light is sometimes measured in terms of its **RGB** values (i.e. the magnitudes of the red, green, and blue colors), and so a color picture is represented by a function

$$\boxed{\text{ColorImage} : \text{VerticalSpace} \times \text{HorizontalSpace} \rightarrow \text{Intensity}^3}.$$

The RGB values assigned by *ColorImage* at any point (x, y) in its domain is the triple $(r, g, b) \in \text{Intensity}^3$ given by

$$(r, g, b) = \text{ColorImage}(x, y).$$

Different images will be represented by functions with different spatial domains (the size of the image might be different), different ranges (we may consider a more or less detailed



Figure 1.6: Grayscale image on the left, and its enlarged pixels on the right.

way of representing light intensity and color than grayscale or RGB values), and different assignments of color values to points in the domain.

Since a computer has finite memory and finite wordlength, an image is stored by discretizing both the domain and the range, similarly to the *ComputerVoice* function. So, for example, your computer may represent an image by storing a function of the form

$$\begin{aligned} \text{ComputerImage:} \\ \text{DiscreteVerticalSpace} \times \text{DiscreteHorizontalSpace} \rightarrow \text{Integers8} \end{aligned}$$

where

$$\begin{aligned} \text{DiscreteVerticalSpace} &= \{1, 2, \dots, 300\}, \\ \text{DiscreteHorizontalSpace} &= \{1, 2, \dots, 200\}, \text{ and} \\ \text{Integers8} &= \{0, 1, \dots, 255\}. \end{aligned}$$

It is customary to say that *ComputerImage* stores 300×200 pixels, where a **pixel** is an individual picture element. The value of a pixel is

$$\text{ComputerImage}(row, column) \in \text{Integers8},$$

where $row \in \text{DiscreteVerticalSpace}$, $column \in \text{DiscreteHorizontalSpace}$. In this example the range *Integers8* has 256 elements, so in the computer these elements can be represented by an 8-bit integer (hence the name of the range, *Integers8*). An example of such an image is shown in Figure 1.6, where the right-hand version of the image is magnified to show the discretization implied by the individual pixels.

A computer can store a color image in one of two ways. One way is to represent it as a function

$$\begin{aligned} \text{ColorComputerImage:} \\ \text{DiscreteVerticalSpace} \times \text{DiscreteHorizontalSpace} \rightarrow \text{Integers8}^3 \end{aligned} \quad (1.2)$$

so each pixel value is an element of $\{0, 1, \dots, 255\}^3$. Such a pixel can be represented as three 8-bit integers. A common method that saves memory is to use a **colormap**. Define the set *ColorMapIndexes* = $\{0, \dots, 255\}$, together with a *Display* function,

$$\text{Display: ColorMapIndexes} \rightarrow \text{Intensity}^3. \quad (1.3)$$

Display assigns to each element of *ColorMapIndexes* the three (r, g, b) color intensities. This is depicted in the block diagram in Figure 1.7. Use of a colormap reduces the required memory to store an image by a factor of three because each pixel is now represented by a single 8-bit number. But only 256 colors can be represented in any given image. The function *Display* is typically represented in the computer as a lookup table.

Probing Further: Color and light

The human eye is sensitive to electromagnetic waves of certain frequency. The frequency f in Hertz of a purely sinusoidal electromagnetic wave is related to its *wavelength* λ in meters by the formula, $f = c/\lambda$, where c is the speed of light (about 3×10^8 meters/second). The wavelengths of visible light range from about 350-400 nm (nanometers or 10^{-9} meters) to 750-800 nm. We experience light of different wavelengths as having different colors: violet (350 nm), indigo, blue, green, yellow, orange, red (800 nm).

The retina has three different groups of cones, each sensitive to one of the three primary colors—red, green, and blue. Other colors are perceived when these three groups are stimulated in different combinations, as shown below:



By combining its red, green, and blue light sources in different amounts, a computer monitor can create the perception of all colors. The color white is obtained by adding all three primary colors, and the absence of any light is perceived as black. This “additive” model of color perception was proposed in 1802 by Thomas Young and H.L.F. Helmholtz.

In a computer, if the amount of each primary color is typically represented by an 8-bit word, and each color is represented by three 8-bit words, giving a total of $2^8 \times 2^8 \times 2^8 = 2^{24} = 16,777,216$ different colors. An 8-bit colormap by contrast can only generate 256 different colors.

Painting works by subtraction: different pigments of color absorb (subtract) light of different wavelengths. The primary subtractive colors are magenta, yellow, and cyan.

The ear and eye are quite different perceptual systems. If we listen to a sound consisting of the sum of two pure tones, we can distinguish the two tones. However, we cannot perceive the difference between, say, a yellow light source and an appropriate combination of red and green sources. The ear can be modeled as a [linear time-invariant system](#), see Chapter 5. The eye cannot.

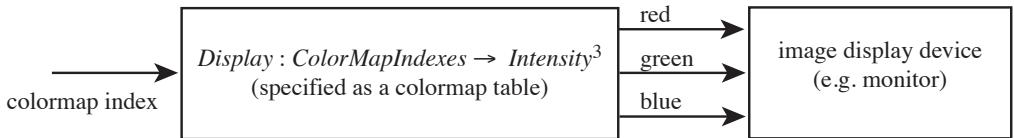


Figure 1.7: In a computer representation of a color image that uses a colormap, pixel values are elements of the set *ColorMapIndexes*. The function *Display* converts these indexes to an RGB representation.

1.1.3 Video signals

A **video** is a sequence of still images displayed at a certain rate (frequency) ranging from 25 frames per second to much higher (for specialty video). To the human visual system, a sequence of still images displayed at a high enough rate looks like continuous motion.

At 30 frames per second, the domain of a video signal is discrete time, $\text{FrameTimes} = \{0, 1/30, 2/30, \dots\}$, and its range is a set of images, ImageSet . A video signal, therefore, is a function

$$\text{Video} : \text{FrameTimes} \rightarrow \text{ImageSet}. \quad (1.4)$$

For any time $t \in \text{FrameTimes}$, the image $\text{Video}(t) \in \text{ImageSet}$ is displayed. The signal *Video* is illustrated in Figure 1.8.

An alternative way of specifying a video signal is by the function *Video'* whose domain is a product set as follows:

$$\text{Video}' : \text{FrameTimes} \times \text{DiscreteVerticalSpace} \times \text{HorizontalSpace} \rightarrow \text{Intensity}^3.$$

Similarly to Figure 1.8, we can depict *Video'* as in Figure 1.9. The RGB value assigned to a point (x, y) at time t is

$$(r, g, b) = \text{Video}'(t, x, y). \quad (1.5)$$

If the signals specified in (1.4) and (1.5) represent the same video, then for all $t \in \text{FrameTimes}$ and $(x, y) \in \text{DiscreteVerticalSpace} \times \text{HorizontalSpace}$,

$$(\text{Video}(t))(x, y) = \text{Video}'(t, x, y). \quad (1.6)$$

It is worth pausing to understand the notation used in (1.6). *Video* is a function of t , so $\text{Video}(t)$ is an element in its range *ImageSet*. Since elements in *ImageSet* themselves are functions, $\text{Video}(t)$ is a function. The domain of $\text{Video}(t)$ is the product set *DiscreteVerticalSpace* \times *HorizontalSpace*, so $(\text{Video}(t))(x,y)$ is the value of this function at the point (x,y) in its domain. This value is an element of *Intensity*³. On the right-hand side of (1.6), Video' is a function of (t,x,y) and so $\text{Video}'(t,x,y)$ is an element in its range, *Intensity*³. The equality (1.6) asserts that for all values of t,x,y the two sides are the same. On the left-hand side of (1.6) the parentheses enclosing $\text{Video}(t)$ are not necessary; we could equally well write $\text{Video}(t)(x,y)$. However, the parentheses improve readability.

1.1.4 Signals representing physical attributes

The change over time in the attributes of a physical object or device can be represented as functions of time or space.

Example 1.11: The position of an airplane can be expressed as

$$\text{Position: Time} \rightarrow \mathbb{R}^3,$$

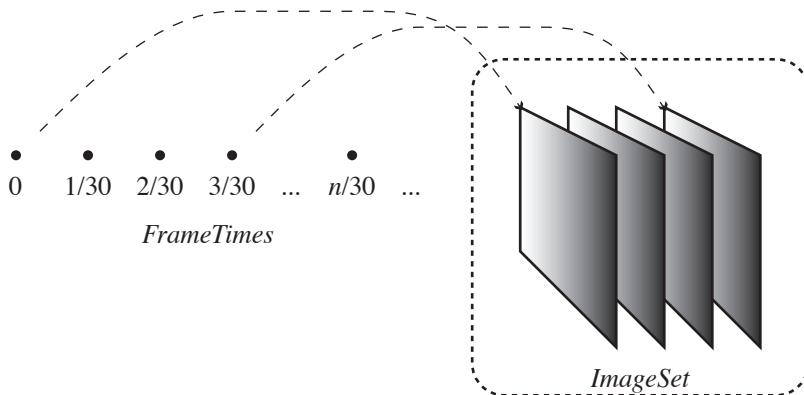
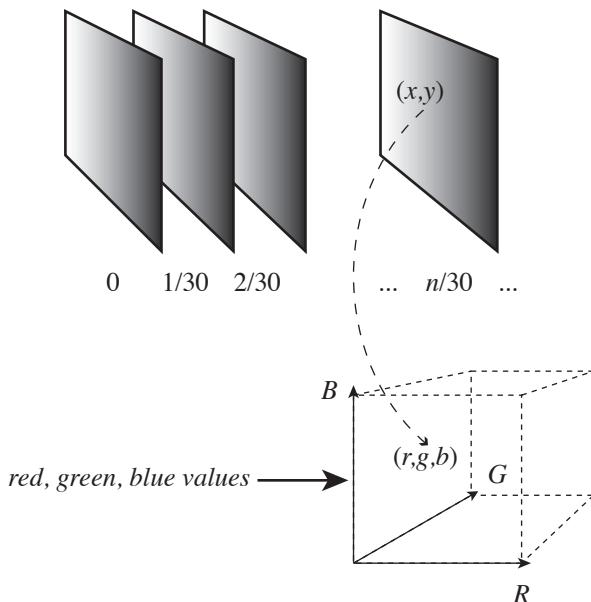


Figure 1.8: Illustration of the function *Video*.

Figure 1.9: Illustration of the function Video' .

where for all $t \in \text{Time}$,

$$\text{Position}(t) = (x(t), y(t), z(t))$$

is its position in 3-dimensional space at time t . The position and velocity of the airplane is a function

$$s: \text{Time} \rightarrow \mathbb{R}^6, \quad (1.7)$$

where

$$s(t) = (x(t), y(t), z(t), v_x(t), v_y(t), v_z(t)) \quad (1.8)$$

gives its position and velocity at $t \in \text{Time}$.

The position of the pendulum shown in the left panel of figure 1.10 is represented by the function

$$\theta: \text{Time} \rightarrow [-\pi, \pi],$$

where $\theta(t)$ is the angle with the vertical made by the pendulum at time t .

The position of the upper and lower arms of a robot depicted in the right panel of Figure 1.10 can be represented by the function

$$(\theta_u, \theta_l) : \text{Time} \rightarrow [-\pi, \pi]^2,$$

where $\theta_u(t)$ is the angle at the elbow made by the upper arm with the vertical, and $\theta_l(t)$ is the angle made by the lower arm with the upper arm at time t . Note that we can regard (θ_u, θ_l) as a single function with range as the product set $[-\pi, \pi]^2$ or as two functions θ_u and θ_l each with range $[-\pi, \pi]$. Similarly, we can regard s in (1.7) as a single function with range \mathbb{R}^6 or as a collection of six functions, each with range \mathbb{R} , as suggested by (1.8).

Example 1.12: The spatial variation of temperature over some volume of space can be represented by a function

$$\text{AirTemp} : X \times Y \times Z \rightarrow \mathbb{R}$$

where $X \times Y \times Z \subset \mathbb{R}^3$ is the volume of interest, and $\text{AirTemp}(x, y, z)$ is the temperature at the point (x, y, z) .

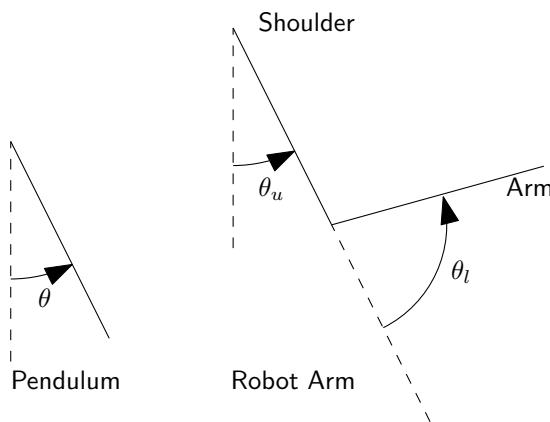


Figure 1.10: Position of a pendulum and upper and lower arms of a robot.

1.1.5 Sequences

Above we studied examples in which temporal or spatial information is represented by functions of a variable representing time or space. The domain of time or space may be continuous as in *Voice* and *Image* or discrete as in *ComputerVoice* and *ComputerImage*.

In many situations, information is represented as **sequences** of symbols rather than as functions of time or space. These sequences occur in two ways: as a representation of **data** or as a representation of an **event stream**. Sequences, in fact, are special sorts of functions.

Examples of data represented by sequences are common. A file stored in a computer in binary form is a sequence of bits, or binary symbols, i.e. a sequence of 0's and 1's. A text is a sequence of words. A sheet of music represents a sequence of notes.

Example 1.13: Consider an N -bit long binary file,

$$b_1, b_2, \dots, b_N,$$

where each $b_i \in \text{Binary} = \{0, 1\}$. We can regard this file as a function

$$\text{File}: \{1, 2, \dots, N\} \rightarrow \text{Binary},$$

with the assignment $\text{File}(n) = b_n$ for every $n \in \{1, \dots, N\}$.

Sometimes we can give a mathematical expression for a binary signal. For instance, the N -bit long binary file *Alt* consisting of an alternating sequence of 0's and 1's is given by for all n ,

$$\text{Alt}(n) = \begin{cases} 0, & n \text{ even} \\ 1, & n \text{ odd} \end{cases}$$

If instead of *Binary* we take the range to be *EnglishWords*, then an N -word long English text is a function

$$\text{EnglishText}: \{1, 2, \dots, N\} \rightarrow \text{EnglishWords}.$$

In general, data sequences are functions of the form

$$\boxed{\text{Data: Indices} \rightarrow \text{Symbols},} \quad (1.9)$$

where $\text{Indices} \subset \mathbb{N}$, where \mathbb{N} is the set of natural numbers, is an appropriate index set such as $\{1, 2, \dots, N\}$, and Symbols is an appropriate set of symbols such as *Binary* or *EnglishWords*.

One advantage of the representation (1.9) is that we can then interpret *Data* as a discrete-time signal, and so some of the techniques that we will develop in later chapters for those signals will automatically apply to data sequences. However, the domain *Indices* in (1.9) does not necessarily represent uniformly spaced instances of time. All we can say is that if m and n are in *Indices* with $m < n$, then the m -th symbol $\text{Data}(m)$ occurs in the data sequence *before* the n -th symbol $\text{Data}(n)$, but we cannot say how much time elapses between the occurrence of those two symbols.

The second way in which sequences arise is as representations of event streams. An **event stream** or **event trace** is a record or log of the significant events that occur in a system of interest. Here are some everyday examples.

Example 1.14: When you send a file to a printer, the normal trace of events is

CommandPrintFile, FilePrinting, PrintingComplete

but if the printer has run out of paper, the trace might be

CommandPrintFile, FilePrinting, MessageOutofPaper, InsertPaper, …

When you enter your car the starting trace of events might be

StartEngine, SeatbeltSignOn, BuckleSeatbelt, SeatbeltSignOff, …

Thus event streams are functions of the form

$$\boxed{\text{EventStream: Indices} \rightarrow \text{EventSet}.}$$

We will see in Chapter 3 that the behavior of finite state machines is best described in terms of event traces, and that systems that operate on event streams are often best described as finite state machines.

1.1.6 Discrete signals and sampling

Voice and *PureTone* are said to be continuous-time signals because their domain *Time* is a continuous interval of the form $[\alpha, \beta] \subset \mathbb{R}$. The domain of *Image*, similarly, is a continuous 2-dimensional rectangle of the form $[a, b] \times [c, d] \subset \mathbb{R}^2$. The signals *ComputerVoice* and *ComputerImage* have domains of time and space that are discrete sets. *Video* is also a discrete-time signal, but in principle it could be a function of a space continuum. We can define a function *ComputerVideo* where all three sets that are composed to form the domain are discrete.

Discrete signals often arise from signals with continuous domains by **sampling**. We briefly motivate sampling here, with a detailed discussion to be taken up later. Continuous domains have an infinite number of elements. Even the domain $[0, 1] \subset \text{Time}$ representing a finite time interval has an infinite number of elements. The signal assigns a value in its range to each of these infinitely many elements. Such a signal cannot be stored in a finite digital memory device such as that in a computer. If we wish to store, say, *Voice*, we must approximate it by a signal with a finite domain.

A common way to approximate a function with a continuous domain like *Voice* and *Image* by a function with a finite domain is by uniformly sampling its continuous domain.

Example 1.15: If we sample a 10-second long domain of *Voice*,

$$\text{Voice} : [0, 10] \rightarrow \text{Pressure},$$

10,000 times a second (i.e. at a frequency of 10 kHz) we get the signal

$$\text{SampledVoice} : \{0, 0.0001, 0.0002, \dots, 9.9998, 9.9999, 10\} \rightarrow \text{Pressure}, \quad (1.10)$$

with the assignment

$$\begin{aligned} \text{SampledVoice}(t) &= \text{Voice}(t), \\ \text{for all } t &\in \{0, 0.0001, 0.0002, \dots, 9.9999, 10\}. \end{aligned} \quad (1.11)$$

Notice from (1.10) that uniform sampling means picking a uniformly spaced subset of points of the continuous domain $[0, 10]$.

In the example, the **sampling interval** or **sampling period** is 0.0001 sec, corresponding to a **sampling frequency** or **sampling rate** of 10,000 Hz. Since the continuous domain is 10 seconds long, the domain of *SampledVoice* has 100,000 points. A sampling frequency of 5,000 Hz would give the domain $\{0, 0.0002, \dots, 9.9998, 10\}$, which has half as many points. The sampled domain is finite, and its elements are discrete values of time.

Figure 1.11 shows an exponential function $Exp: [-1, 1] \rightarrow \mathbb{R}$ defined by

$$Exp(x) = e^x.$$

SampledExp is obtained by sampling with a sampling interval of 0.2. So its domain is

$$\{-1, -0.8, \dots, 0.8, 1.0\}.$$

The continuous domain of *Image* given by (1.1), which describes a grayscale image on an 8.5 by 11 inch sheet of paper, is the rectangle $[0, 11] \times [0, 8.5]$, representing the space of

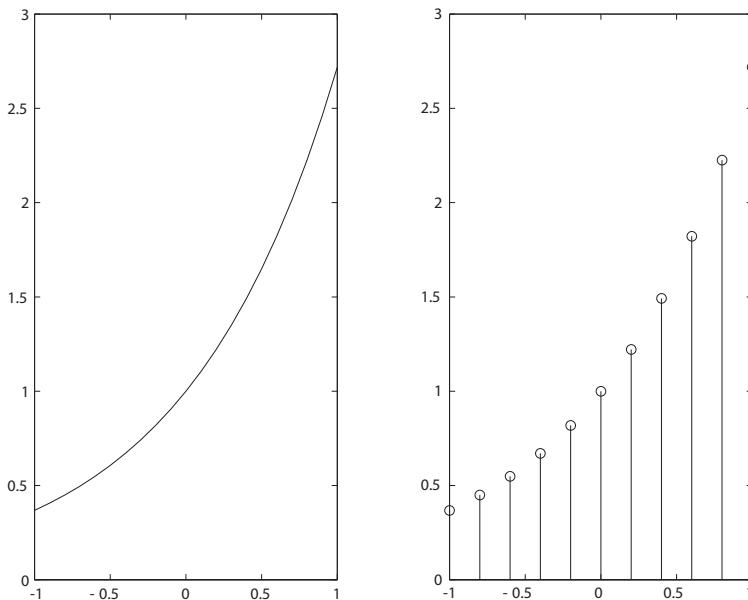


Figure 1.11: The exponential functions Exp and $SampledExp$, obtained by sampling with a sampling interval of 0.2.

the page. In this case, too, a common way to approximate *Image* by a signal with finite domain is to sample the rectangle. Uniform sampling with a **spatial resolution** of say, 100 dots per inch, in each dimension, gives the finite domain $D = \{0, 0.01, \dots, 8.49, 8.5\} \times \{0, 0.01, \dots, 10.99, 11.0\}$. So the sampled grayscale picture is

$$\text{SampledImage}: D \rightarrow [0, \text{MaxIntensity}]$$

with

$$\text{SampledImage}(x, y) = \text{Image}(x, y), \text{ for all } (x, y) \in D.$$

As mentioned before, each sample of the image is called a **pixel**, and the size of the image is often given in pixels. The size of your computer screen display, for example, may be 600×800 or 768×1024 pixels.

Sampling and approximation

Let f be a continuous-time function, and let *Sampledf* be the discrete-time function obtained by sampling f . Suppose we are given *Sampledf*, as, for example, in the left panel of Figure 1.12. Can we reconstruct or recover f from *Sampledf*? This question lies at the heart of digital storage and communication technologies. The general answer to this question tells us, for example, what audio quality we can obtain from a given discrete representation of a sound. The format for a compact disc is based on the answer to this question. We will discuss it in much detail in later chapters.

For the moment, let us note that the short answer to the question above is no. For example, we cannot tell whether the discrete-time function in the left panel of Figure 1.12 was obtained by sampling the continuous-time function in the middle panel or the function in the right panel. Indeed there are infinitely many such functions, and one must make a choice. One option is to connect the sampled values by straight line segments, as shown in the middle panel. Another choice is shown in the right panel. The choice made by your CD player is different from both of these, as explored further in Chapter 11.

Similarly, an image like *Image* cannot be uniquely recovered from its sampled version *SampledImage*. Several different choices are commonly used.

Digital signals and quantization

Even though *SampledVoice* in example 1.15 has a finite domain, we may yet be unable to store it in a finite amount of memory. To see why, suppose that the range *Pressure*

of the function *SampledVoice* is the continuous interval $[a, b]$. To represent every value in $[a, b]$ requires infinite **precision**. In a computer, where data are represented digitally as finite collections of bits, such precision would require an infinite number of bits for just one sample. But a finite digital memory has a finite wordlength in which we can store only a finite number of values. For instance, if a word is 8 bits long, it can have $2^8 = 256$ different values. So we must approximate each number in the range $[a, b]$ by one of 256 values. The most common approximation method is to **quantize** the signal. A common approach is to choose 256 uniformly-spaced values in the range $[a, b]$, and to approximate each value in $[a, b]$ by the one of these 256 values that is closest. An alternative approximation, called **truncation**, is to choose the largest of the 256 values that is less than or equal to the desired value.

Example 1.16: Figure 1.13 shows a *PureTone* signal, *SampledPureTone* obtained after sampling, and a quantized *DigitalPureTone* obtained using 4-bit or 16-

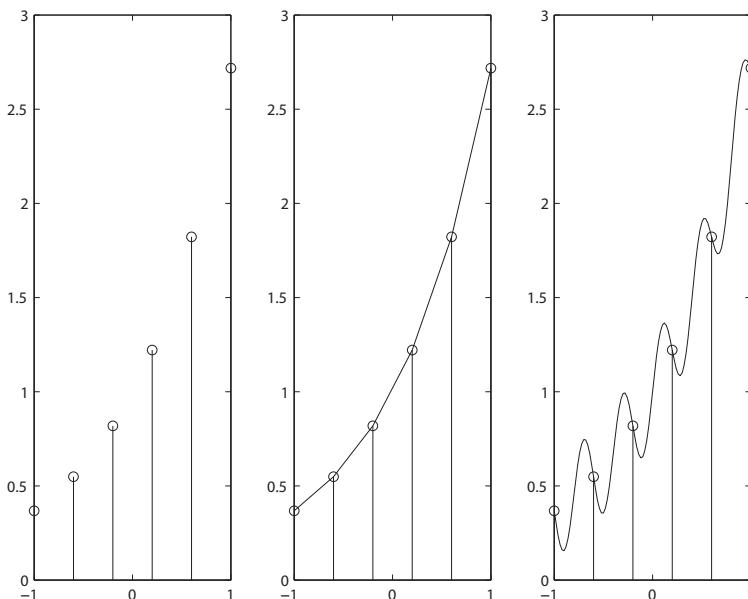


Figure 1.12: The discrete-time signal on the left is obtained by sampling the continuous-time signal in the middle or the one on the right.

level truncation. *PureTone* has continuous domain and continuous range, while *SampledPureTone* (depicted with circles) has discrete domain and continuous range, and *DigitalPureTone* (depicted with x's) has discrete domain and discrete range. Only the last of these can be precisely represented on a computer.

It is customary to call a signal with continuous domain and continuous range like *PureTone* an **analog signal**, and a signal with discrete domain and range, like *DigitalPureTone*, a **digital signal**.

Example 1.17: In digital telephones, voice is sampled every $125\mu\text{sec}$, or at a sampling frequency of 8,000 Hz. Each sample is quantized into an 8-bit word, or 256 levels. This gives an overall rate of $8,000 \times 8 = 64,000$ bits per second. The

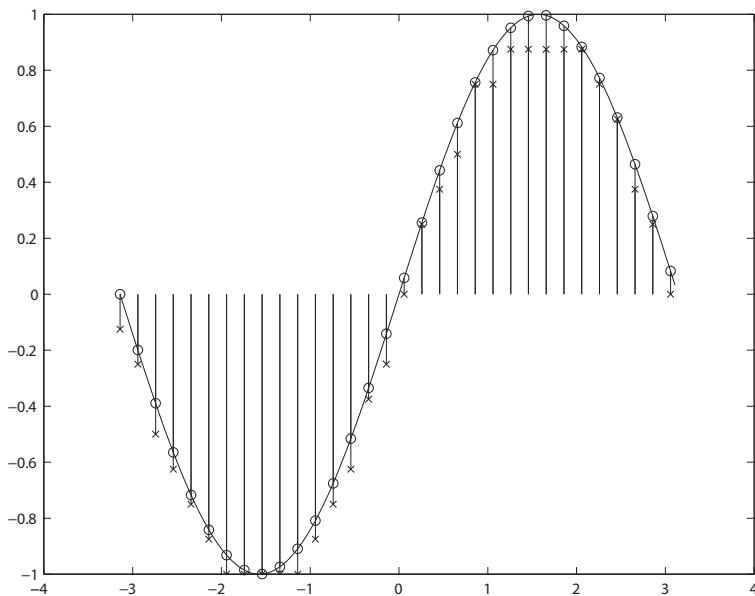


Figure 1.13: *PureTone* (continuous curve), *SampledPureTone* (circles), and *DigitalPureTone* signals (x's).

worldwide digital telephony network, therefore, is composed primarily of channels capable of carrying 64,000 bits per second, or multiples of this (so that multiple telephone channels can be carried together). In cellular phones, voice samples are further compressed to bit rates of 8,000 to 32,000 bits per second.

1.2 Systems

Systems are functions that transform signals. There are many reasons for transforming signals. A signal carries information. A transformed signal may carry the same information in a different way. For example, in a live concert, music is represented as sound. A recording system may convert that sound into a sequence of numbers stored on a magnetic disk drive. The original signal, the sound, is difficult to preserve for posterity. The disk has a more persistent representation of the same information. Thus, **storage** is one of the tasks accomplished by systems.

A system may transform a signal into a form that is more convenient for **transmission**. Sound signals cannot be carried by the Internet. There is simply no physical mechanism in the Internet for transporting rapid variations in air pressure. The Internet provides instead a mechanism for transporting sequences of bits. A system must convert a sound signal into a sequence of bits. Such a system is called an **encoder** or **coder**. At the far end, a **decoder** is needed to convert the sequence back into sound. When a coder and a decoder are combined into the same physical device, the device is often called a **codec**.

A system may transform a signal to hide its information so that snoops do not have access to it. This is called **encryption**. To be useful, we need matching **decryption**.

A system may **enhance** a signal by emphasizing some of the information it carries and deemphasizing some other information. For example, an **audio equalizer** may compensate for poor room acoustics by reducing the magnitude of certain low frequencies that happen to resonate in the room. In transmission, signals are often degraded by **noise** or distorted by physical effects in the transmission medium. A system may attempt to reduce the noise or reverse the distortion. When the signal is carrying digital information over a physical channel, the extraction of the digital information from the degraded signal is called **detection**.

Systems are also designed to **control** physical processes such as the heating in a room, the ignition in an automobile engine, the flight of an aircraft. The state of the physical process (room temperature, cylinder pressure, aircraft speed) is sensed. The sensed signal is processed to generate signals that drive actuators, such as motors or switches. Engineers design a system called the **controller** which, on the basis of the processed sensor signal, determines the signals that control the physical process (turn the heater on or off, adjust the ignition timing, change the aircraft flaps) so that the process has the desired behavior (room temperature adjusts to the desired setting, engine delivers more torque, aircraft descends smoothly).

Systems are also designed for **translation** from one format to another. For example, a command sequence from a musician may be transformed into musical sounds. Or the detection of risk of collision in an aircraft might be translated into control signals that perform evasive maneuvers.

1.2.1 Systems as functions

Consider a system S that transforms input signal x into output signal y . The system is a function, so $y = S(x)$. Suppose $x: D \rightarrow R$ is a signal with domain D and range R . For example, x might be a sound, $x: \mathbb{R} \rightarrow Pressure$. The domain of S is the set X of all such sounds, which we write

$$X = [D \rightarrow R] = \{x \mid x: D \rightarrow R\} \quad (1.12)$$

This notation reads “ X , also written $[D \rightarrow R]$, is the set of all x such that x is a function from D to R .” This set is called a **signal space** or **function space**. A signal or function space is a set of all functions with a given domain and range.

Example 1.18: The set of all sound segments with duration $[0,1]$ and range *Pressure* is written

$$[[0, 1] \rightarrow Pressure].$$

Notice that square brackets are used for both a subset of reals, as in $[0, 1]$, and for a function space, as in $[D \rightarrow R]$, although obviously the meanings of these two notations are very different.

The set *ImageSet* considered in section 1.1.3 is the function space

$$\text{ImageSet} = [\text{DiscreteVerticalSpace} \times \text{HorizontalSpace} \rightarrow \text{Intensity}^3].$$

Since this is a set, we can define functions that use it as a domain or range, as we have done above with

$$\text{Video}: \text{FrameTimes} \rightarrow \text{ImageSet}.$$

Similarly, the set of all binary files of length N is

$$\text{BinaryFiles} = [\text{Indices} \rightarrow \text{Binary}].$$

where $\text{Indices} = \{1, \dots, N\}$.

A system S is a function mapping a signal space into a signal space,

$$S: [D \rightarrow R] \rightarrow [D' \rightarrow R'].$$

Systems, therefore, are much like signals, except that their domain and range are both signal spaces. Thus, if $x \in [D \rightarrow R]$ and $y = S(x)$, then it must be that $y \in [D' \rightarrow R']$. Furthermore, if z is an element of D' , $z \in D'$, then

$$y(z) = S(x)(z) = (S(x))(z) \in R'.$$

The parentheses around $S(x)$ in $(S(x))(z)$ are not necessary, but may improve readability.

1.2.2 Telecommunications systems

We give some examples of systems that occur in or interact with the global telecommunications network. This network is unquestionably one of the most remarkable accomplishments of humankind. It is astonishingly complex, composed of hundreds of distinct corporations and linking billions of people. It originated with a basic service, **POTS**, or plain-old telephone service, but the network has evolved into a global, high-speed, wireless and wired digital network that carries not just voice, but also video, images, and computer data, including much of the traffic in the Internet.

Figure 1.14 depicts a small portion of the global telecommunications network. POTS service is represented at the upper right, where a **twisted pair** of copper wires connects a central office to a home telephone. This twisted pair is called the **local loop** or **subscriber line**. At the central office, the twisted pair is connected to a **line card**, which usually converts the signal from the telephone immediately into digital form. The line card, in turn, is

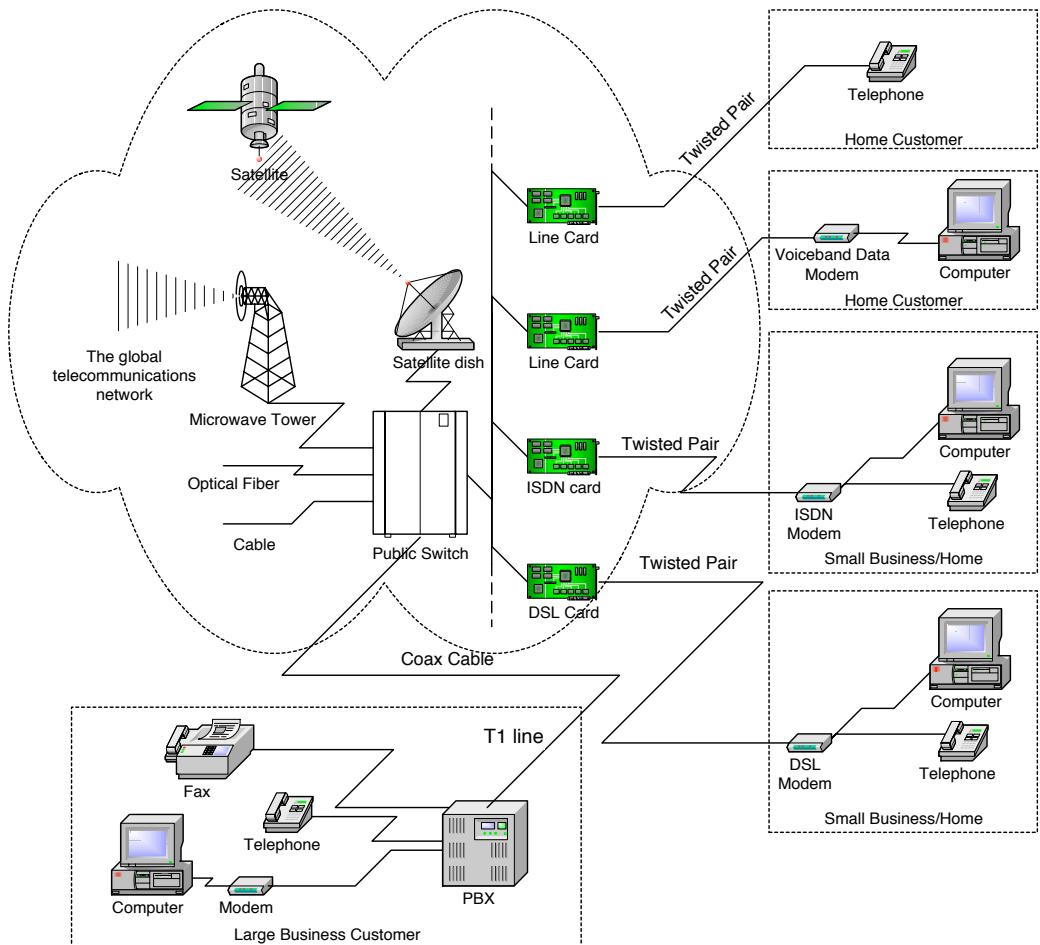


Figure 1.14: A portion of the global telecommunications network.

connected to a **switch**, which routes incoming and outgoing telephone connections. The Berkeley central office is located on Bancroft, between Oxford and Shattuck.

The digital representation of a voice signal, a sequence of bits, is routed through the telephone network. Usually it is combined with other bit sequences, which are other voices or computer data, and sent over high-speed links implemented with optical fiber, microwave radio, coaxial cable, or satellites.

Of course, a telephone conversation usually involves two parties, so the network delivers to the same line card a digital sequence representing the far-end speaker. That digital sequence is decoded and delivered to the telephone via the twisted pair. The line card, therefore, includes a codec.

The telephone itself, of course, is a system. It transforms the electrical signal that propagates down the twisted pair into a sound signal, and transforms a local sound signal into an electrical signal that can propagate down the twisted pair.

POTS can be abstracted as shown in Figure 1.15. The entire network is reduced to a model that accepts an electrical representation of a voice signal and transports it to a remote telephone. In this abstraction, the digital nature of the telephone network is irrelevant. The system simply transports (and degrades somewhat) a voice signal.

DTMF

Even in POTS, not all of the information transported is voice. At a minimum, the telephone needs to be able to convey to the central office a telephone number in order to

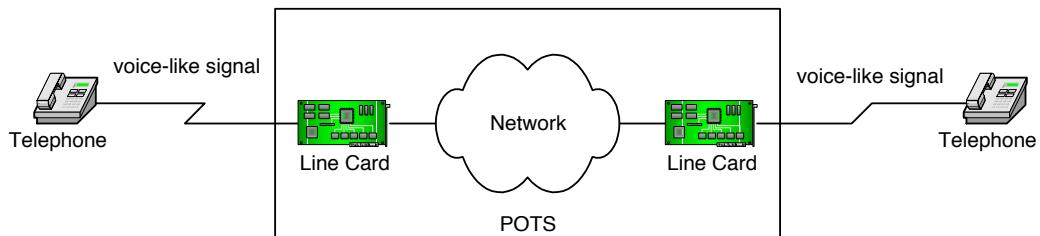


Figure 1.15: Abstraction of plain-old telephone service (POTS).

Probing Further: Wireless communication

The telephone network has been steadily freeing itself of its dependence on wires. **Cellular telephones**, which came into widespread use in the 1990s, use radio waves to connect a small, hand-held telephone to a nearby **base station**. The base station connects directly to the telephone network.

There are three major challenges in the design of cellular networks. First, radio spectrum is scarce. Frequencies are allocated by regulatory bodies, often constrained by international treaties. Finding frequencies for new technologies is difficult. Thus, wireless communication devices have to be efficient in their use of the available frequencies. Second, the power available to drive a cellular phone is limited. Cellular phones must operate for long periods of time using only small batteries that fit easily within the handset. Although battery technology has been improving, the power that these batteries can deliver severely limits the range of a cellular phone (how far it can be from a base station) and the processing complexity (the microprocessors in a cellular phone consume considerable power). Third, networking is complicated. In order to be able to route telephone calls to a cellular phone, the network needs to know where the phone is (which base station is closest). Moreover, the network needs to support phone calls in moving vehicles, which implies that a phone may move out of range of one base station and into the range of another during the course of a telephone call. The network must **hand off** the call seamlessly.

Although “radio telephones” have existed for a long time, particularly for maritime applications where wireline telephony is impossible, it was the cellular concept that made it possible to offer radio telephony to large numbers of users. Radio waves propagating along the surface of the earth lose power approximately proportionally to the inverse of the fourth power of distance. That is, if at distance d meters from a transmitter you receive w watts of radio power, then at distance $2d$ you will receive approximately $w/2^4 = w/16$ watts of radio power. This fourth-power propagation loss was traditionally considered to be a hindrance to wireless communication. It had to be overcome by boosting the transmitted power. The cellular concept turns this hindrance into an advantage. It observes that since the loss is so high, beyond a certain distance the same frequencies can be re-used without significant interference. The service area is divided into cells. A second benefit is that the distance to base station is smaller than it would be in a more centralized system, so less radio power is required.

establish a connection. A telephone number is not a voice signal. It is intrinsically discrete. Since the system is designed to carry voice signals, one option is to convert the

Probing Further: LEO telephony

Ideally, a cellular phone, with its one phone number, could be called anywhere in the world, wherever it happens to be, without the caller needing to know where it is. The technological and organizational infrastructure has evolved to make this possible in most places. When a phone “roams” out of its primary service area, it negotiates with the local service provider in a new area for service. If that service provider has a business agreement with the customer’s main service provider, then it provides service. This requires complex networking so that telephone calls to the customer are routed to the correct locale.

However, digital cellular service is difficult to make universal, with many remote areas not served. Providing such service by installing base stations is expensive. Moreover, marine service away from coastlines is technically impossible with cellular technology.

One candidate technology for truly global telephony services is based on low-earth-orbit (**LEO**) satellites. One such project (which failed in the marketplace) was the Iridium project, spearheaded by Motorola, and so named because in the initial conception, there would be 77 satellites. The iridium atom has 77 electrons. The idea is that enough satellites are put into orbit that one is always near enough to communicate with a hand-held telephone. When the orbit is low enough that a hand-held telephone can reach the satellite (a few hundred kilometers above the surface of the earth), the satellites move by fairly quickly. As a consequence, during the course of a telephone conversation, the connection may have to be handed off from one satellite to another. In addition, in order to be able to serve enough users simultaneously, each satellite has to re-use frequencies according to the cellular concept. To do that, it focuses multiple beams on the surface of the earth using multi-element antenna arrays.

As of this writing, this approach has not yet proved economically viable. The investment already has been huge, with at least one high-profile bankruptcy already, so the risks are high. Better networking of terrestrial cellular services may provide formidable competition, particularly as service improves to rural areas. The LEO approach, however, has one advantage that terrestrial services cannot hope to match anytime soon: truly worldwide service. The satellites provide service essentially everywhere, even in remote wilderness areas and at sea.

telephone number into a voice-like signal. A system is needed with the structure shown in Figure 1.16. The block labeled “DTMF” is a system that transforms a sequence of numbers (coming from the keypad on the left) into a voice-like signal.

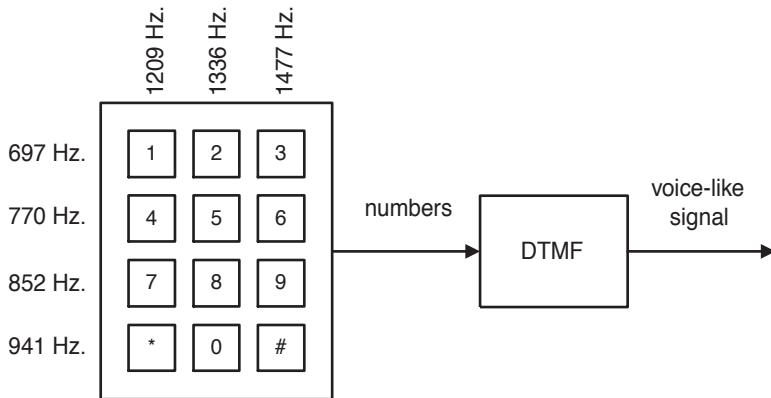


Figure 1.16: DTMF converts numbers from a keypad into a voice-like signal.

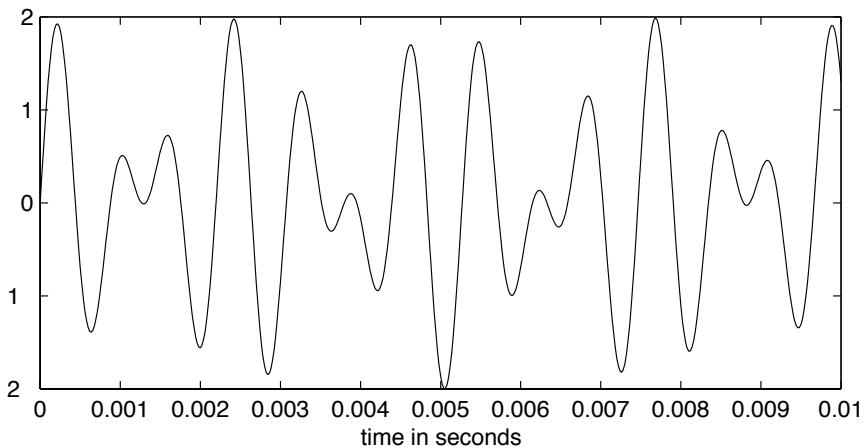


Figure 1.17: Waveform representing the “0” key in DTMF.

The **DTMF** standard—dual-tone, multi-frequency—provides precisely such a mechanism. As indicated at the left in the figure, when the customer pushes one of the buttons on the telephone keypad, a sound is generated that is the sum of two sinusoidal signals. The frequencies of the two sinusoids are given by the row and column of the key. For example, a “0” is represented as a sum of two sinusoids with frequencies 941 Hz and 1336 Hz. The waveform for such a sound is shown in Figure 1.17. The line card in the central office measures these frequencies to determine which digit was dialed.

Signal degradation

A voice received via the telephone network is different from the original in several respects. These differences can be modeled by a system that degrades the voice signal.

First, there is a loss of information because of sampling and quantization in the encoder, as discussed in the section 1.1.6. Moreover, the media that carry the signal, such as the twisted pair, are not perfect. They distort the signal. One cause of distortion is addition of **noise** to the signal. Noise, by definition, is any undesired component in the signal. Noise in the telephone network is sometimes audible as background hiss, or as **crosstalk**, i.e., leakage from other telephone channels into your own. Another degradation is that the medium attenuates the signal, and this attenuation depends on the signal frequency. The line card, in particular, usually contains a **bandlimiting filter** that discards the high frequency components of the signal. This is why telephone channels do not transport music well. Finally, the signal propagates over a physical medium at a finite speed, bounded by the speed of light, and so there is a delay between the time you say something and the time when the person at the other end hears what you say. Light travels through 1 km of optical fiber in approximately $5 \mu\text{s}$, so the 5,000 km between Berkeley and New York causes a delay of about 25 ms, which is not easily perceptible.[‡]

[‡] A phone conversation relayed by satellite has a much larger delay. Most satellites traditionally used in the telecommunications network are **geosynchronous**, meaning that they hover at the same point over the surface of the earth. To do that, they have to orbit at a height of 22,300 miles or 35,900 kilometers. It takes a radio signal about 120 ms to traverse that distance; since a signal has to go up and back, there is an end-to-end delay of at least 240 ms (not counting delays in the electronics). If you are using this channel for a telephone conversation, then the round-trip delay from when you say something to when you get a reaction is a minimum of 480 ms. This delay can be quite annoying, impeding your ability to converse until you got used to it. If you use Internet telephony, the delays are even larger, and they can be irregular depending upon how congested the Internet is when you call.

Communications engineering is concerned with how to minimize the degradation for all kinds of communication systems, including radio, TV, cellular phones, and computer networks (such as the Internet).

1.2.3 Audio storage and retrieval

We have seen how audio signals can be represented as sequences of numbers. Digital audio storage and retrieval is all about finding a physical and persistent representation for these numbers. These numbers can be converted into a single sequence of bits (binary digits) and then “printed” onto some physical medium from which they can later be read back. The transformation of sound into its persistent representation can be modeled as a system, as can the reverse or playback process.

Example 1.19: In the case of compact discs (CDs), the physical medium is a layer of aluminum on a platter into which tiny pits are etched. In the playback device, a laser aimed at the platter uses an interference pattern to determine whether or not a pit exists at a particular point in the platter. These pits, thus, naturally represent binary digits, since they can have two states (present or not present).

While a voiceband data modem converts bit sequences into voice-like signals, a musical recording studio does the reverse, creating a representation of the sound that is a bit sequence,

$$\text{RecordingStudio} : \text{Sounds} \rightarrow \text{BitStreams}.$$

There is a great deal of engineering in the details, however. For instance, CDs are vulnerable to surface defects, which may arise in manufacturing or in the hands of the user. These defects may obscure some of the pits, or fool the reading laser into detecting a pit where there is none. To guard against this, a very clever error-correcting code called a Reed-Solomon code is used. The coding process can be viewed as a function

$$\text{Encoding} : \text{BitStreams} \rightarrow \text{RedundantBitStreams}.$$

where $\text{RedundantBitStreams} \subset \text{BitStreams}$ is the set of all possible encoded bit sequences. These bit sequences are redundant, in that they contain more bits than

are necessary to represent the original bit sequence. The extra bits are used to detect errors, and (sometimes) to correct them. Of course, if the surface of the CD is too badly damaged, even this clever scheme fails, and the audio data will not be recoverable.

CDs also contain **meta data**, which is extra information about the audio signal. This information allows the CD player to identify the start of a musical number and its length, and sometimes the title and the artist.

The CD format can also be used to contain purely digital data. Such a CD is called a **CD ROM** (read-only memory). It is called this because, like a computer memory, it contains digital information. But unlike a computer memory, that information cannot be modified.

DVD (digital video discs) take this concept much further, including much more meta data. They may eventually replace CDs. They are entirely compatible, in that they can contain exactly the same audio data that a CD can. DVD players can play CDs, but not the reverse, however. DVDs can also contain digital video information and, in fact, any other digital data. **DAT (digital audio tape)** is also a competitor to CDs, but has failed to capture much of a market.

1.2.4 Modem negotiation

A very different kind of system is the one that manages the establishment of a connection between two voiceband data modems. These two modems are at physically different locations, are probably manufactured by different manufacturers, and possibly use different communication standards. Both modems convert bit streams to and from voice-like signals, but other than that, they do not have much in common.

When a connection is established through the telephone network, the answering modem emits a tone that announces “I am a modem.” The initiating modem listens for this tone, and if it fails to detect it, assumes that no connection can be established and hangs up. If it does detect the tone, then it answers with a voice-like signal that announces “I am a modem that can communicate according to ITU standard x ,” where x is one of the many modem standard published by the International Telecommunication Union, or **ITU**.

The answering modem may or may not recognize the signal from the initiating modem. The initiating modem, for example, may be a newer modem using a standard that was

established after the answering modem was manufactured. If the answering modem does recognize the signal, then it responds with a signal that says “good, I too can communication using standard x , so let’s get started.” Otherwise, it remains silent. The initiating modem, if it fails to get a response, tries another signal, announcing “I am a modem that can communicate according to ITU standard y ,” where y is typically now an older (and slower) standard. This process continues until the two modems agree on a standard.

Once agreement is reached, the modems need to make measurements of the telephone channel to compensate for its distortion. They do this by sending each other pre-agreed signals called **training signals**, defined by the standard. The training signal is distorted by the channel, and, since the receiving modem knows the signal, it can measure the distortion. It uses this measurement to set up a device called an **adaptive equalizer**. Once both modems have completed their setup, they begin to send data to one another.

As systems go, modem negotiation is fairly complex. It involves both event sequences and voice-like signals. The voice like signals need to be analyzed in fairly sophisticated ways, sometimes producing events in the event sequences. It will take this entire book to analyze all parts of this system. The handling of the event sequences will be treated using finite state machines, and the handling of the voice-like signals will be treated using frequency-domain concepts and filtering.

1.2.5 Feedback control systems

Feedback control systems are composite systems where a **plant** embodies a physical process whose behavior is guided by a control signal. A plant may be a mechanical device, such as the power train of a car, or a chemical process, or an aircraft with certain inertial and aerodynamic properties, for example. Sensors attached to the plant produce signals that are fed to the controller, which then generates the control signal. This arrangement, where the plant feeds the controller and the controller feeds the plant, is a complicated sort of composite system called a **feedback control system**. It has extremely interesting properties which we will explore in much more depth in subsequent chapters.

In this section, we construct a model of a feedback control system using the syntax of block diagrams. The model consists of several interconnected components. We will identify the input and output signals of each component and how the components are interconnected, and we will argue on the basis of a common-sense physics how the overall system will behave.

Example 1.20: Consider a forced air heating system, which heats a room in a home or office to a desired temperature. Our first task is to identify the individual components of the heating system. These are

- a furnace/blower unit (which we will simply call the heater) that heats air and blows the hot air through vents into a room,
- a temperature sensor that measures the temperature in a room, and
- the control system that compares the specified desired temperature with the sensed temperature and turns the furnace/blower unit on or off depending on whether the sensed temperature is below or above the demanded temperature.

The interconnection of these components is shown in Figure 1.18.

Our second task is to specify the input and output signals of each component system (the domain and range of the function), ensuring the input-output matching conditions. The heater produces hot air depending on whether it is turned on or off. So its input signal is simply a function of time which takes one of two values, *On* or *Off*. We call input to the heater (a signal) *OnOff*,

$$\text{OnOff}: \text{Time} \rightarrow \{\text{On}, \text{Off}\},$$

and we take $\text{Time} = \mathbb{R}_+$, the non-negative reals. So the input signal space is

$$\text{OnOffProfiles} = [\mathbb{R}_+ \rightarrow \{\text{On}, \text{Off}\}].$$

(Recall that the notation $[D \rightarrow R]$ defines a function space, as explained in Section 1.2.1.) When the heater is turned on it produces heat at some rate that depends on the capacity of the furnace and blower. We measure this heating rate in BTUs per hour. So the output signal of the heater, which we name *Heat* is of the form

$$\text{Heat}: \mathbb{R}_+ \rightarrow \{0, B_c\},$$

where B_c is the heater capacity measured in BTU/hour. If we name the output signal space *HeatProfiles*, then

$$\text{HeatProfiles} = [\mathbb{R}_+ \rightarrow \{0, B_c\}].$$

Thus the *Heater* system is described by a function

$$\text{Heater}: \text{OnOffProfiles} \rightarrow \text{HeatProfiles}. \quad (1.13)$$

Common-sense physics tells us that when the heater is turned on the room will begin to warm up and when the heater is turned off the room temperature will fall until it reaches the outside temperature. So the room temperature depends on both the heat delivered by the heater and the outside temperature. Thus the input signal to the room is the pair $(Heat, OutsideTemp)$. We can take $OutsideTemp$ to be of the form

$$OutsideTemp: \mathbb{R}_+ \rightarrow [min, max],$$

where $[min, max]$ is the range of possible outside temperatures, measured in degrees Celsius, say. The output signal of the room is of course the room temperature,

$$RoomTemp: \mathbb{R}_+ \rightarrow [min, max].$$

If we denote

$$OutsideTempProfiles = [\mathbb{R}_+ \rightarrow [min, max]],$$

and

$$RoomTempProfiles = [\mathbb{R}_+ \rightarrow [min, max]],$$

then the behavior of the *Room* system is described by a function

$$Room: HeatProfiles \times OutsideTempProfiles \rightarrow RoomTempProfiles \quad (1.14)$$

In a similar manner, the *Sensor* system is described by a function

$$Sensor: RoomTempProfiles \rightarrow SensedTempProfiles \quad (1.15)$$

with input signal space *RoomTempProfiles* and output signal space

$$SensedTempProfiles = [\mathbb{R}_+ \rightarrow [min, max]].$$

The *Controller* is described by the function

$$Controller: DesiredTempProfile \times SensedTempProfile \rightarrow OnOffProfile, \quad (1.16)$$

where

$$DesiredTempProfiles = [\mathbb{R}_+ \rightarrow [min, max]].$$

We have constructed a model where the input-output matching condition is satisfied everywhere.

The overall forced air heating system (the shaded part of Figure 1.18) has a pair of input signals, desired temperature and outside temperature, and one output signal, room temperature. So it is described by the function

$$\begin{aligned} \text{ForcedHeat: } & \text{DesiredTempProfiles} \times \text{OutsideTempProfiles} \\ & \rightarrow \text{RoomTempProfiles}. \end{aligned}$$

If we are given the input signal values x of desired temperature and the value y of outside temperature, we can compute the value $z = \text{ForcedHeat}(x, y)$ by solving the following four simultaneous equations

$$\begin{aligned} u &= \text{Controller}(x, w) \\ v &= \text{Heater}(u) \\ z &= \text{Room}(y, v) \\ w &= \text{Sensor}(z) \end{aligned} \tag{1.17}$$

Given x and y , we must solve these four equations to determine the four unknown functions u, v, w, z of which u, v, w are the internal signals, and z is the output signal. Of course to solve these simultaneous equations, we need to specify the four system functions. So far we have simply given names to those functions and identified their domain and range. To complete the specification we must describe how those functions assign output signals to input signals.

If the sensor is functioning properly we expect *Sensor*'s output signal to be the room temperature, that is, for all z and for all $t \in \mathbb{R}_+$,

$$w(t) = \text{Sensor}(z)(t) = z(t).$$

A thermostatic controller has a simple behavior: it turns the heater on if the sensed temperature falls below the desired temperature by a certain amount, say δ_1 , and it turns the heater off if the sensed temperature rises above the desired temperature by, say δ_2 . That is, for all x, w and for all $t \in \mathbb{R}_+$,

$$u(t) = \text{Controller}(x, w)(t) = \begin{cases} \text{On}, & \text{if } w(t) - x(t) \leq -\delta_1 \\ \text{Off}, & \text{if } w(t) - x(t) \geq \delta_2 \end{cases}$$

Suppose finally that the desired temperature is set to some constant, say x^* , i.e. for all $t \in \mathbb{R}_+$,

$$x(t) = x^*.$$

We can expect the behavior depicted in Figure 1.19. When $w(t) - x^*$ drops below $-\delta_1$, the controller will turn on the heater, the room temperature will increase until $w(t) - x^*$ rises above δ_2 , and then the controller will turn off the heater. Thus the room temperature will fluctuate around the desired temperature, x^* .

1.3 Summary

Signals are functions that represent information. We studied examples of three classes of signals. In the first class are functions of discrete or continuous time and space that occur in human perception and electromechanical sensors. In the second class are functions of time and space representing attributes of physical objects or devices. The third class of signals consist of sequences of symbols representing data or the occurrences of events. In each case, the domain and the range can be defined precisely.

Systems are functions that transform signals. We looked at telecommunication systems, where a network that was originally designed for carrying voice signals is used for many other kinds of signals today. One way to accomplish this is to design systems such as modems that transform signals so that they masquerade as voice-like signals. We also looked at system models for signal degradation and for storage of signals. We looked at systems that are primarily concerned with discrete events and command sequences, and we examined a feedback control system. The telephone system and the forced air heating system were both described using block diagrams as interconnections of simpler component systems. In all cases, systems were given as functions where the domain and the range are function spaces, or sets of functions.

Probing Further: Modems and Encrypted speech

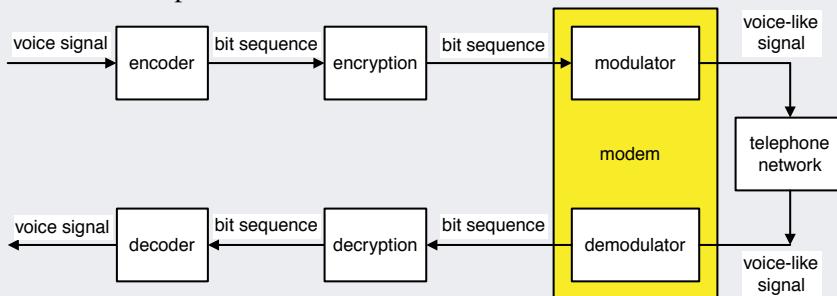
POTS service is designed to carry speech signals. With proper encoding, however, it can carry any signal that resembles speech in certain technical ways that we will discuss. Data can be transmitted over POTS networks using a **voiceband data modem**, shown just below the upper right in Figure 1.14. This used to provide a routine way to connect to the Internet, but has since been supplanted (mostly) by **broadband** connections.

Data are represented by bit sequences, which are functions of the form

$$\boxed{\text{BitSequence} : \text{Indices} \rightarrow \text{Binary},}$$

where $\text{Indices} \subset \mathbb{N}$, the natural numbers, and $\text{Binary} = \{0, 1\}$. In order for a bit sequence to traverse a POTS phone line, it has to be transformed into something that resembles a voice signal. Furthermore, a system is needed to transform the voice-like signal back into a bit sequence. A **modem** does this. The word modem is a contraction of modulator, demodulator. Pairs of modems are used at opposite ends of a POTS connection, each with a transmitter and a receiver to achieve bidirectional (called **full duplex**) communication.

One of the strangest uses is to transmit digitally represented and encrypted voice signals. Here is a depiction:



What is actually sent through the telephone network sounds like hiss, which by itself provides a modicum of privacy. Casual eavesdroppers will be unable to understand the encoded speech. However, this configuration also provides protection against sophisticated listeners. A listener that is able to extract the bit sequence from this sound will still not be able to reconstruct the voice signal because the bit sequence is encrypted.

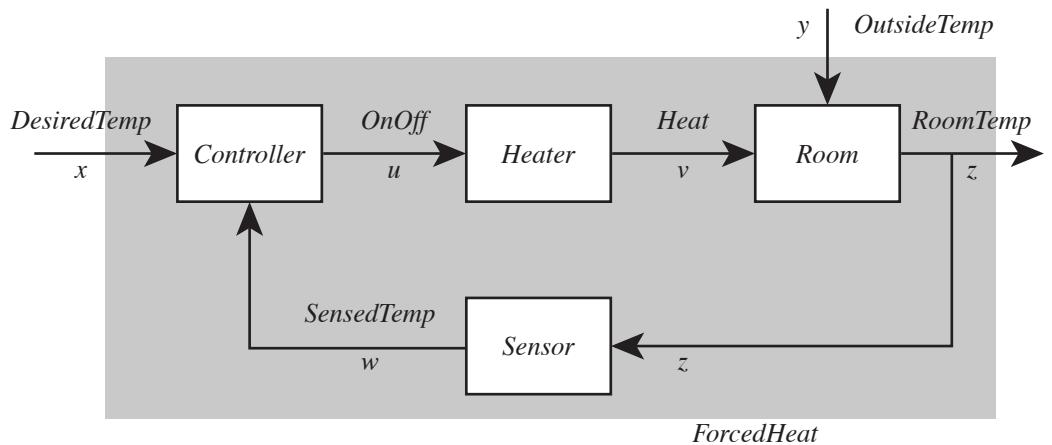


Figure 1.18: The interconnected components of a forced air heating system.

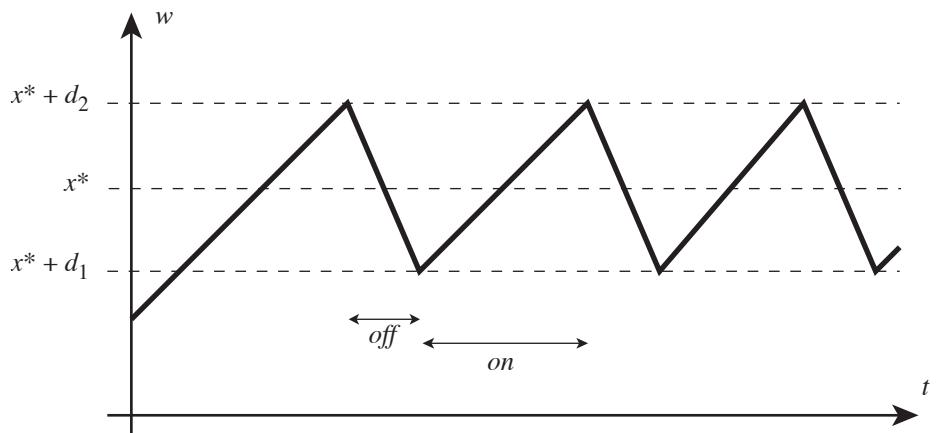


Figure 1.19: With a thermostatic controller the room temperature will fluctuate around the desired temperature setting, x^* .

Exercises

Each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **E** The function $x : \mathbb{R} \rightarrow \mathbb{R}$ given by

$$\forall t \in \mathbb{R} \quad x(t) = \sin(2\pi \times 440t)$$

is a mathematical example of a signal in the signal space $[\mathbb{R} \rightarrow \mathbb{R}]$. Give a mathematical example of a signal x in each of the following signal spaces.

- (a) $[\mathbb{Z} \rightarrow \mathbb{R}]$
 (b) $[\mathbb{R} \rightarrow \mathbb{R}^2]$
 (c) $[\{0, 1, \dots, 600\} \times \{0, 1, \dots, 400\} \rightarrow \{0, 1, \dots, 255\}]$
 (d) Describe a practical application for the signal space $[\{0, 1, \dots, 600\} \times \{0, 1, \dots, 400\} \rightarrow \{0, 1, \dots, 255\}]$. That is, what might a function in this space represent?
2. **C** For each of the continuous-time signals below, represent the signal in the form of $f : X \rightarrow Y$ and as a sketch like Figure 1.1. Carefully identify the range and domain in each case.
 - The voltage across the terminals of a car battery.
 - The closing prices on each day of a share of a company.
 - The position of a moving vehicle on a straight one-lane road of length L .
 - The simultaneous position of two moving vehicles on the same straight one-lane road of length L .
 - The sound heard in both of your ears.
3. **E** In digital telephony, voice is sampled at a rate of 8,000 samples/second, so the sampling period is $1/8000 = 125 \mu\text{s}$ (microseconds). What is the sampling period and the sampling frequency of sound in a compact disc (CD)?

4. E Figure 1.4 displays the plots of two sinusoidal signals and their sum. Sketch by hand the plots of the four functions, *Step*, *Triangle*, *Sum*, *Diff*, all with domain $[-1, 1]$ and range \mathbb{R} , where the four functions are defined by: $\forall t \in [-1, 1]$,

$$\begin{aligned} \text{Triangle}(t) &= 1 - |t|, \\ \text{Step}(t) &= 0 \text{ if } t < 0, = 1 \text{ if } t \geq 0, \\ \text{Sum}(t) &= \text{Triangle}(t) + \text{Step}(t), \\ \text{Diff}(t) &= \text{Triangle}(t) - \text{Step}(t). \end{aligned}$$

5. C The following examples of spatial information can be represented as a signal in the form of $f: X \rightarrow Y$. Specify a reasonable choice for the range and domain in each case.
- An image impressed on photographic paper.
 - An image stored in computer memory.
 - The height of points on the surface of the earth.
 - The location of the chairs in a room.
 - The household voltage in Europe, which has frequency 50 Hz and is 210 volts RMS.
6. C The image called *Albers* consists of an eight-inch yellow square in the center of a white twelve-inch square background. Express *Albers* as a function, by choosing the domain, range, and function assignment.
7. E How many bits are there in a 1024×768 pixel image in which each pixel is represented as a 16-bit word? How long would it take to download this image over a 28 Kbps voice-band modem, a 384 Kbps DSL modem, a 10 Mbps Ethernet local area network?
8. C Represent these examples as data or event sequences. Specify reasonable choices for the range and domain in each case.
- The result of 100 tosses of a coin,
 - The sequence of button presses inside an elevator,
 - The sequence of main events in a soda vending machine,
 - Your response to a motorist who is asking directions,
 - A play-by-play account of a game of chess.

9. **C** Formulate the following items of information as functions. Specify reasonable choices for the domain and range in each case.
- The population of U.S. cities,
 - The white pages in a phone book (careful: the white pages may list two identical names, and may list the same phone number under two different names),
 - The birth dates of students in class,
 - The broadcast frequencies of AM radio stations,
 - The broadcast frequencies of FM radio stations, (look at your radio dial, or at the web page:
<http://www.eecs.berkeley.edu/~eal/eecs20/sidebars/radio/index.html>.
10. **E** Use Matlab to plot the graph of the following continuous-time functions defined over $[-1, 1]$, and on the same plot display 11 uniformly spaced samples (0.2 seconds apart) of these functions. Are these samples good representations of the waveforms?
- $f: [-1, 1] \rightarrow \mathbb{R}$, where for all $x \in [-1, 1]$, $f(x) = e^{-x} \sin(10\pi x)$.
 - $\text{Chirp}: [-1, 1] \rightarrow \mathbb{R}$, where for all $t \in [-1, 1]$, $\text{Chirp}(t) = \cos(10\pi t^2)$.
11. **E** Suppose the pendulum of Figure 1.10 is rotating counter-clockwise at a speed of one revolution per second over the five-second interval $[0, 5]$. Sketch a plot of the resulting function: $\theta : [0, 5] \rightarrow [-\pi, \pi]$. Assume $\theta(0) = 0$. Also specify this function mathematically. Your plot is discontinuous, but the pendulum's motion is continuous. Explain this apparent inconsistency.
12. **T** There is a large difference between the sets X , Y , and $[X \rightarrow Y]$. This exercise explores some of that difference.
- Suppose $X = \{a, b, c\}$ and $Y = \{0, 1\}$. List all the functions from X to Y , i.e. all the elements of $[X \rightarrow Y]$. Note that part of the problem here is to figure out *how* to list all the functions.
 - If X has m elements and Y has n elements, how many elements does $[X \rightarrow Y]$ have?

(c) Suppose

$$\begin{aligned} \textit{ColormapImages} = \\ [\textit{DiscreteVerticalSpace} \times \textit{DiscreteHorizontalSpace} \\ \rightarrow \textit{ColorMapIndexes}]. \end{aligned}$$

Suppose the domain of each image in this set has 6,000 pixels and the range has 256 values. How many distinct images are there? Give an approximate answer in the form of 10^n . **Hint:** $a^b = 10^{b\log_{10}(a)}$.

2

Defining Signals and Systems

Contents

2.1 Defining functions	50
2.1.1 Declarative assignment	52
2.1.2 Graphs	54
<i>Probing Further: Relations</i>	56
2.1.3 Tables	57
2.1.4 Procedures	58
2.1.5 Composition	58
2.1.6 Declarative vs. imperative	62
<i>Probing Further: Declarative and imperative</i>	63
2.2 Defining signals	66
2.2.1 Declarative definitions	66
2.2.2 Imperative definitions	66
2.2.3 Physical modeling	68
2.3 Defining systems	68
<i>Probing Further: Physics of a Tuning Fork</i>	70
2.3.1 Memoryless systems and systems with memory	71
2.3.2 Differential equations	72
2.3.3 Difference equations	74
<i>Basics: Trigonometric Identities</i>	76
<i>Basics: Summations</i>	77
2.3.4 Composing systems using block diagrams	78
<i>Probing Further: Composition of graphs</i>	80
2.4 Summary	82
Exercises	84

The previous chapter describes the representation of signals and systems as functions, concentrating on how to select the domain and range. This chapter is concerned with how to give more complete definitions of these functions. In particular, we need an **assignment rule**, which specifies how to assign an element in the range to each element in the domain.

There are many ways to give an assignment rule. A theme of this chapter is that these different ways have complementary uses. Procedural descriptions of the assignment rule, for example, are more convenient for synthesizing signals or constructing implementations of a system in software or hardware. Mathematical descriptions are more convenient for analyzing signals and systems and determining their properties.

In practice it is often necessary to use several descriptions of assignment rules in combination, because of their complementary uses. In designing systems, a practicing engineer is often reconciling these diverse views to ensure, for instance, that a particular hardware device or piece of software indeed implements a system that is specified mathematically. We begin with a discussion of functions in general, and then specialize to signals and systems.

2.1 Defining functions

A function $f: X \rightarrow Y$ assigns to each element in X a single element in Y , as illustrated in Figure 2.1. This assignment can be defined by declaring the mathematical relationship between the value in X and the value in Y , by graphing or enumerating the possible assignments, by giving a procedure for determining the value in Y given a value in X , or by composing simpler functions. We go over each of these in more detail in this section.

Example 2.1: In Section 1.1.5 we mentioned that sequences are a special kind of function. An infinite sequence s is a function that maps the natural numbers into some set Y , as illustrated in Figure 2.2. This function fully defines any infinite sequence of elements in Y .

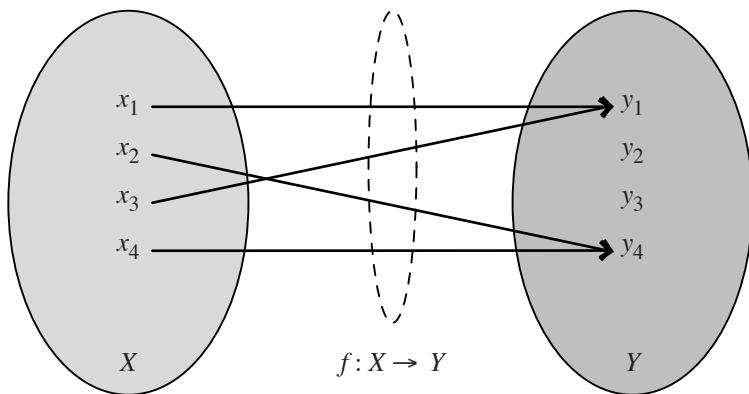


Figure 2.1: A function $f: X \rightarrow Y$ assigns to each element in X a single element in Y .

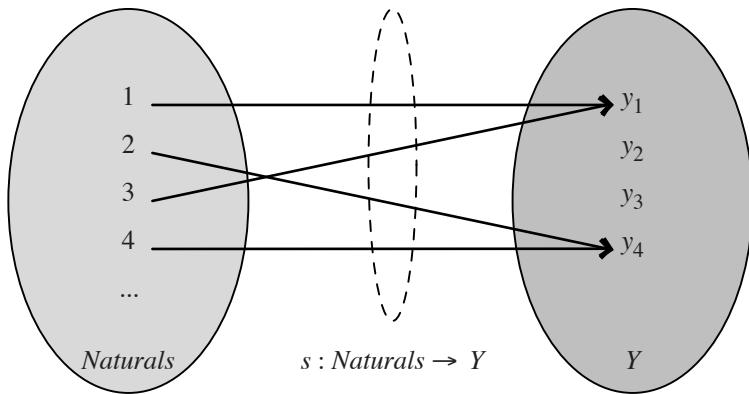


Figure 2.2: An infinite sequence s is a function $s: \mathbb{N} \rightarrow Y$ that assigns to each element in \mathbb{N} a single element in Y .

2.1.1 Declarative assignment

Consider the function $\text{Square}: \mathbb{R} \rightarrow \mathbb{R}$ given by

$$\forall x \in \mathbb{R}, \quad \text{Square}(x) = x^2. \quad (2.1)$$

In (2.1), we have used the **universal quantifier** symbol ‘ \forall ’, which means ‘for all’ or ‘for every’ to declare the relationship between values in the domain of the function and values in the range. Statement (2.1) is read: “for every value of x in \mathbb{R} , the function Square evaluated at x is assigned the value x^2 .” The expression “ $\text{Square}(x) = x^2$ ” in (2.1) is an assignment.¹

Expression (2.1) is an instance of the following prototype for defining functions. Define $f: X \rightarrow Y$ by

$$\boxed{\forall x \in X, \quad f(x) = \text{expression in } x.} \quad (2.2)$$

In this prototype, f is the name of the function to be defined, such as Square , X is the domain of f , Y is the range of f , and ‘expression in x ’ specifies the value in Y assigned to $f(x)$.

The prototype (2.2) does not say how the ‘expression in x ’ is to be evaluated. In the Square example above, it was specified by the algebraic expression $\text{Square}(x) = x^2$. Such a definition of a function is said to be **declarative**, because it declares properties of the function without directly explaining how to construct the function.

Example 2.2: Here are some examples of functions of complex variables. (See Appendix B for a review of complex variables.)

The magnitude of a complex number is given by $\text{abs}: \mathbb{C} \rightarrow \mathbb{R}_+$, where \mathbb{C} is the set of complex numbers and \mathbb{R}_+ is the set of non-negative real numbers, and

$$\forall z = x + iy \in \mathbb{C}, \quad \text{abs}(z) = \sqrt{(x^2 + y^2)}.$$

The complex conjugate of a number, $\text{conjugate}: \mathbb{C} \rightarrow \mathbb{C}$, is given by

$$\forall z = x + iy \in \mathbb{C}, \quad \text{conjugate}(z) = x - iy.$$

¹See Appendix A for a discussion of the use of “ $=$ ” as an assignment, vs. its use as an assertion.

The exponential of a complex number, $\exp: \mathbb{C} \rightarrow \mathbb{C}$, is given by

$$\forall z \in \mathbb{C}, \quad \exp(z) = \sum_{n=0}^{\infty} \frac{z^n}{n!}.$$

If this notation is unfamiliar, see box on page 77.) It is worth emphasizing that the last definition is declarative: it does not give a procedure for calculating the exponential function, since the sum is infinite. Such a calculation would never terminate.

Example 2.3: The signum function gives the sign of a real number, $\text{signum}: \mathbb{R} \rightarrow \{-1, 0, 1\}$,

$$\forall x \in \mathbb{R}, \quad \text{signum}(x) = \begin{cases} -1 & \text{if } x < 0 \\ 0 & \text{if } x = 0 \\ 1 & \text{if } x > 0 \end{cases} \quad (2.3)$$

The right side of this assignment tabulates three expressions for three different subsets of the domain. Below we will consider a more extreme case of this where every value in the domain is tabulated with a value in the range.

Example 2.4: The size of a matrix, $\text{size}: \text{Matrices} \rightarrow \mathbb{N} \times \mathbb{N}$, is given by

$$\forall M \in \text{Matrices}, \quad \text{size}(M) = (m, n),$$

where m is the number of rows of the matrix M , n is the number of columns of M , and Matrices is the set of all matrices.

This definition relies not only on formal mathematics, but also on the English sentence that defines m and n . Without that sentence, the assignment would be meaningless.

2.1.2 Graphs

Consider a function $f: X \rightarrow Y$. To each $x \in X$, f assigns the value $f(x)$ in Y . The pair $(x, f(x))$ is an element of the product set $X \times Y$. The set of all such pairs is called the **graph** of f , written $\text{graph}(f)$. Using the syntax of sets, $\text{graph}(f)$ is the subset of $X \times Y$ defined by

$$\text{graph}(f) = \{(x, y) \mid x \in X \text{ and } y = f(x)\}, \quad (2.4)$$

or slightly more simply,

$$\text{graph}(f) = \{(x, f(x)) \mid x \in X\}.$$

The vertical bar $|$ is read “such that,” and the expression after it is a **predicate** that defines the set.²

When $X \subset \mathbb{R}$ and $Y \subset \mathbb{R}$, we can plot $\text{graph}(f)$ on a page.

Example 2.5: Consider the graph of the function *Square*,

$$\text{graph}(\text{Square}) = \{(x, x^2) \mid x \in \mathbb{R}\},$$

which is plotted in Figure 2.3. In that figure, the horizontal and vertical axes represent the domain and the range, respectively (more precisely, a subset of the domain and the range). The rectangular region enclosed by these axes represents the product of the domain and the range (every point in that region is a member of $(\mathbb{R} \times \mathbb{R})$). The graph is visually rendered by placing a black dot at every point in that region that is a member of $\text{graph}(\text{Square})$. The resulting picture is the familiar plot of the *Square* function.

While the graph of $f: X \rightarrow Y$ is a subset of $X \times Y$, it is a very particular sort of subset. For each element $x \in X$, there is exactly one element $y \in Y$ such that $(x, y) \in \text{graph}(f)$. In particular, there cannot be more than one such $y \in Y$, and there cannot be no such $y \in Y$. This is, in fact, what we mean when we say that f is a function.

²See appendix A for a review of this notation.

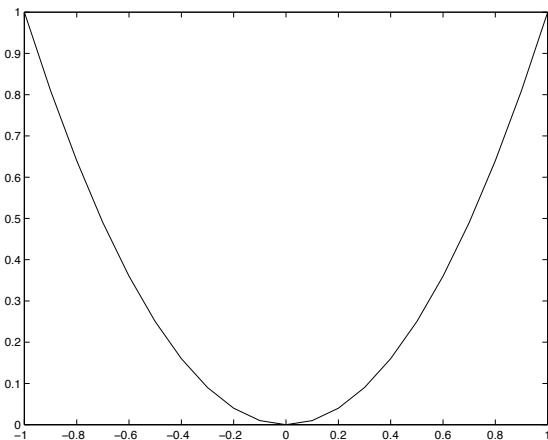


Figure 2.3: Graph of *Square*

Example 2.6: Let $X = \{1, 2\}$ and $Y = \{a, b\}$. Then

$$\{(1, a), (2, a)\}$$

is the graph of a function, but

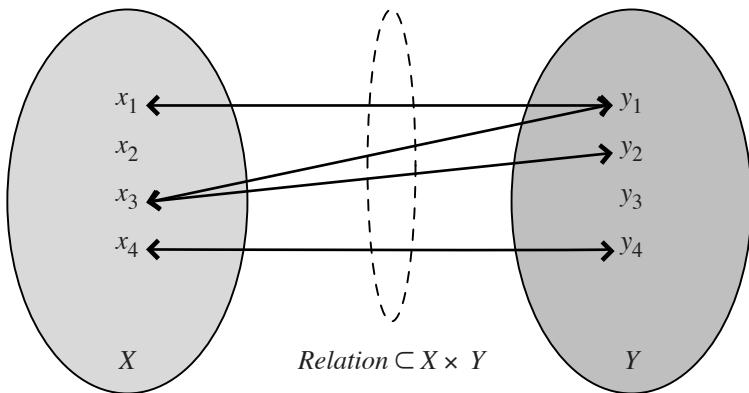
$$\{(1, a), (1, b)\}$$

is not, because two points a and b are assigned to the same point, 1, in the domain. Neither is

$$\{(1, a)\},$$

because no point in the range is assigned to the point 2 in the domain.

The graph of *Square*, $\text{graph}(\text{Square})$, is given by the algebraic expression (x, x^2) . In other cases, no such algebraic expression exists. For example, *Voice* is specified through its graph in Figure 1.1, not through an algebraic expression. Thus, graphs can be used to define functions that cannot be conveniently given by declarative assignments.

Figure 2.4: Any subset of $X \times Y$ is a relation.

Consider again the prototype in (2.2),

$$\forall x \in X, \quad f(x) = \text{expression in } x$$

The graph of f is

$$\text{graph}(f) = \{(x, y) \in X \times Y \mid y = \text{expression in } x\}.$$

The expression ‘ $y = \text{expression in } x$ ’ is a predicate in the variable (x, y) and so this prototype definition conforms to the prototype new set constructor given in (A.4) of Appendix A:

$\text{NewSet} = \{z \in \text{Set} \mid \text{Pred}(z)\}.$

Probing Further: Relations

The graph of a function $f: X \rightarrow Y$ is a subset of $X \times Y$, as defined in (2.4). An arbitrary subset of $X \times Y$ is called a **relation**. A relation is a set of tuples (x, y) that pair an element $x \in X$ with an element $y \in Y$, as suggested in Figure 2.4. For relations, it is common to call X the **domain** and Y the **codomain**. A function is a special kind of relation in which for every $x \in X$ there is exactly one $y \in Y$ such that (x, y) is an element of the relation. So a particular relation $R \subset X \times Y$ is a function if for every $x \in X$ there is a $y_1 \in Y$ such that $(x, y_1) \in R$, and if in addition $(x, y_2) \in R$, then $y_1 = y_2$.

Name	Marks
John Brown	90.0
Jane Doe	91.2
...	...

Table 2.1: Tabular representation of *Score*.

Since the graph of f is a set, we can define the function f via its graph using the same techniques we use to define sets.

2.1.3 Tables

If $f: X \rightarrow Y$ has finite domain, then $\text{graph}(f) \subset X \times Y$ is a finite set, so it can be specified simply by a list of all its elements. This list can be put in the form of a table. This table defines the function.

Example 2.7: Suppose the function

$$\text{Score}: \text{Students} \rightarrow [0, 100]$$

gives the outcome of the first midterm exam for each student in the class. Obviously, this function cannot be given by an algebraic declarative assignment. But it can certainly be given as a table, as shown in table 2.1.

Example 2.8: The command nslookup on a networked computer is a function that maps hostnames into their IP (Internet) address. For example, if you type:

```
nslookup cory.eecs.berkeley.edu
```

you get the IP address 128.32.134.240. The **domain name server** attached to your machine stores the nslookup function as a table.

2.1.4 Procedures

Sometimes the value $f(x)$ that a function f assigns to an element $x \in \text{domain}(f)$ is obtained by executing a procedure.

Example 2.9: Here is a Matlab procedure to compute the factorial function

$$\text{fact}: \{1, \dots, 10\} \rightarrow \mathbb{N},$$

where \mathbb{N} is the set of natural numbers:

```
fact(1) = 1;
for n = 2:10
    fact(n) = n * fact(n-1);
end
```

Unlike previous mechanisms for defining a function, this one gives a constructive method to determine an element in the range given an element in the domain. This style is called **imperative** to distinguish it from declarative. The relationship between these two styles is interesting, and quite subtle. It is explored further in Section 2.1.6.

2.1.5 Composition

Functions can be combined to define new functions. The simplest mechanism is to connect the output of one function to the input of another. We have been doing this informally to define systems by connecting components in block diagrams.

If the first function is f_1 and the second is f_2 , then we write the **function composition** as $f_2 \circ f_1$. That is, for every x in the domain of f_1 ,

$$(f_2 \circ f_1)(x) = f_2(f_1(x)).$$

A fundamental requirement for such a composition to be valid is that the range of f_1 must be a subset of the domain of f_2 . In other words, any output from the first function

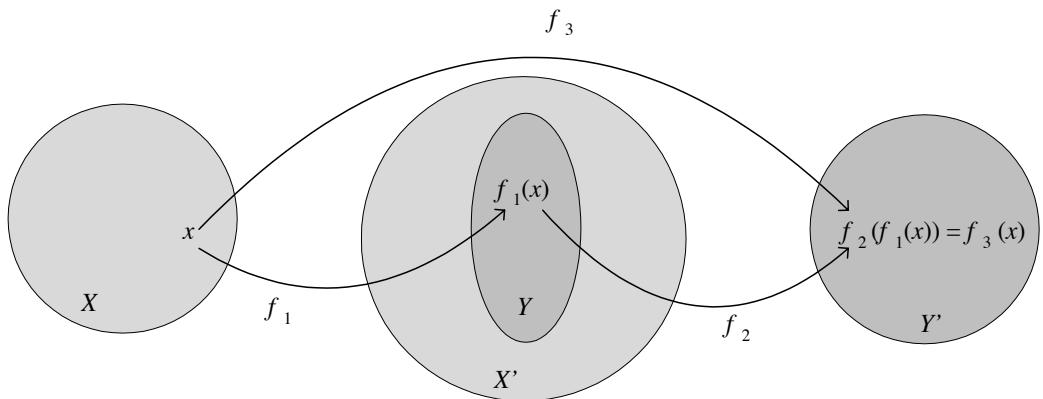


Figure 2.5: Function composition: $f_3 = f_2 \circ f_1$.

must be in the set of possible inputs for the second. Without this input-output **connection restriction**, the interconnection would be meaningless.³

It is worth pausing to study the notation $f_2 \circ f_1$. Assume $f_1: X \rightarrow Y$ and $f_2: X' \rightarrow Y'$. Then if $Y \subset X'$, we can define

$$f_3 = f_2 \circ f_1,$$

where $f_3: X \rightarrow Y'$ such that

$$\forall x \in X, \quad f_3(x) = f_2(f_1(x)) \quad (2.5)$$

Notice that f_1 is applied first, and then f_2 . Why is f_1 listed second in $f_2 \circ f_1$? This convention simply mirrors the ordering of $f_2(f_1(x))$ in (2.5). We can visualize f_3 as in Figure 2.5.

Example 2.10: Consider the representation of a color image using a colormap. The decoding of the image is depicted in Figure 1.7. The image itself might be given by the function

$$\begin{aligned} \text{ColormapImage: } & \text{DiscVerticalSpace} \times \text{DiscHorizontalSpace} \\ & \rightarrow \text{ColorMapIndexes}. \end{aligned}$$

³We just called an element in the domain of a function its input and the corresponding value of the function its output. This interpretation of domain as inputs and range as outputs is natural, and it is the reason that systems are described by functions.

The function

$$\text{Display} : \text{ColorMapIndexes} \rightarrow \text{Intensity}^3$$

decodes the colormap indexes. If ColorMapIndexes has 256 values, it could be identified with the set Integers_8 of all 8-bit words, as we have seen. If we compose these functions

$$\text{ColorComputerImage} = \text{Display} \circ \text{ColormapImage}$$

then we get the decoded representation of the image

$$\begin{aligned} \text{ColorComputerImage} : & \quad \text{DiscVerticalSpace} \times \text{DiscHorizontalSpace} \\ & \rightarrow \text{Intensity}^3. \end{aligned}$$

$\text{ColorComputerImage}$ describes how an image looks when it is displayed, whereas ColormapImage describes how it is stored in the computer.

If $f : X \rightarrow X$, i.e. the domain and range of f are the same, we can form the function

$$f^2 = f \circ f.$$

We can compose f^2 with f to form f^3 , and so on.

Example 2.11: Consider the function $S : \mathbb{R}^2 \rightarrow \mathbb{R}^2$, where the assignment $(y_1, y_2) = S(x_1, x_2)$ is defined by matrix multiplication,

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}. \quad (2.6)$$

The function $S^2 = S \circ S : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ is also defined by matrix multiplication, and the corresponding matrix is the square of the matrix in (2.6).

To see this, let $(y_1, y_2) = S(x_1, x_2)$ and $(z_1, z_2) = S(y_1, y_2) = (S \circ S)(x_1, x_2)$. Then we see that

$$\begin{aligned} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} &= \underbrace{\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}}_A \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \left(\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \right) \\ &= \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}^2 \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \underbrace{\begin{bmatrix} 7 & 10 \\ 15 & 22 \end{bmatrix}}_{A^2} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \\ &= A^2 \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}. \end{aligned}$$

Example 2.12: Consider another example in the context of the telephone system. Let *Voices* be the set of possible voice input signals of the form

$$Voice : Time \rightarrow Pressure.$$

Voices is a function space,

$$Voices = [Time \rightarrow Pressure].$$

A telephone converts a *Voice* signal into a signal in the set

$$LineSignals = [Time \rightarrow Voltages].$$

Thus, we could define

$$Mouthpiece : Voices \rightarrow LineSignals.$$

The twisted wire pair may distort this signal, so we define a function

$$LocalLoop : LineSignals \rightarrow LineSignals.$$

The input to the line card therefore is

$$(LocalLoop \circ Mouthpiece)(Voice).$$

Similarly let *BitStreams* be the set of possible bitstreams of the form:

$$\text{BitStream}: \text{DiscreteTime} \rightarrow \text{Binary}$$

where $\text{DiscreteTime} = \{0, 1/64,000, 2/64,000, \dots\}$, since there are 64,000 bits/sec. So,

$$\text{BitStreams} = [\text{DiscreteTime} \rightarrow \text{Binary}].$$

The encoder in a line card can be mathematically described as a function

$$\text{Encoder}: \text{LineSignals} \rightarrow \text{BitStreams}$$

or, with more detail, as a function

$$\text{Encoder}: [\text{Time} \rightarrow \text{Voltages}] \rightarrow [\text{DiscreteTime} \rightarrow \text{Binary}].$$

The digital telephone network itself might be modeled as a function

$$\text{Network}: \text{BitStreams} \rightarrow \text{BitStreams}.$$

We can continue in this fashion until we model the entire path of a voice signal through the telephone network as the function composition

$$\begin{aligned} & \text{Earpiece} \circ \text{LocalLoop}_2 \circ \text{Decoder} \circ \text{Network} \circ \text{Encoder} \\ & \quad \circ \text{LocalLoop}_1 \circ \text{Mouthpiece}. \end{aligned} \tag{2.7}$$

Given a complete definition of each of these functions, we would be well equipped to understand the degradations experienced by a voice signal in the telephone network.

2.1.6 Declarative vs. imperative

Declarative definitions of functions assert a relationship between elements in the domain and elements in the range. Imperative definitions give a procedure for finding an element in the range given one in the domain. Often, both types of specifications can be given for the same function. However sometimes the specifications are subtly different.

Consider the function

$$\text{SquareRoot}: \mathbb{R}_+ \rightarrow \mathbb{R}_+$$

defined by the statement “ $\text{SquareRoot}(x)$ is the unique value of $y \in \mathbb{R}_+$ such that $y^2 = x$.” This declarative definition of SquareRoot does not tell us how to calculate its value at any point in its domain. Nevertheless, it defines SquareRoot perfectly well. By contrast, an imperative definition of SquareRoot would give us a procedure, or algorithm, for calculating $\text{SquareRoot}(x)$ for a given x . Call the result of such an algorithm \hat{y} . Since the algorithm would yield an approximation in most cases, \hat{y}^2 would not be exactly equal to x . So the declarative and imperative definitions are not always the same.

Any definition of a function following the prototype (2.2) is a declarative definition. It does not give a procedure for evaluating ‘expression in x ’.

Probing Further: Declarative and imperative

The declarative approach establishes a relation between the domain and the range of a function. For example, the equation

$$y = \sin(x)/x$$

can be viewed as defining a subset of $\mathbb{R} \times \mathbb{R}$. This subset is the graph of the function $\text{Sinc}: \mathbb{R} \rightarrow \mathbb{R}$.

The imperative approach also establishes a function, but it is a function that maps the program state before the statement is executed into a program state after the statement is executed. Consider for example the Java statement

```
y = Math.sin(x)/x;
```

Considering only this statement (rather than a larger program), the program state is the value of the two variables, x and y . Suppose that these have been declared to be of type `double`, which in Java represents double-precision floating-point numbers encoding according to an IEEE standard. Let the set Doubles be the set of all numbers so encoded, and note that $\text{NaN} \in \text{Doubles}$, not a number, the result of division by zero. The set of possible program states is therefore $\text{Doubles} \times \text{Doubles}$. The Java statement therefore defines a function

Statement: $(\text{Doubles} \times \text{Doubles}) \rightarrow (\text{Doubles} \times \text{Doubles})$.

Example 2.13: As another example where declarative and imperative definitions differ in subtle ways, consider the following mathematical equation:

$$y = \frac{\sin(x)}{x}. \quad (2.8)$$

Consider the following Java statement:

```
y = Math.sin(x)/x;
```

or an equivalent Matlab statement

```
y = sin(x)/x
```

Superficially, these look very similar to (2.8). There are minor differences in syntax in the Java statement, but otherwise, it is hard to tell the difference. But there are differences. For one, the mathematical equation (2.8) has meaning if y is known and x is not. It declares a relationship between x and y . The Java and Matlab statements define a procedure for computing y given x . Those statements have no meaning if y is known and x is not.

The mathematical equation (2.8) can be interpreted as a predicate that defines a function, for example the function $Sinc: \mathbb{R} \rightarrow \mathbb{R}$, where

$$\text{graph}(Sinc) = \{(x, y) \mid x \in \mathbb{R}, y = \sin(x)/x\}. \quad (2.9)$$

The Java and Matlab statements can be interpreted as imperative definitions of a function. Confusingly, many programming languages, including Matlab, use the term “function” to mean something a bit different from a mathematical function. They use it to mean a **procedure** that can compute an element in the range of a function given an element in its domain. Under certain restrictions (avoiding global variables for example), Matlab functions do in fact compute mathematical functions. But in general, they do not. .

To interpret the Java and Matlab statements as imperative definitions of a function, note that given an element in the domain, they specify how to compute an element in the range. However, these two statements do not define the same function as

in (2.9). To see this, consider the value of y when $x = 0$. Given the mathematical equation, it is not entirely trivial to determine the value of y . You can verify that $y = 1$ when $x = 0$ using **l'Hôpital's rule**, which states that if $f(a) = g(a) = 0$, then

$$\lim_{x \rightarrow a} \frac{f(x)}{g(x)} = \lim_{x \rightarrow a} \frac{f'(x)}{g'(x)}, \quad (2.10)$$

if the limit exists, where $f'(x)$ is the derivative of f with respect to x , and $g'(x)$ is the derivative of g with respect to x .

In contrast, the meaning of the Java and Matlab statements is that $y = 0/0$ when $x = 0$, which Java and Matlab (and most modern languages) define to be NaN, not a number. Thus, given $x = 0$, the procedures yield different values for y than the mathematical expression. (An exception is symbolic algebra programs, such as Mathematica or Maple, which will evaluate $\sin(x)/x$ to 1 when $x = 0$. These programs use sophisticated, rule-based solution techniques, and, in effect, recognize the need and apply l'Hôpital's rule.)

We can see from the above example some of the strengths and weaknesses of imperative and declarative approaches. Given only a declarative definition, it is difficult for a computer to determine the value of y . Symbolic mathematical software, such as Maple and Mathematica, is designed to deal with such situations, but these are very sophisticated programs. In general, using declarative definitions in computers requires quite a bit more sophistication than using imperative definitions.

Imperative definitions are easier for computers to work with. But the Java and Matlab statements illustrate one weakness of the imperative approach: it is arguable that $y = \text{NaN}$ is the wrong answer, so the Java and Matlab statements have a bug. This bug is unlikely to be detected unless, in testing, these statements happen to be executed with the value $x = 0$. A correct Java program might look like this:

```
if (x == 0.0) y = 1.0;
else y = Math.sin(x)/x;
```

Thus, the imperative approach has the weakness that ensuring correctness is more difficult. Humans have developed a huge arsenal of techniques and skills for thoroughly

understanding declarative definitions (thus lending confidence in their correctness), but we are only beginning to learn how to ensure correctness in imperative definitions.

2.2 Defining signals

Signals are functions. Thus, both declarative and imperative approaches can be used to define them.

2.2.1 Declarative definitions

Consider for example an audio signal s , a pure tone at 440 Hz (middle A on the piano keyboard). Recall that audio signals are functions $\text{Sound} : \text{Time} \rightarrow \text{Pressure}$, where the set $\text{Time} \subset \mathbb{R}$ represents a range of time and the set Pressure represents air pressure.⁴ To define this function, we might give the declarative description

$$\forall t \in \text{Time}, \quad s(t) = \sin(440 \times 2\pi t). \quad (2.11)$$

In many texts, you will see the shorthand

$$s(t) = \sin(440 \times 2\pi t)$$

used as the definition of the function s . Using the shorthand is only acceptable when the domain of the function is well understood from the context. This shorthand can be particularly misleading when considering systems, and so we will only use it sparingly. A portion of the graph of the function (2.11) is shown in Figure 1.3.

2.2.2 Imperative definitions

We can also give an imperative description of such a signal. When thinking of signals rather than more abstractly of functions, there is a subtle question that arises when we attempt to construct an imperative definition. Do you give the value of $s(t)$ for a particular t ? Or for all t in the domain? Suppose we want the latter, which seems like a more

⁴Recall further that we normalize Pressure so that zero represents the ambient air pressure. We also use arbitrary units, rather than a physical unit such as millibars.

complete definition of the function. Then we have a problem. The domain of this function may be any time interval, or all time! Suppose we just want one second of sound. Define $t = 0$ to be the start of that one second. Then the domain is $[0, 1]$. But there are an (uncountably) infinite number of values for t in this range! No Java or Matlab program could provide the value of $s(t)$ for all these values of t .

Since a signal is function, we give an imperative description of the signal exactly as we did for functions. We give a procedure that has the potential of providing values for $s(t)$, given any t .

Example 2.14: We could define a Java **method** as follows:

```
double s(double t) {
    return (Math.sin(440*2*Math.PI*t));
}
```

Calling this method with a value for t as an argument yields a value for $s(t)$. Java (and most object-oriented languages) use the term “method” for most procedures.

Another alternative is to provide a set of samples of the signal.

Example 2.15: In Matlab, we could define a vector t that gives the values of time that we are interested in:

```
t = [0:1/8000:1];
```

In the vector t there are 8001 values evenly spaced between 0 and 1, so our sampling rate is 8000 samples per second. Then we can compute values of s for these values of t and listen to the resulting sound:

```
s = cos(2*pi*440*t);
sound(s, 8000)
```

The vector s also has 8001 elements, representing evenly spaced samples of one second of A-440.

2.2.3 Physical modeling

An alternative way to define a signal is to construct a model for a physical system that produces that signal.

Example 2.16: A pure tone might be defined as a solution to a differential equation that describes the physics of a tuning fork.

A tuning fork consists of a metal finger (called a **tine**) that is displaced by striking it with a hammer. After being displaced, it vibrates. If the tine has no friction, it will vibrate forever. We can denote the displacement of the tine after being struck at time zero as a function $y: \mathbb{R}_+ \rightarrow \mathbb{R}$. If we assume that the initial displacement introduced by the hammer is one unit, then using our knowledge of physics we can determine that for all $t \in \mathbb{R}_+$, the displacement satisfies the differential equation

$$\ddot{y}(t) = -\omega_0^2 y(t) \quad (2.12)$$

where ω_0 is constant that depends on the mass and stiffness of the tine, and where $\ddot{y}(t)$ denotes the second derivative with respect to time of y (see box).

It is easy to verify that y given by

$$\forall y \in \mathbb{R}_+, \quad y(t) = \cos(\omega_0 t) \quad (2.13)$$

is a solution to this differential equation (just take its second derivative). Thus, the displacement of the tuning fork is sinusoidal. This displacement will couple directly with air around the tuning fork, creating vibrations in the air (sound). If we choose materials for the tuning fork so that $\omega_0 = 2\pi \times 440$, then the tuning fork will produce the tone of A-440 on the musical scale.

2.3 Defining systems

All of the methods that we have discussed for defining functions can be used, in principle, to define systems. However, in practice, the situation is much more complicated for systems than for signals. Recall from Section 1.2.1 that a system is a function where the domain and range are sets of signals called signal spaces. Elements of these domains and

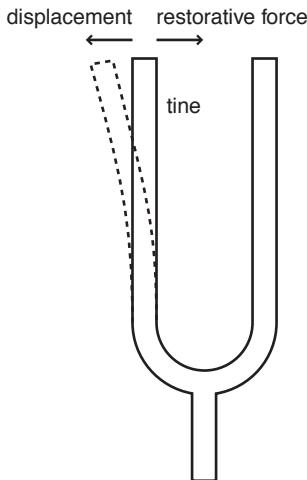


Figure 2.6: A tuning fork.

ranges are considerably more difficult to specify than, say, an element of \mathbb{R} or \mathbb{Z} . For this reason, it is almost never reasonable to use a graph or a table to define a system. Much of the rest of this book is devoted to giving precise ways to define systems where some analysis is possible. Here we consider some simple techniques that can be immediately motivated. Then we show how more complicated systems can be constructed from simpler ones using block diagrams. We give a rigorous meaning to these block diagrams so that we can use them without resorting to perilous intuition to interpret them.

Consider a system S where

$$S: [D \rightarrow R] \rightarrow [D' \rightarrow R']. \quad (2.14)$$

Suppose that $x \in [D \rightarrow R]$ and $y = S(x)$. Then we call the pair (x, y) a **behavior** of the system. A behavior is an input, output pair. The set of all behaviors is

$$\boxed{\text{Behaviors}(S) = \{(x, y) \mid x \in [D \rightarrow R] \text{ and } y = S(x)\}}.$$

Giving the set of behaviors is one way to define a system. Explicitly giving the set *Behaviors*, however, is usually impractical, because it is a huge set, typically infinite (see boxes on pages 681 and 683). Thus, we seek other ways of talking about the relationship between a signal x and a signal y when $y = S(x)$.

To describe a system, one must specify its domain (the space of input signals), its range (the space of output signals), and the rule by which the system assigns an output signal to each input signal. This assignment rule is more difficult to describe and analyze than the input and output signals themselves. A table is almost never adequate, for example. Indeed for most systems we do not have effective mathematical tools for describing or

Probing Further: Physics of a Tuning Fork

A tuning fork consists of two fingers called tines, as shown in Figure 2.6. If you displace one of these tines by hitting it with a hammer, it will vibrate with a nearly perfect sinusoidal characteristic. As it vibrates, it pushes the air, creating a nearly perfect sinusoidal variation in air pressure that propagates as sound. Why does it vibrate this way?

Suppose the displacement of the tine (relative to its position at rest) at time t is given by $x(t)$, where $x: \mathbb{R} \rightarrow \mathbb{R}$. There is a force on the tine pushing it towards its at-rest position. This is the restorative force of the elastic material used to make the tine. The force is proportional to the displacement (the greater the displacement, the greater the force), so

$$F(t) = -kx(t),$$

where k is the proportionality constant that depends on the material and geometry of the tine. In addition, Newton's second law of motion tells us the relationship between force and acceleration,

$$F(t) = ma(t),$$

where m is the mass and $a(t)$ is the acceleration at time t . Of course,

$$a(t) = \frac{d^2}{dt^2}x(t) = \ddot{x}(t),$$

so

$$m\ddot{x}(t) = -kx(t)$$

or

$$\ddot{x}(t) = -(k/m)x(t).$$

Comparing with (2.12), we see that $\omega_0^2 = k/m$.

A solution to this equation needs to be some signal that is proportional to its own second derivative. A sinusoid as in (2.13) has exactly this property. The sinusoidal behavior of the tine is called **simple harmonic motion**.

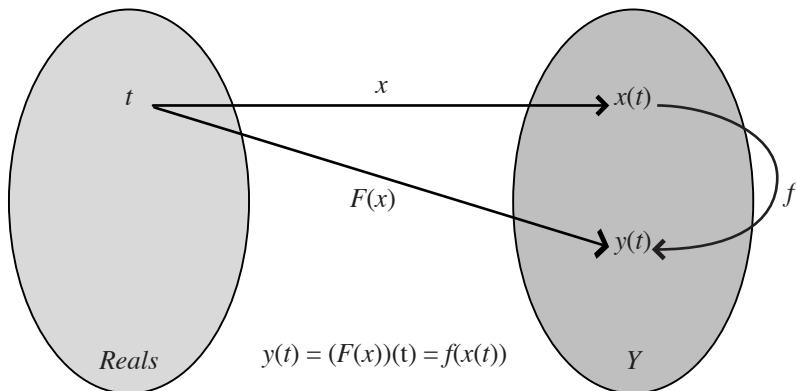


Figure 2.7: A memoryless system F has an associated function f that can be used to determine its output $y(t)$ given only the current input $x(t)$ at time t . In particular, it does not depend on values of the function x for other values of time.

understanding their behavior. Thus, it is useful to restrict our system designs to those we can understand. We first consider some simple examples.

2.3.1 Memoryless systems and systems with memory

Memoryless systems are characterized by the property that previous input values are not remembered when determining the current output value. More precisely, a system $F : [\mathbb{R} \rightarrow Y] \rightarrow [\mathbb{R} \rightarrow Y]$ is **memoryless** if there is a function $f : Y \rightarrow Y$ such that

$$\forall t \in \mathbb{R} \text{ and } \forall x \in [\mathbb{R} \rightarrow Y], \quad (F(x))(t) = f(x(t)).$$

This is illustrated in Figure 2.7. In other words, at any time t , the output $(F(x))(t)$ depends only on the input $x(t)$ at that same time t ; in particular, it does not depend on t nor on previous or future values of x .

Specification of a memoryless system reduces to specification of the function f . If Y is finite, then a table may be adequate.

Example 2.17: Consider a continuous-time system with input x and output y , where for all $t \in \mathbb{R}$,

$$y(t) = x^2(t).$$

This example defines a simple system, where the value of the output signal at each time depends only on the value of the input signal at that time. Such systems are said to be memoryless because you do not have to remember previous values of the input in order to determine the current value of the output.

By contrast, here is an example of a system with memory.

Example 2.18: Consider a continuous-time system with input x and output $y = F(x)$ such that $\forall t \in \mathbb{R}$,

$$y(t) = \frac{1}{M} \int_{t-M}^t x(\tau) d\tau.$$

By a change of variables this can also be written

$$y(t) = \frac{1}{M} \int_0^M x(t-\tau) d\tau.$$

This system is clearly not memoryless. It has the effect of smoothing the input signal. We will study it and many related systems in detail in later chapters.

2.3.2 Differential equations

Consider a class of systems given by functions $S: ContSignals \rightarrow ContSignals$ where *ContSignals* is a set of **continuous-time signals**. Depending on the scenario, we could have $ContSignals = [Time \rightarrow \mathbb{R}]$ or $ContSignals = [Time \rightarrow \mathbb{C}]$, where $Time = \mathbb{R}$ or $Time = \mathbb{R}_+$. These are often called **continuous-time systems** because they operate on continuous-time signals. Frequently, such systems can be defined by [differential equations](#) that relate the input signal to the output signal.

Example 2.19: Consider a particle constrained to move forward or backwards along a straight line with an externally imposed force. We will consider this particle to be a system where the output is its position and the externally imposed force is the input.

Denote the position of the particle by x : $\text{Time} \rightarrow \mathbb{R}$, where $\text{Time} = \mathbb{R}_+$. By considering only the non-negative reals, we are assuming that the model has a starting time. We denote the acceleration by a : $\text{Time} \rightarrow \mathbb{R}$. By Newton's law, which relates force, mass, and acceleration,

$$f(t) = ma(t),$$

where $f(t)$ is the force at time t , and m is the mass. By the definition of acceleration,

$$\forall t \in \mathbb{R}_+, \quad \ddot{x}(t) = a(t) = f(t)/m,$$

where $\ddot{x}(t)$ denotes the second derivative with respect to time of x . If we know the initial position $x(0)$ and initial speed $\dot{x}(0)$ of the particle at time 0, and if we are given the input force f , we can evaluate the position at any t by integrating this differential equation

$$x(t) = x(0) + \dot{x}(0)t + \int_0^t [\int_0^s (f(\tau)/m)d\tau]ds. \quad (2.15)$$

We can regard the initial position and velocity as inputs, together with force, in which case the system is a function

$$\text{Particle}: \mathbb{R} \times \mathbb{R} \times [\mathbb{R}_+ \rightarrow \mathbb{R}] \rightarrow [\mathbb{R}_+ \rightarrow \mathbb{R}],$$

where for any inputs $(x(0), \dot{x}(0), f)$, $x = \text{Particle}(x(0), \dot{x}(0), f)$ must satisfy (2.15).

Suppose for example that the input is $(1, -1, f)$ where $m = 1$ and $\forall t \in \mathbb{R}_+, f(t) = 1$. We can calculate the position by carrying out the integration in (2.15) to find that

$$\forall t \in \mathbb{R}_+, \quad x(t) = 1 - t + 0.5t^2.$$

Suppose instead that $x(0) = \dot{x}(0) = 0$ and $\forall t \in \mathbb{R}_+, f(t) = \cos(\omega_0 t)$, where ω_0 is some fixed number. Again, we can carry out the integration to get

$$\int_0^t \int_0^s \cos(\omega_0 u) du ds = -\frac{\cos(\omega_0 t) - 1}{\omega_0^2}.$$

Notice that the position of the particle is sinusoidal. Notice further that the amplitude of this sinusoid decreases as ω_0 increases. Intuitively, this has to be the case. If the externally imposed force is varying more rapidly back and forth, the particle has less time to respond to each direction of force, and hence its excursion is less. In subsequent chapters, we will study how the response of certain kinds of systems varies with the frequency of the input.

2.3.3 Difference equations

Consider a class of systems given by functions $S: DiscSignals \rightarrow DiscSignals$ where *DiscSignals* is a set of [discrete-time signals](#). Depending on the scenario, we could have $DiscSignals = [\mathbb{Z} \rightarrow \mathbb{R}]$ or $DiscSignals = [\mathbb{Z} \rightarrow \mathbb{C}]$, or even $DiscSignals = [\mathbb{N}_0 \rightarrow \mathbb{R}]$, or $DiscSignals = [\mathbb{N}_0 \rightarrow \mathbb{C}]$. These are often called **discrete-time systems** because they operate on discrete-time signals. Frequently, such systems can be defined by **difference equations** that relate the input signal to the output signal.

Example 2.20: Consider a system

$$S: [\mathbb{N}_0 \rightarrow \mathbb{R}] \rightarrow [\mathbb{N}_0 \rightarrow \mathbb{R}]$$

where for all $x \in [\mathbb{N}_0 \rightarrow \mathbb{R}]$, $S(x) = y$ is given by

$$\forall n \in \mathbb{Z}, \quad y(n) = (x(n) + x(n-1))/2.$$

The output at each index is the average of two of the inputs. This is a simple example of a **moving average** system, where typically more than two input values get averaged to produce an output value.

Suppose that $x = u$, the **unit step** function, defined by

$$\forall n \in \mathbb{Z}, \quad u(n) = \begin{cases} 1 & \text{if } n \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (2.16)$$

We can easily calculate the output y ,

$$\forall n \in \mathbb{Z}, \quad y(n) = \begin{cases} 1 & \text{if } n \geq 1 \\ 1/2 & \text{if } n = 0 \\ 0 & \text{otherwise} \end{cases}$$

The system smoothes the transition of the unit step a bit.

A slightly more interesting input is a sinusoidal signal given by

$$\forall n \in \mathbb{Z}, \quad x(n) = \cos(2\pi fn).$$

The output is given by

$$\forall n \in \mathbb{Z}, \quad y(n) = (\cos(2\pi fn) + \cos(2\pi f(n-1)))/2.$$

Using the trigonometric identities in the box on page 76 this can be written as

$$y(n) = R \cos(2\pi fn + \theta)$$

where

$$\begin{aligned} \theta &= \arctan\left(\frac{\sin(-2\pi f)}{1 + \cos(-2\pi f)}\right)/2, \\ R &= \sqrt{2 + 2\cos(2\pi f)} \end{aligned}$$

As in the previous example, a sinusoidal input stimulates a sinusoidal output with the same frequency. In this case, the amplitude of the output varies (in a fairly complicated way) as a function of the input frequency. We will examine this phenomenon in more detail in subsequent chapters by studying the *frequency response* of such systems.

Example 2.21: The general form for a moving average is given by

$$\forall n \in \text{Integers}, \quad y(n) = \frac{1}{M} \sum_{k=0}^{M-1} x(n-k),$$

where x is the input and y is the output. (If this notation is unfamiliar, see box on page 75.)

This system is called an **M -point moving average**, since at any n it gives the average of the M most recent values of the input. It computes an average, just like example 2.18 but the integral has been replaced by its discrete counterpart, the sum.

Moving averages are widely used on Wall Street to smooth out momentary fluctuations in stock prices to try to determine general trends. We will study the smoothing properties of this system. We will also study more general forms of difference equations of which the moving average is a special case.

The examples above give declarative definitions of systems. Imperative definitions require giving a procedure for computing the output signal given the input signal. It is clear how to do that with the memoryless system, assuming that an imperative definition of the function f is available, and with the moving average. The integral equation, however, is harder to define imperatively. An imperative description of such systems that is suitable for computation on a computer requires approximation via solvers for differential equations. Simulink, for example, which is part of the Matlab package, provides such solvers. Alternatively, an imperative description can be given in terms of analog circuits or other physical systems that operate directly on the pertinent continuous domain. Discrete-time systems often have reasonable imperative definitions as **state machines**, considered in detail in the next chapter.

Basics: Trigonometric Identities

The following trigonometric identities will prove useful repeatedly:

$$A \cos(\theta + \alpha) + B \cos(\theta + \beta) = C \cos\theta - S \sin\theta = R \cos(\theta + \phi)$$

where

$$\begin{aligned}C &= A \cos \alpha + B \cos \beta \\S &= A \sin \alpha + B \sin \beta \\R &= \sqrt{C^2 + S^2} \\\phi &= \arctan(S/C)\end{aligned}$$

Basics: Summations

In example 2.21, a discrete-time moving average system is defined by

$$\forall n \in \text{Integers}, \quad y(n) = \frac{1}{M} \sum_{k=0}^{M-1} x(n-k),$$

where x is the input and y is the output. The notation $\sum_{k=0}^{M-1}$ indicates a **sum** of M terms. The terms are $x(n-k)$, where k takes on values from 0 to $M - 1$. Thus,

$$\sum_{k=0}^{M-1} x(n-k) = x(n) + x(n-1) + \cdots + x(n-M+1).$$

Such summations are related to integrals. Example 2.18 describes a continuous-time system with input x and output y where

$$\forall t \in \mathbb{R}, \quad y(t) = \frac{1}{M} \int_{t-M}^t x(\tau) d\tau.$$

This is similar to the discrete-time moving average in that it sums values of x , but it sums over a continuum of values of the dummy variable τ . In the discrete-time version, the sum is over discrete values of the dummy variable k , which takes only integer values. The summation notation has an ambiguity that it does not share with the integral notation. In particular, it is not clear how to interpret an expression like

$$\sum_{k=0}^{M-1} 1 + 2.$$

There are two possibilities, depending on whether the 2 is included in the summation or is interpreted as being outside the summation. One possibility gives a sum of $3M$, while the other gives $M + 2$. In integration, this ambiguity does not occur because of the explicit reference to the dummy variable as $d\tau$. In particular, it is clear that

$$\int_0^T 1 + 2 d\tau \neq \int_0^T 1 d\tau + 2.$$

The left integral is equal to $3T$, while the right integral is $T + 2$.

2.3.4 Composing systems using block diagrams

We have been using **block diagrams** informally to describe systems. But it turns out that block diagrams can have as rigorous and formal a meaning as mathematical notations. We begin the exploration of this concept here, and pursue it much further in Chapter 4.

A block diagram is a **visual syntax** for describing a system as an interconnection of other (component) systems, each of which emphasizes one particular input-to-output transformation of a signal. A block diagram is a collection of blocks interconnected by arrows. Arrows are labeled by signals. Each block represents an individual system that transforms an incoming or **input signal** into an outgoing or **output signal**.

A block diagram, which is a composition of systems, is itself a system. We can use function composition, as discussed in Section 2.1.5, to give a precise meaning to this larger system. A block represents a function, and the connection of an output from one block to the input of another represents the composition of their two functions. The only requirement for interconnecting two blocks is that the output of the first block must be an acceptable input for the second.

Block diagrams can be much more readable than symbolic function composition, particularly for complicated interconnections. They also offer a natural hierarchy, where we can combine blocks to hide certain signals and component systems and to emphasize others.

For certain sorts of blocks, composing them in a block diagram results in a new system whose properties are easy to determine. In chapter 4 we will show how to combine state machine blocks to define a new state machine. In Chapter 8 we will show how to combine filter blocks to define new filter blocks. Here, we consider the composition of blocks when all we know about the blocks is that they represent functions with a given domain and range. No further structure is available.

The simplest block diagram has a single block, as in Figure 2.8. The block represents a system with input signal x and output signal y . Here, x denotes a variable over the set X , and y denotes a variable over the set Y . The system is described by the function $S: X \rightarrow Y$. Both X and Y are sets of functions or signals. Therefore the variables x and y themselves denote functions.

In general, a system obtained by a **cascade composition** of two blocks is given by the composition of the functions describing those blocks. In figure 2.9 the function S describes the system obtained by connecting the systems S_1 and S_2 , with $S = S_2 \circ S_1$, i.e.

$$\forall x \in X, \quad S(x) = S_2(S_1(x)).$$

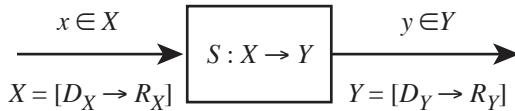


Figure 2.8: The simplest block diagram represents a function S that maps an input signal $x \in X$ to an output signal $y \in Y$. The domain and range of the input are D_X and R_X , respectively, and of the output, D_Y and R_Y .

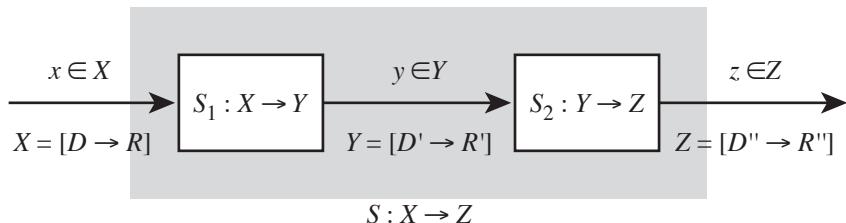


Figure 2.9: The cascade composition of the two systems is described by $S = S_2 \circ S_1$.

The combined system has input signal x , output signal z , and internal signal y . (The internal signal is not visible in the input or output of the combined system.) Of course, the range of the first system must be contained by the domain of the second for this composition to make sense. In the figure, the typical case is shown where this range and domain are the same. The voice path in (2.7) is an example of cascade composition.

Consider two more block diagrams with slightly more complicated structure. Figure 2.10 is similar to Figure 2.9. The system described by S_1 is the same as before, but the system described by S_2 has a pair of input signals $(w, y) \in W \times Y$. The combined system has the pair $(x, w) \in X \times W$ as input signal, z as output signal, y as internal signal, and it is described by the function $S : X \times W \rightarrow Z$, where

$$\forall (x, w) \in X \times W, \quad S(x, w) = S_2(w, S_1(x)). \quad (2.17)$$

Probing Further: Composition of graphs

We suggest a general method for writing down a declarative specification of the interconnected system S in Figure 2.9 in terms of the subsystems S_1 and S_2 and the **connection restriction** that the output of S_1 be acceptable as an input of S_2 .

We describe S_1 and S_2 by their graphs,

$$\text{graph}(S_1) = \{(x, y_1) \in X \times Y \mid y_1 = S_1(x)\},$$

$$\text{graph}(S_2) = \{(y_2, z) \in Y \times Z \mid z = S_2(y_2)\},$$

and we specify the connection restriction as the predicate

$$y_1 = y_2.$$

We use different dummy variables y_1 and y_2 to distinguish between the two systems and the connection restriction.

The graph of the combined system S is then given by

$$\begin{aligned} \text{graph}(S) = & \{(x, z) \in X \times Z \mid \exists y_1, \exists y_2 \\ & (x, y_1) \in \text{graph}(S_1) \wedge (y_2, z) \in \text{graph}(S_2) \wedge y_1 = y_2\}. \end{aligned}$$

Here, \wedge denotes logical **conjunction**, “and.” It is now straightforward to show that $\text{graph}(S) = \text{graph}(S_2 \circ S_1)$ so that $S = S_2 \circ S_1$.

In the case of the cascade composition of Figure 2.9 this elaborate method is unnecessary, since we can write down $S = S_2 \circ S_1$ simply by inspecting the figure. But for feedback connections, we may not be able to write down the combined system directly.

There are three other reasons to understand this method. First, we use it later to obtain a description of interconnected state machines from their component machines. Second, this method is used to describe electronic circuits. Third, if we want a computer to figure out the description of the interconnected system from a description of the subsystems and the connection restrictions, we have to design an algorithm that the computer must follow. Such an algorithm can be based on this general method.

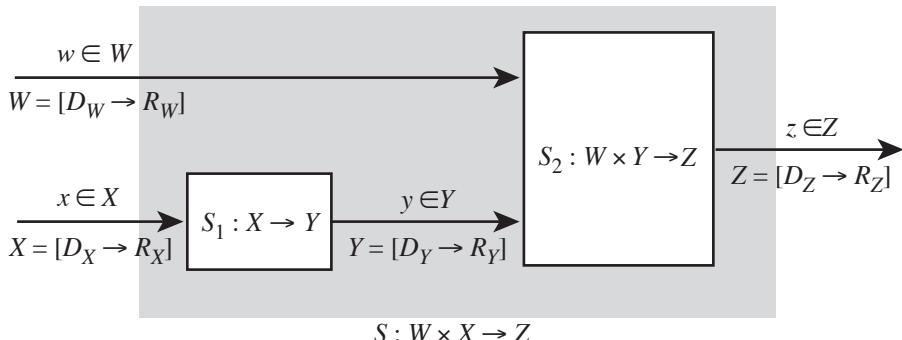


Figure 2.10: The combined system with input signals x, w and output signal z is described by the function S , where $\forall (x, w), S(x, w) = S_2(w, S_1(x))$.

Notice that it is now much harder to define this system using the function composition notation, \circ , yet the block diagram makes its definition evident. In fact, the block diagram notation is much more flexible.

The system of Figure 2.11 is obtained from that of figure 2.10 by connecting the output signal z to the input signal w . As a result the new system has input signal x , output signal z , internal signals y and w , and it is described by the function $S' : X \rightarrow Z$, where

$$\forall x \in X, S'(x) = S_2(S'(x), S_1(x)). \quad (2.18)$$

The connection of z to w is called a **feedback** connection because the output z is fed back as input w . Of course, such a connection has meaning only if Z , the range of S_2 , is a subset of W . The system in Figure 2.11 is again difficult to define using function composition notation, \circ , yet again the block diagram definition is clear.

There is one enormous difference between (2.17) and (2.18). Expression (2.17) serves as a definition of the function S : to every (x, w) in its domain S assigns the value given by the right-hand side which is uniquely determined by the given functions S_1 and S_2 . But in expression (2.18) the value $S'(x)$ assigned to x may not be determined by the right-hand side of (2.18), since the right-hand side itself depends on $S'(x)$. In other words, (2.18) is an *equation* that must be solved to determine the value of $S'(x)$ for a given x ; i.e. $S'(x) = y$ where y is a solution of

$$y = S_2(y, S_1(x)). \quad (2.19)$$

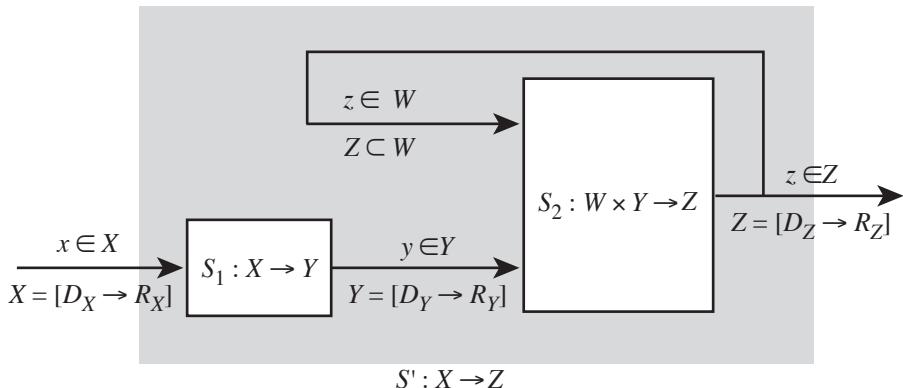


Figure 2.11: The combined system is described by the function S' , where $S'(x) = S_2(S'(x), S_1(x))$.

Such a solution, if it exists, is called a **fixed point**. We now face the difficulty that this equation may have no solution, exactly one solution, or several solutions. Another difficulty is that the value y that solves (2.19) is not a number but a function. So it will not be easy to solve such an equation. Since feedback connections always arise in control systems, we will study how to solve them. We will first solve them in the context of state machines, which are introduced in the next chapter.

All of these block diagrams follow the same principles. They use component systems to define composite systems. To be useful, of course, it is necessary to be able to infer properties of the composite systems. Fortunately, this is often the case, although feedback connections will prove subtle. This idea is explored further in chapters 4 and 8.

2.4 Summary

Signals and systems both are modeled as functions. It is often straightforward to figure out the domain and range of a particular signal and system. It is more difficult to specify the function's assignment rule. Since the domain and range of a system are themselves signal spaces, the assignment rule for a system is more complex than for a signal. The domain and range signal spaces of a system can be quite different: a modem converts bit sequences into sounds, an encoder converts sounds into bit sequences.

The assignment rule of a function takes a declarative or imperative form. The declarative form is usually mathematical, as in: define $\text{Chirp} : [-1, 1] \rightarrow \mathbb{R}$ by

$$\forall t \in [-1, 1], \quad \text{Chirp}(t) = \cos(20\pi t^2).$$

The imperative form is a procedure to evaluate the function at an arbitrary point in its domain. The procedure may involve a table lookup (if the domain is finite) or a computer program. If the domain is infinite, the evaluation procedure may only yield an approximation of the declarative form of the “same” function.

A physical system is often described using differential or difference equations that embody its “law of motion.” A mechanical system’s law of motion is derived from Newton’s laws. An electrical circuit’s law of motion is derived from Kirchhoff’s laws and the laws of the circuit’s constitutive elements: resistors, capacitors, inductors, transistors.

Most systems are built by composing smaller subsystems. The composition may be expressed in the visual syntax of block diagrams or, mathematically, using function composition. Feedback is the most complex form of system composition: a feedback specification requires the solution of a fixed point equation.

Exercises

Each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, and requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **E** The broadcast signal of an AM radio station located at 110 on your dial has a carrier frequency of 110 kHz. An AM signal that includes the carrier has the form

$$\forall t \in \text{Time}, \quad \text{AMSignal}(t) = (1 + m(t)) \sin(2\pi \times 110,000t),$$

where m is an audio signal like *Voice* in figure 1.1, except that $\forall t \in \text{Time}, |m(t)| < 1$. Since you cannot easily plot such a high frequency signal, give an expression for and plot *AMSignal* (using Matlab) for the case where $\text{Time} = [0, 1]$, $m(t) = \cos(\pi t)$, and the carrier frequency is 20 Hz.

2. **T** This problem studies the relationship between the notion of **delay** and the graph of a function.

- (a) Consider two functions f and g from \mathbb{R} into \mathbb{R} where $\forall t \in \mathbb{R}, f(t) = t$ and $g(t) = f(t - t_0)$, where t_0 is a fixed number. Sketch a plot of f and g for $t_0 = 1$ and $t_0 = -1$. Observe that if $t_0 > 0$ then $\text{graph}(g)$ is obtained by moving $\text{graph}(f)$ to the right, and if $t_0 < 0$ by moving it to the left.
- (b) Show that if $f: \mathbb{R} \rightarrow \mathbb{R}$ is any function whatsoever, and $\forall t, g(t) = f(t - t_0)$, then if $(t, y) \in \text{graph}(f)$, then $(t + t_0, y) \in \text{graph}(g)$. This is another way of saying that if $t_0 > 0$ then the graph is moved to the right, and if $t_0 < 0$ then the graph is moved to the left.
- (c) If t represents time, and if $t_0 > 0$, we say that g is obtained by *delaying* f . Why is it reasonable to say this?

3. **E** Indicate whether the following statements are true or false.

- (a) $[\{1, 2, 3\} \rightarrow \{a, b\}] \subset [\mathbb{N} \rightarrow \{a, b\}]$
- (b) $\{g \mid g = \text{graph}(f) \wedge f: X \rightarrow Y\} \subset X \times Y$
- (c) $F: [\mathbb{R} \rightarrow \mathbb{R}] \rightarrow [\mathbb{R} \rightarrow \mathbb{R}]$, such that $\forall t \in \mathbb{R}$, and $\forall x \in [\mathbb{R} \rightarrow \mathbb{R}]$,

$$(F(x))(t) = \sin(2\pi \cdot 440t)$$

is a memoryless system.

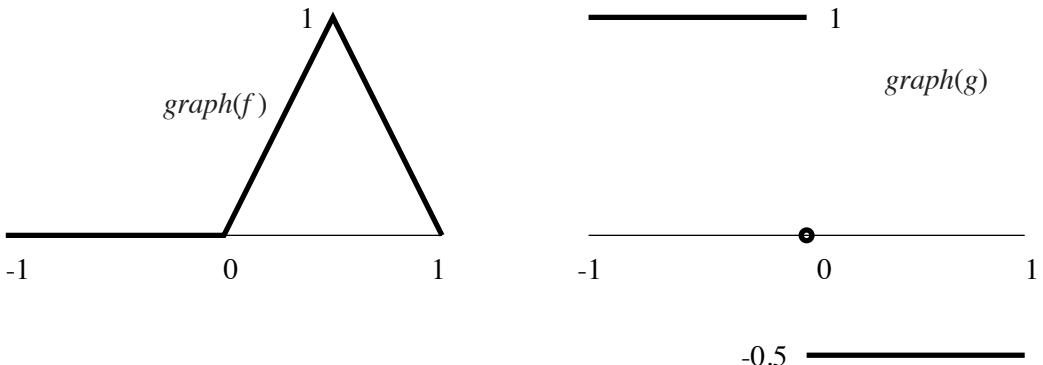


Figure 2.12: Graphs of two functions. The bold line is the graph.

- (d) Let $f: \mathbb{R} \rightarrow \mathbb{R}$ and $g: \mathbb{R} \rightarrow \mathbb{R}$, where g is obtained by delaying f by $\tau \in \mathbb{R}$. That is,

$$\forall t \in \mathbb{R}, \quad g(t) = f(t - \tau).$$

Then $graph(g) \subset graph(f)$.

4. **E** Figure 2.12 shows graphs of two functions $f: [-1, 1] \rightarrow [-1, 1]$ and $g: [-1, 1] \rightarrow [-1, 1]$. For each case, define the function by giving an algebraic expression for its value at each point in its domain. This expression will have several parts, similar to the definition of the *signum* function in (2.3). Note that $g(0) = 0$ for the graph on the right. Plot $graph(f \circ g)$ and $graph(g \circ f)$.
5. **T** Let $X = \{a, b, c\}$, $Y = \{1, 2\}$. For each of the following subsets $G \subset X \times Y$, determine whether G is the graph of a function from X to Y , and if it is, describe the function as a table.
- (a) $G = \{(a, 1), (b, 1), (c, 2)\}$
 - (b) $G = \{(a, 1), (a, 2), (b, 1), (c, 2)\}$
 - (c) $G = \{(a, 1), (b, 2)\}$
6. **C** A router in the Internet is a switch with several input ports and several output ports. A packet containing data arrives at an input port at an arbitrary time, and the switch forwards the packet to one of the outgoing ports. The ports of different routers are connected by transmission links. When a packet arrives at an input port,

the switch examines the packet, extracting from it a destination address d . The switch then looks up the output port in its routing table, which contains entries of the form $(d, \text{outputPort})$. It then forwards the packet to the specified output port. The Internet works by setting up the routing tables in the routers.

Consider a simplified router with one input port and two output ports, named O_1, O_2 . Let D be the set of destination addresses.

- (a) Explain why the routing table can be described as a subset $T \subset D \times \{O_1, O_2\}$.
 - (b) Is it reasonable to constrain T to be the graph of a function from $D \rightarrow \{O_1, O_2\}$? Why?
 - (c) Assume the signal at the input port is a sequence of packets. How would you describe the space of input signals to the router and output signals from the router?
 - (d) How would you describe the switch as a function from the space of input signals to the space of output signals?
7. C For each of the following expressions, state whether it can be interpreted as an assignment, an assertion, or a predicate. More than one choice may be valid because the full context is not supplied.
- (a) $x = 5$,
 - (b) $A = \{5\}$,
 - (c) $x > 5$,
 - (d) $3 > 5$,
 - (e) $x > 5 \wedge x < 3$.
8. T A logic circuit with m binary inputs and n binary outputs is shown in Figure 2.13. It is described by a function $F : X \rightarrow Y$ where $X = \text{Binary}^m$ and $Y = \text{Binary}^n$. (In a circuit, the signal values 1 and 0 in *Binary* correspond to voltage *High* and *Low*, respectively.) How many such distinct logic functions F are there?
9. E The function $H : [\mathbb{R}_+ \rightarrow \mathbb{R}] \rightarrow [\mathbb{N}_0 \rightarrow \mathbb{R}]$ given by: $\forall x \in [\mathbb{R}_+ \rightarrow \mathbb{R}],$

$$\forall n \in \mathbb{N}_0, \quad H(x)(n) = x(10n),$$

is a mathematical example of a system with input signal space $[\mathbb{R}_+ \rightarrow \mathbb{R}]$ and output signal space $[\mathbb{N}_0 \rightarrow \mathbb{R}]$. Give a mathematical example of a system H whose

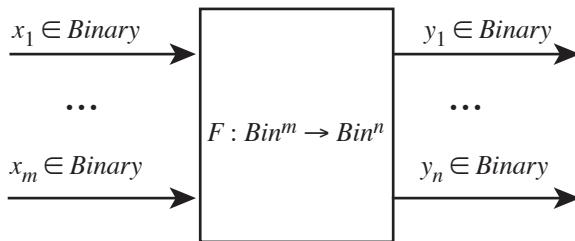


Figure 2.13: The logic circuit has m binary inputs (x_1, \dots, x_m) and n binary outputs (y_1, \dots, y_n) .

- (a) input and output signal spaces both are $[\mathbb{N}_0 \rightarrow \text{Binary}]$.
- (b) input signal space is $[\mathbb{N}_0 \rightarrow \mathbb{R}]$ and output signal space is $[\mathbb{N}_0 \rightarrow \{0, 1\}]$.
- (c) input signal space is $[\mathbb{Z} \rightarrow \mathbb{R}]$ and output signal space is $[\mathbb{R} \rightarrow \mathbb{R}]$.

10. E Consider the functions

$$g: Y \rightarrow \mathbb{R} \quad \text{and} \quad f: \mathbb{N} \rightarrow Y.$$

where Y is a set.

- (a) Draw a block diagram for $(g \circ f)$, with one block for each of g and f , and label the inputs and output of the blocks with the domain and range of g and f .
- (b) Suppose Y is given by

$$Y = [\{1, \dots, 100\} \rightarrow \mathbb{R}]$$

(Thus, the function f takes a natural number and returns a sequence of length 100, while the function g takes a sequence of length 100 and returns a real number.)

Suppose further that g is given by: for all $y \in Y$,

$$g(y) = \sum_{i=1}^{100} y(i) = y(1) + y(2) + \dots + y(100),$$

and f by: for all $x \in \mathbb{N}$ and $z \in \{1, \dots, 100\}$,

$$(f(x))(z) = \cos(2\pi z/x).$$

(Thus, x gives the period of a cosine waveform, and f gives 100 samples of that waveform.) Give a one-line Matlab expression that evaluates $(g \circ f)(x)$ for any $x \in \mathbb{N}$. Assume the value of x is already in a Matlab variable called \mathbf{x} .

- (c) Find $(g \circ f)(1)$.

11. **T** The following system S takes a discrete-time signal $x \in X$ and transforms it into a discrete-time signal $y \in Y$ whose value at index n is the average of the previous 4 values of x . Such a system is called a **moving average**. Suppose that $X = Y = [\mathbb{N} \rightarrow \mathbb{R}]$, where \mathbb{N} is the set of natural numbers. More precisely, the system is described by the function S such that for any $x \in X$, $y = S(x)$ is given by

$$y(n) = \begin{cases} [x(1) + \dots + x(n)]/4 & \text{for } 1 \leq n < 4 \\ [x(n-3) + x(n-2) + x(n-1) + x(n)]/4 & \text{for } n \geq 4 \end{cases}$$

Notice that the first three samples are averages only if we assume that samples prior to those that are available have value zero. Thus, there is an initial **transient** while the system collects enough data to begin computing meaningful averages.

Write a Matlab program to calculate and plot the output signal y for time $1 \leq n \leq 20$ for the following input signals:

- x is a unit step delayed by 10, i.e. $x(n) = 0$ for $n \leq 9$ and $x(n) = 1$ for $n \geq 10$.
 - x is a unit step delayed by 15.
 - x alternates between +1 and -1, i.e. $x(n) = 1$ for n odd, and $x(n) = -1$ for n even. **Hint:** Try computing $\cos(\pi n)$ for $n \in \mathbb{N}$.
 - Comment on what this system does. Qualitatively, how is the output signal different from the input signal?
12. **T** The following system is similar to problem 11, but time is continuous. Now $X = Y = [\mathbb{R} \rightarrow \mathbb{R}]$ and the system $F: X \rightarrow Y$ is defined as follows. For all $x \in X$ and $t \in \mathbb{R}$

$$(F(x))(t) = \frac{1}{10} \int_{t-10}^t x(s) ds.$$

Show that if x is the sinusoidal signal

$$\forall t \in \mathbb{R} \quad x(t) = \sin(\omega t),$$

then y is also sinusoidal

$$\forall t \in \mathbb{R}, \quad y(t) = A \sin(\omega t + \phi).$$

You do not need to give precise expressions for A and ϕ , but just show that the result has this form. Also, show that as ω gets large, the amplitude of the output gets small. Higher frequencies, which represent more abrupt changes in the input, are more attenuated by the system than lower frequencies.

Hint: The following fact from calculus may be useful:

$$\int_a^b \sin(\omega s) ds = \frac{1}{\omega} (\cos(\omega a) - \cos(\omega b)).$$

Also, the identity in the footnote on page 76 might be useful to show that the output is sinusoidal with the appropriate frequency.

13. E Suppose that $f: \mathbb{R} \rightarrow \mathbb{R}$ and $g: \mathbb{R} \rightarrow \mathbb{Z}$ such that for all $x \in \mathbb{R}$,

$$g(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases}$$

and

$$f(x) = 1 + x.$$

- (a) Define $h = g \circ f$.
- (b) Suppose that

$$\begin{aligned} F: [\mathbb{R} \rightarrow \mathbb{R}] &\rightarrow [\mathbb{R} \rightarrow \mathbb{R}] \\ G: [\mathbb{R} \rightarrow \mathbb{R}] &\rightarrow [\mathbb{R} \rightarrow \mathbb{Z}] \end{aligned}$$

such that for all $s \in [\mathbb{R} \rightarrow \mathbb{R}]$ and $x \in \mathbb{R}$,

$$\begin{aligned} (F(s))(x) &= f(s(x)) \\ (G(s))(x) &= g(s(x)) \end{aligned}$$

where f and g are as given above. Sketch a block diagram for $H = G \circ F$, where you have one block for each of G and F . Label the inputs and outputs of your blocks with the domain and range of the functions in the blocks.

- (c) Let $s \in [\mathbb{R} \rightarrow \mathbb{R}]$ be such that for all $x \in \mathbb{R}$,

$$s(x) = \cos(\pi x).$$

Define u where

$$u = (G \circ F)(s).$$

Give the domain, range, and assignment rule for u .

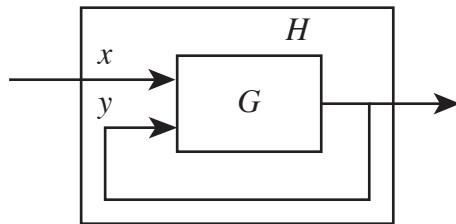
14. T Let $D = DiscSignals = [\mathbb{Z} \rightarrow \mathbb{R}]$ and let

$$G: D \times D \rightarrow D$$

such that for all $x, y \in D$ and for all $n \in \mathbb{Z}$,

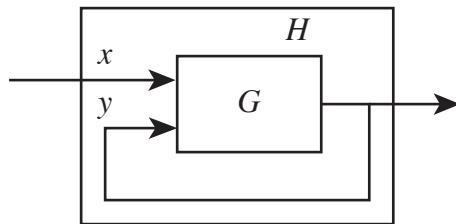
$$(G(x, y))(n) = x(n) - y(n-1).$$

Now suppose we construct a new system H as follows:



Define H (as much as you can).

15. T Consider a similar system H to that in the previous problem,



but where now $x \in \mathbb{R}_+$ and $y \in \mathbb{R}_+$. The inputs and outputs are no longer signals, but rather just non-negative real numbers. So $G: \mathbb{R}_+ \times \mathbb{R}_+ \rightarrow \mathbb{R}_+$. Block diagrams, of course, work just as well for such simpler functions.

In this problem, we explore fixed points by considering a classic algorithm for calculating the square root of a non-negative real number. Let the function G above be given by

$$\forall x, y \in \mathbb{R}_+, \quad G(x, y) = 0.5(y + x/y). \quad (2.20)$$

- (a) Show that for a given $x \in \mathbb{R}_+$, if the fixed point exists, then $H: \mathbb{R}_+ \rightarrow \mathbb{R}_+$ is given by

$$\forall x \in \mathbb{R}_+, \quad H(x) = \sqrt{x}.$$

- (b) To use the system above to calculate a square root, we simply start with a guess for y , say 1, and calculate $G(x,y)$ repeatedly until it converges to a stable value for y . That stable value is the fixed point. Do this calculation for $x = 4$ and for $x = 12$, repeating the evaluation of G until you obtain a close approximation to the true square root. You may want to use Matlab for this.

State Machines

Contents

3.1	Structure of state machines	94
3.1.1	Updates	95
3.1.2	Stuttering	97
3.2	Finite state machines	98
3.2.1	State transition diagrams	99
3.2.2	Update table	103
3.3	Nondeterministic state machines	107
3.3.1	State transition diagram	107
3.3.2	Sets and functions model	110
3.4	Simulation relations	112
3.4.1	Relating behaviors	119
3.5	Summary	121
Exercises		129

Systems are functions that transform signals. The domain and the range of these functions are both signal spaces, which significantly complicates specification of the functions. A broad class of systems can be characterized using the concept of **state** and the idea that a system evolves through a sequence of changes in state, or **state transitions**. Such characterizations are called **state-space models**.

A state-space model describes a system procedurally, giving a sequence of step-by-step operations for the evolution of a system. It shows how the input signal drives changes in

state, and how the output signal is produced. It is thus an imperative description. Implementing a system described by a state-space model in software or hardware is straightforward. The hardware or software simply needs to sequentially carry out the steps given by the model. Conversely, given a piece of software or hardware, it is often useful to describe it using a state-space model, which yields better to analysis than more informal descriptions.

In this chapter, we introduce state-space models by discussing systems with a finite (and relatively small) number of states. Such systems typically operate on event streams, often implementing control logic. For example, the decision logic of modem negotiation described in Chapter 1 can be modeled using a finite state model. Such a model is much more precise than the English-language descriptions that are commonly used for such systems.

3.1 Structure of state machines

A description of a system as a function involves three entities: the set of input signals, the set of output signals, and the function itself,

$$F : \text{InputSignals} \rightarrow \text{OutputSignals}.$$

For a **state machine**, the input and output signals have the form

$$\text{EventStream} : \mathbb{N}_0 \rightarrow \text{Symbols},$$

where $\mathbb{N}_0 = \{0, 1, 2, \dots\}$, and *Symbols* is an arbitrary set. The domain of these signals represents *ordering* but not necessarily time (neither discrete nor continuous time). The ordering of the domain means that we can say that one event occurs *before* or *after* another event. But we cannot say how much time elapsed between these events. In Chapter 5 we will study how state-space models can be used with functions of time.

A state machine constructs the output signal one symbol at a time by observing the input signal one symbol at a time. Specifically, a state machine *StateMachine* is a 5-tuple,

$$\text{StateMachine} = (\text{States}, \text{Inputs}, \text{Outputs}, \text{update}, \text{initialState}) \quad (3.1)$$

where *States*, *Inputs*, *Outputs* are sets, *update* is a function, and $\text{initialState} \in \text{States}$. The meaning of these names is:

States is the **state space**,

Inputs is the **input alphabet**,

Outputs is the **output alphabet**,

initialState \in *States* is the **initial state**, and

update: $States \times Inputs \rightarrow States \times Outputs$ is the **update function**.

This five-tuple is called the **sets and functions model** of a state machine.

Inputs and *Outputs* are the sets of possible input and output symbols. The set of **input signals** consists of all infinite sequences of input symbols,

$$InputSignals = [\mathbb{N}_0 \rightarrow Inputs].$$

The set of **output signals** consists of all infinite sequences of output symbols,

$$OutputSignals = [\mathbb{N}_0 \rightarrow Outputs].$$

Let $x \in InputSignals$ be an input signal. A particular symbol in the signal can be written $x(n)$ for any $n \in \mathbb{N}_0$. We write the entire input signal as a sequence

$$(x(0), x(1), \dots, x(n), \dots).$$

This sequence defines the function x in terms of symbols $x(n) \in Inputs$, which represent particular input symbols.

We reiterate that the index n in $x(n)$ does not refer to time, but rather to the **step number**. This is an **ordering constraint** only: step n occurs after step $n - 1$ and before step $n + 1$. The state machine evolves (i.e. moves from one state to the next) in **steps**.¹

3.1.1 Updates

The interpretation of *update* is this. If $s(n) \in States$ is the current state at step n , and $x(n) \in Inputs$ is the current input symbol, then the current output symbol and the next state are given by

$$(s(n+1), y(n)) = update(s(n), x(n)).$$

¹Of course the steps could last a fixed duration of time, in which case there would be a simple relationship between step number and time. The relationship may be a mixed one, where some input symbols are separated by a fixed amount of time and some are not.

Thus the *update* function makes it possible for the state machine to construct the output signal step by step by observing the input signal step by step.

The state machine *StateMachine* of (3.1) defines a function

$$F : InputSignals \rightarrow OutputSignals \quad (3.2)$$

such that for any input signal $x \in InputSignals$ the corresponding output signal is $y = F(x)$. However, it does much more than just define this function. It also gives us a procedure for evaluating this function on a particular input signal. The **state response** $(s(0), s(1), \dots)$ and output signal y are constructed as follows:

$$s(0) = initialState, \quad (3.3)$$

$$\forall n \geq 0, (s(n+1), y(n)) = update(s(n), x(n)), \quad (3.4)$$

Observe that if the initial state is changed, the function F will change, so the initial state is an essential part of the definition of a state machine.

Each evaluation of (3.4) is called a **reaction** because it defines how the state machine reacts to a particular input symbol. Note that exactly one output symbol is produced for each input symbol. Thus, it is not necessary to have access to the entire input sequence to start producing output symbols. This feature proves extremely useful in practice, since it is usually impractical to have access to the entire input sequence (it is infinite in size!). The procedure summarized by (3.3)–(3.4) is **causal**, in that the next state $s(n+1)$ and current output symbol $y(n)$ depend only on the initial state $s(0)$ and current and past input symbols $x(0), x(1), \dots, x(n)$.

It is sometimes convenient to decompose *update* into two functions:

nextState: $States \times Inputs \rightarrow States$ is the **next state function**,

output: $States \times Inputs \rightarrow Outputs$ is the **output function**.

The interpretation is this. If $s(n)$ is the current state, and $x(n)$ is the current input symbol at step n , the next state is

$$s(n+1) = nextState(s(n), x(n)),$$

and the current output symbol is

$$y(n) = output(s(n), x(n)).$$

Evidently, for all $s(n) \in States$ and $x(n) \in Inputs$,

$$(s(n+1), y(n)) = update(s(n), x(n)) = (nextState(s(n), x(n)), output(s(n), x(n))).$$

3.1.2 Stuttering

A state machine produces exactly one output symbol for each input symbol. For each input symbol, it may also change state (of course, it could also remain in the same state by changing back to the same state). This means that with no input symbol, there is neither an output symbol nor a change of state.

Later, when we compose simpler state machines to construct more complicated ones, it will prove convenient to be explicit in the model about the fact that no input triggers no output and no state change. We do that by insisting that the input and output symbol sets include a **stuttering symbol**, typically denoted *absent*. That is,

$$\text{absent} \in \text{Inputs}, \text{ and } \text{absent} \in \text{Outputs}.$$

Moreover, we require that for any $s \in \text{States}$,

$$\text{update}(s, \text{absent}) = (s, \text{absent}). \quad (3.5)$$

This is called a **stuttering reaction** because no progress is made. An absent input symbol triggers an absent output symbol and no state change. Now any number of *absent* symbols may be inserted into the input sequence, anywhere, without changing the non-absent output symbols. Stuttering reactions will prove essential for hybrid systems models, considered in Chapter 6.

Example 3.1: Consider a 60-minute parking meter. There are three (non-stuttering) input symbols: *in5* and *in25* which represent feeding the meter 5 and 25 cents respectively, and *tick* which represents the passage of one minute. The meter displays the time in minutes remaining before the meter expires. When *in5* occurs, this time is incremented by 5, and when *in25* occurs it is incremented by 25, up to a maximum of 60 minutes. When *tick* occurs, the time is decremented by 1, down to a minimum of 0. When the remaining time is 0, the display reads *expired*.

We can construct a finite state machine model for this parking meter. The set of states is

$$\text{States} = \{0, 1, 2, \dots, 60\}.$$

The input and output alphabets are

$$\text{Inputs} = \{\text{in5}, \text{in25}, \text{tick}, \text{absent}\},$$

$$Outputs = \{expired, 1, 2, \dots, 60, absent\}.$$

The initial state is

$$initialState = 0.$$

The update function

$$update : States \times Inputs \rightarrow States \times Outputs$$

is given by, $\forall s(n) \in States, x(n) \in Inputs,$

$$update(s(n), x(n)) = \begin{cases} (0, expired) & \text{if } x(n) = tick \wedge (s(n) = 0 \vee s(n) = 1) \\ (s(n) - 1, s(n) - 1) & \text{if } x(n) = tick \wedge s(n) > 1 \\ (\min(s(n) + 5, 60), \min(s(n) + 5, 60)) & \text{if } x(n) = in5 \\ (\min(s(n) + 25, 60), \min(s(n) + 25, 60)) & \text{if } x(n) = in25 \\ (s(n), absent) & \text{if } x(n) = absent \end{cases}$$

where \min is a function that returns the minimum of its arguments.

If the input sequence is $(in25, tick^{20}, in5, tick^{10}, \dots)$, for example, then the output sequence is

$$(expired, 25, 24, \dots, 6, 5, 10, 9, 8, \dots, 2, 1, expired, \dots).$$

Here, we are using the common notation $tick^{10}$ to mean a sequence of 10 consecutive ticks.

3.2 Finite state machines

Often, $States$ is a finite set. In this case, the state machine is called a **finite state machine**, abbreviated **FSM**. FSMs yield to powerful analytical techniques because, in principle, it is possible to explore all possible sequences of states. The parking meter above is a finite

state machine. The remainder of this chapter and the next chapter will focus on finite state machines. We will return to infinite state systems in Chapter 5.

When the number of states is small, and the input and output alphabets are finite (and small), we can describe the state machine using a very readable and intuitive diagram called a **state transition diagram**.

Example 3.2: A verbal description of an automatic telephone answering service or voice-mail service might go like this.

When a call arrives, the phone rings. If the phone is not picked up, then on the third ring, the service answers. It plays a pre-recorded greeting requesting that the caller leave a message (“Hello, sorry I can’t answer your call right now ... Please leave a message after the beep”), then records the caller’s message, and then automatically hangs up. If the phone is answered before the third ring, the service does nothing.

Figure 3.1 shows a state transition diagram for the state machine model of this answering service.

You can probably read the diagram in Figure 3.1 without any further explanation. It is sufficiently intuitive. Nonetheless, we will explain it precisely.

3.2.1 State transition diagrams

Figure 3.1 consists of bubbles linked by arcs. (The arcs are also called arrows.) In this bubbles-and-arcs syntax each bubble represents one state of the answering service, and each arc represents a **transition** from one state to another. The bubbles and arcs are annotated, i.e. they are labeled with some text. The execution of the state machine consists of a sequence reactions, where each reaction involves a transition from one state to another (or back to the same state) along one of the arcs. The tables at the bottom of the figure are not part of the state transition diagram, but they improve our understanding of the diagram by giving the meanings of the names of the states, input symbols, and output symbols.

The notation for state transition diagrams is summarized in Figure 3.2. Each bubble is labeled with the name of the **state** it represents. The state names can be anything, but they

must be distinct. The state machine of Figure 3.1 has five states. The state names define the state space,

$$\text{States} = \{\text{idle}, \text{count1}, \text{count2}, \text{play greeting}, \text{recording}\}.$$

Each arc is labeled by a **guard** and (optionally) an **output**. If an output symbol is given, it is separated from the guard by a forward slash, as in the example $\{\text{ring}\}/\text{answer}$ going from state *count2* to *play greeting*. A guard specifies which input symbols might trigger the associated transition. It is a subset of the *Inputs*, the input alphabet, which for the answering service is

$$\text{Inputs} = \{\text{ring}, \text{offhook}, \text{end greeting}, \text{end message}, \text{absent}\}.$$

In Figure 3.1, some guards are labeled “*else*.” This special notation designates an arc that is taken when there is no match on any other guard emerging from a given state. The arc with the guard *else* is called the **else arc**. Thus, *else* is the set of all input symbols not included in any other guard emerging from the state. More precisely, for a given state, *else* is the complement with respect to *Inputs* of the union of the guards on emerging arcs. For example in Figure 3.1, for state *recording*,

$$\text{else} = \{\text{ring}, \text{end greeting}\}.$$

For the example in Figure 3.2, *else* is defined by

$$\text{else} = \{i \in \text{Inputs} \mid i \notin (\text{guard1} \cup \text{guard2})\}.$$

If no *else* arc is specified, and the set *else* is not empty, then the *else* arc is implicitly a **self loop**, as shown by the dashed arc in figure 3.2. A self loop is an arc that transitions back to the same state. When the *else* arc is a self loop, then the stuttering symbol may be a member of the set *else*.

Initially, the system of Figure 3.1 is in the *idle* state. The initial state is indicated by the bold arc on the left that leads into the state *idle*. Each time an input symbol arrives, the state machine reacts. It checks the guards on arcs going out of the current state and determines which of them contains the input symbol. It then takes that transition.

Two problems might occur.

- The input symbol may not be contained in the guard of any outgoing arc. In our state machine models, for every state, there is at least one outgoing transition that

matches the input symbol (because of the *else* arc). This property is called **receptiveness**; it means that the machine can always react to an input symbol. That is, there is always a transition out of the current state that is enabled by the current input symbol. (The transition may lead back to current state if it is a self loop.) Our state machines are said to be **receptive**.

- More than one guard going out from the current state may contain the input symbol. A state machine that has such a structure is said to be **nondeterministic**. The machine is free to choose any arc whose guard contains the input symbol, so more than one behavior is possible for the machine. Nondeterministic state machines will be discussed further below. Until then, we assume that the guards are always defined to give **deterministic** state machines. Specifically, the guards on outgoing arcs from any state are mutually exclusive. In other words, the intersection of any two guards on outgoing arcs of a state is empty, as indicated in Figure 3.2. Of course, by the definition of the *else* set, for any *guard* that is not *else*, it is true that $\text{guard} \cap \text{else} = \emptyset$.

A sequence of input symbols thus triggers a sequence of state transitions. The resulting sequence of states is called the **state response**.

Example 3.3: In Figure 3.1, if the input sequence is

$$(ring, ring, offhook, \dots)$$

then the state response is

$$(idle, count1, count2, idle, \dots).$$

The ellipsis (“...”) are there because the answering service generally responds to an infinite input sequence, and we are showing only the beginning of that response. This behavior can be compactly represented by a **trace**,

$$\text{idle} \xrightarrow{\text{ring}} \text{count1} \xrightarrow{\text{ring}} \text{count2} \xrightarrow{\text{offhook}} \text{idle} \dots$$

A trace represents the state response together with the input sequence that triggers it. This trace describes the behavior of the answering service when someone picks up a telephone extension after two rings.

A more elaborate trace illustrates the behavior of the answering service when it takes a message:

$$\begin{array}{ccccccc}
 idle & \xrightarrow{\text{ring}} & count1 & \xrightarrow{\text{ring}} & count2 & \xrightarrow{\text{ring}} & play\ greeting \\
 & \xrightarrow{\text{end greeting}} & & \xrightarrow{\text{recording}} & & \xrightarrow{\text{end message}} & idle \\
 & & & & & & \dots
 \end{array} \tag{3.6}$$

A state machine also produces outputs. In Figure 3.1, the output alphabet is

$$Outputs = \{answer, record, recorded, absent\}.$$

An output symbol is produced as part of a reaction. The output symbol that is produced is indicated after a slash on an arc. If the arc annotation shows no output symbol, then the output symbol is **absent**.

Example 3.4: The output sequence for the trace (3.6) is

$$(absent, absent, answer, record, recorded, \dots).$$

There is an output symbol for every input symbol, and some of the output symbols are *absent*.

It should be clear how to obtain the state response and output sequence for any input sequence. We begin in the initial state and then follow the state transition diagram to determine the successive state transitions for successive input symbols. Knowing the sequence of transitions, we also know the sequence of output symbols.

Shorthand

State transition diagrams can get very verbose, with many arcs with complicated labels. A number of shorthand options can make a diagram clearer by reducing the clutter.

- If no guard is specified on an arc, then that transition is always taken when the state machine reacts and is in the state from which arc emerges, as long as the input is

not the stuttering symbol. That is, giving no guard is equivalent to giving the entire set *Inputs* as a guard, minus the stuttering symbol. The stuttering symbol, recall, always triggers a transition back to the same state, and always produces a stuttering symbol on the output.

- Any clear notation for specifying subsets can be used to specify guards. For example, if *Inputs* = {*a*, *b*, *c*}, then the guard {*b*, *c*} can be given by $\neg a$ (read “not *a*”).
- An *else* transition for a state need not be given explicitly. It is an implied self-loop if it is not given. This is why it is shown with a dashed line in Figure 3.2.
- The output symbol is the stuttering symbol of *Outputs* if it is not given.

These shorthand notations are not always a good idea. For example, the *else* transitions often correspond to exceptional (unexpected) input sequences, and staying in the same state might not be the right behavior. For instance, in Figure 3.1, all *else* transitions are shown explicitly, and all exceptional input sequences result in the machine ending up in state *idle*. This is probably reasonable behavior, allowing the machine to recover. Had we left the *else* transitions implicit, we would likely have ended up with less reasonable behavior. Use your judgment in deciding whether or not to explicitly include *else* transitions.

3.2.2 Update table

An alternative way to describe a finite state machine is by an **update table**. This is simply a tabular representation of the state transition diagram.

For the diagram of Figure 3.1, the table is shown in Figure 3.3. The first column lists the current state. The remaining columns list the next state and the output symbol for each of the possible input symbols.

The first row, for example, corresponds to the current state *idle*. If the input symbol is *ring*, the next state is *count1* and the output symbol is *absent*. Under any of the other input symbols, the state remains *idle* and the output symbol remains *absent*.

Types of State Machines

The type of state machines introduced in this section are known as **Mealy machines**, after G. H. Mealy, who studied them in 1955. Their distinguishing feature is that output symbols are associated with state transitions. That is, when a transition is taken, an output symbol is produced. Alternatively, we could have associated output symbols with states, resulting in a model known as **Moore machines**, after F. Moore, who studied them in 1956. In a Moore machine, an output symbol is produced while the machine is in a particular state. Mealy machines turn out to be more useful when they are composed synchronously, as we will do in the next chapter. This is the reason that we choose this variant of the model.

It is important to realize that state machine models, like most models, are not unique. A great deal of engineering judgment goes into a picture like Figure 3.1, and two engineers might come up with very different pictures for what they believe to be the same system. Often, the differences are in the amount of detail shown. One picture may show the operation of a system in more detail than another. The less detailed picture is called an **abstraction** of the more detailed picture. Also likely are differences in the names chosen for states, input symbols and output symbols, and even in the meaning of the input and output symbols. There may be differences in how the machine responds to exceptional circumstances (input sequences that are not expected). For example, what should the answering service do if it gets the input sequence (*ring, end greeting, end message*)? This probably reflects a malfunction in the system. In figure 3.1, the reaction to this sequence is easy to see: the machine ends up in the *idle* state.

Given these likely differences, it becomes important to be able to talk about **abstraction relations** and **equivalence relations** between state machine models. This turns out to be a fairly sophisticated topic, one that we touch upon below in Section 3.3.

The meaning of state

We have three equivalent ways of describing a state machine: sets and functions, the state transition diagram, and the update table. These descriptions have complementary uses. The table makes obvious the sparsity of output symbols in the answering service example. The table and the diagrams are both useful for a human studying the system to follow its behavior in different circumstances. The sets and functions and the table are useful for

building the state machine in hardware or software. The sets and functions description is also useful for mathematical analysis.

Of course, the tables and the transition diagram can be used only if there are finitely many states and finitely many input and output symbols, i.e. if the sets *States*, *Inputs*, and *Outputs* are finite. The sets and functions description is often equally comfortable with finite and infinite state spaces. We will discuss infinite-state systems in Chapter 5.

Like any state machine, a telephone answering service is a **state-determined** system. Once we know its current state, we can tell what its future behavior is for any future input symbols. We do not need to know what input symbols in the past led to the current state in order to predict how the system will behave in the future. In this sense we can say the current state of the system summarizes the past history of the system. This is, in fact, the key intuitive notion of state.

The number of states equals the number of patterns we need to summarize the past history. If this is intrinsically finite, then a finite-state model exists for the system. If it is intrinsically infinite, then no finite-state model exists. We can often determine which of these two situations applies using simple intuition. We can also show that a system has a finite-state model by finding one. Showing that a system does not have a finite-state model is a bit more challenging.

Example 3.5: Consider the example of a system called *CodeRecognizer* whose input and output signals are sequences of 0 and 1 (with arbitrarily inserted stuttering symbols, which have no effect). The system outputs *recognize* at the end of every subsequence 1100 in the input, and otherwise it outputs *absent*. If the input x is given by a sequence

$$(x(0), x(1), \dots),$$

and the output y is given by the sequence

$$(y(0), y(1), \dots),$$

then, if none of the input symbols is *absent*,

$$y(n) = \begin{cases} \text{recognize} & \text{if } (x(n-3), x(n-2), x(n-1), x(n)) = (1, 1, 0, 0) \\ \text{absent} & \text{otherwise} \end{cases} \quad (3.7)$$

Intuitively, in order to determine $y(n)$, it is enough to know whether the previous pattern of (non-*absent*) inputs is 0, 1, 11, or 110. If this intuition is correct, we

can implement *CodeRecognizer* by a state machine with four states that remember the patterns 0, 1, 11, 110. The machine of Figure 3.4 does the job. The fact that we have a finite-state machine model of this system shows that this is a finite-state system.

The relationship in this example between the number of states and the number of input patterns that need to be stored suggests how to construct functions mapping input sequences to output sequences that cannot be realized by finite state machines. Here is a particularly simple example of such a function called *Equal*.

Example 3.6: An input signal of *Equal* is a sequence of 0 and 1 (again with stuttering symbols arbitrarily inserted). At each step, *Equal* outputs *equal* if the previous inputs contain an equal number of 0's and 1's; otherwise *Equal* outputs *notEqual*. In other words, if the input sequence x is the sequence $(x(0), x(1), \dots)$, with no stuttering symbols, then the output sequence $y = F(x)$ is given by

$$\forall n \in \mathbb{N}_0, \quad y(n) = \begin{cases} \text{equal} & \text{if if number of 1's is the same as 0's} \\ & \text{in } x(0), \dots, x(n) \\ \text{notEqual} & \text{if otherwise} \end{cases} \quad (3.8)$$

Intuitively, in order to realize *Equal*, the machine must remember the difference between the number of 1's and 0's that have occurred in the past. Since these numbers can be arbitrarily large, the machine must have infinite memory, and so *Equal* cannot be realized by a finite-state machine.

We give a mathematical argument to show that *Equal* cannot be realized by any finite-state machine. The argument uses contradiction.

Suppose that a machine with N states realizes *Equal*. Consider an input sequence that begins with N 1's, $(1, \dots, 1, x(N), \dots)$. Let the state response be

$$(s(0), s(1), \dots, s(N), \dots).$$

Since there are only N distinct states, and the state response is of length at least $N + 1$, the state response must visit at least one state twice. Call that state α . Suppose

$s(m) = s(n) = \alpha$, with $m < n \leq N$. Then the two sequences $1^m 0^m$ and $1^n 0^m$ must lead to the same state, hence yield the same last output symbol on entering state α . Recall that 1^m means a sequence of m consecutive 1's, similarly for 0^m . But the last output symbol for $1^m 0^m$ should be *equal*, and the last output symbol for $1^n 0^m$ should be *notEqual*, which is a contradiction. So our hypothesis that a finite-state machine realizes *Equal* must be wrong! Exercise 6 asks you to construct an infinite state machine that realizes *Equal*.

3.3 Nondeterministic state machines

There are situations in which it is sufficient to give an incomplete model of a system. Such models are more compact than complete models because they hide inessential details. This compactness will often make them easier to understand.

A useful form of incomplete model is a nondeterministic state machine. A nondeterministic state machine often has fewer states and transitions than would be required by a complete model. The state machines we have studied so far are deterministic.

3.3.1 State transition diagram

The state transition diagram for a state machine has one bubble for each state and one arc for each state transition. Nondeterministic machines are no different. Each arc is labeled with by “*guard/output*,” where

$$\text{guard} \subset \text{Inputs} \text{ and } \text{output} \in \text{Outputs}.$$

In a deterministic machine, the guards on arcs emerging from any given state are mutually exclusive. That is, they have no common symbols. This is precisely what makes the machine deterministic. For nondeterministic machines, we relax this constraint. Guards can overlap. Thus, a given input symbol may appear in the guard of more than one transition, which means that more than one transition can be taken when that input symbol arrives. This is precisely what makes the machine nondeterministic.

Example 3.7: Consider the state machine shown in Figure 3.5. It begins in state a and transitions to state b the first time it encounters a 1 on the input. It then stays in state b arbitrarily long. If it receives a 1 at the input, it must stay in state b . If it receives a 0, then it can either stay in b or transition to a . Given the input sequence

$$(0, 1, 0, 1, 0, 1, \dots)$$

then the following are all possible state responses and output sequences:

$$\begin{aligned}(a, a, b, a, b, a, b, \dots) \\ (0, 1, 0, 1, 0, 1, \dots)\end{aligned}$$

$$\begin{aligned}(a, a, b, b, b, a, b, \dots) \\ (0, 1, 1, 1, 0, 1, \dots)\end{aligned}$$

$$\begin{aligned}(a, a, b, b, b, b, b, \dots) \\ (0, 1, 1, 1, 1, 1, \dots)\end{aligned}$$

$$\begin{aligned}(a, a, b, a, b, b, \dots) \\ (0, 1, 0, 1, 1, 1, \dots)\end{aligned}$$

Nondeterminism can be used to construct an **abstraction** of a complicated machine, which is a simpler machine that has all the behaviors of the more complicated machine.

Example 3.8: Consider again the 60-minute parking meter. Its input alphabet is

$$\text{Inputs} = \{\text{coin5}, \text{coin25}, \text{tick}, \text{absent}\}.$$

Upon arrival of *coin5*, the parking meter increments its count by five, up to a maximum of 60 minutes. Upon arrival of *coin25*, it increments its count by 25, again up

to a maximum of 60. Upon arrival of *tick*, it decrements its count by one, down to a minimum of zero.

A deterministic state machine model is illustrated schematically in Figure 3.6(a). The state space is

$$\text{States} = \{0, 1, \dots, 60\},$$

which is too many states to draw conveniently. Thus, patterns in the state space are suggested with ellipsis “...”.

Suppose that we are interested in modeling the interaction between this parking meter and a police officer. The police officer does not care what state the parking meter is in, except to determine whether the meter has expired or not. Thus, we need only two nonstuttering output symbols, so

$$\text{Outputs} = \{\text{safe}, \text{expired}, \text{absent}\}.$$

The symbol *expired* is produced whenever the machine enters state 0.

The model has enough states that a full state transition diagram is tedious and complex enough that it might not be useful for generating insight about the design. Moreover, the detail that is modeled may not add insight about the interaction with a police officer.

Figure 3.6(b) is a nondeterministic model of the same parking meter. It has three states,

$$\text{States} = \{0, 1, \text{more}\}.$$

The input symbols *coin5* and *coin25* in state 0 or 1 cause a transition to state *more*. The input symbol *tick* in state *more* nondeterministically moves the state to 1 or leaves it in *more*.

The top state machine has more detail than the bottom machine. Shortly, we will give a precise meaning to the phrase ‘has more detail’ using the concept of *simulation*. For the moment, note that the bottom machine can generate any output sequence that the top machine generates, for the same input sequence. But the bottom machine can also generate output sequences that the top machine cannot. For example, the sequence

$$(\text{expired}, \text{safe}, \text{safe}, \text{expired}, \dots),$$

in which there are two *safe* output symbols between two *expired* output symbols is not a possible output sequence of the top machine, but it is a possible output

sequence of the bottom machine. In the top machine, successive *expired* output symbols must be separated by 0 or at least five *safe* output symbols. This detail is not captured by the bottom machine. But in modeling the interaction with a police officer, this detail may not be important, so omitting it may be entirely appropriate.

The machines that we design and build, including parking meters, are usually deterministic. However, the state space of these machines is often very large, much larger than in this example, and it can be difficult to understand their behavior. We use simpler nondeterministic machine models that hide inessential details of the deterministic machine. The analysis of the simpler model reveals some properties, but not all properties, of the more complex machine. The art, of course, is in choosing the model that reveals the properties of interest.

3.3.2 Sets and functions model

The state machines we have been studying, with definitions of the form (3.1), are deterministic. If we know the initial state and the input sequence, then the entire state trajectory and output sequence can be determined. This is because any current state $s(n)$ and current input symbol $x(n)$ uniquely determine the next state and output symbol $(s(n+1), y(n)) = \text{update}(s(n), x(n))$.

In a nondeterministic state machine, the next state is not completely determined by the current state and input symbol. For a given current state $s(n)$ and input symbol $x(n)$, there may be more than one next state. So we cannot characterize the machine by the function $\text{update}(s(n), x(n))$ because there is no single next state. Instead, we define a function possibleUpdates so that $\text{possibleUpdates}(s(n), x(n))$ is the *set* of possible next states and output symbols. Whereas a deterministic machine has update function

$$\text{update}: \text{States} \times \text{Inputs} \rightarrow \text{States} \times \text{Outputs},$$

a nondeterministic machine has a (nondeterministic) state transition function

$$\text{possibleUpdates}: \text{States} \times \text{Inputs} \rightarrow \wp(\text{States} \times \text{Outputs}), \quad (3.9)$$

where $\wp(\text{State} \times \text{Outputs})$ is the powerset of $\text{State} \times \text{Outputs}$.

In order for a nondeterministic machine to be *receptive*, it is necessary that

$$\forall s(n) \in \text{States}, x(n) \in \text{Inputs} \quad \text{possibleUpdates}(s(n), x(n)) \neq \emptyset.$$

Recall that a receptive machine accepts any input symbol in any state, makes a state transition (possibly back to the same state), and produces an output symbol. That is, there is no situation where the reaction to an input symbol is not defined.

Operationally, a nondeterministic machine arbitrarily selects the next state and current output symbol from *possibleUpdates* given the current state and current input symbol. The model says nothing about how the selection is made.

Similar to deterministic machines, we can collect the specification of a nondeterministic state machine into a 5-tuple

$$\text{StateMachine} = (\text{States}, \text{Inputs}, \text{Outputs}, \text{possibleUpdates}, \text{initialState}). \quad (3.10)$$

The *possibleUpdates* function is different from the *update* function of a deterministic machine.

Deterministic state machines of the form (3.1) are a special case of nondeterministic machines in which $\text{possibleUpdates}(s(n), x(n))$ consists of a single element, namely $\text{update}(s(n), x(n))$. In other words,

$$\text{possibleUpdates}(s(n), x(n)) = \{\text{update}(s(n), x(n))\}.$$

Thus, any deterministic machine, as well as any nondeterministic machine, can be given by (3.10).

In the nondeterministic machine of (3.10), an input sequence may give rise to many state responses and output sequences. If $(x(0), x(1), x(2), \dots)$ is an input sequence, then $(s(0), s(1), s(2), \dots)$ is a (possible) state trajectory and $(y(0), y(1), y(2), \dots)$ is a (possible) output sequence provided that

$$\begin{aligned} s(0) &= \text{initialState} \\ \forall n \geq 0, \quad (s(n+1), y(n)) &\in \text{possibleUpdates}(s(n), x(n)). \end{aligned}$$

A deterministic machine defines a function from an input sequence to an output sequence,

$$F : \text{InputSignals} \rightarrow \text{OutputSignals},$$

where

$$\text{InputSignals} = [\mathbb{N}_0 \rightarrow \text{Inputs}],$$

and

$$\text{OutputSignals} = [\mathbb{N}_0 \rightarrow \text{Outputs}].$$

We define a **behavior** of the machine to be a pair (x, y) such that $y = F(x)$, i.e., a behavior is a possible input, output pair. A deterministic machine is such that for each $x \in InputSignals$, there is exactly one $y \in OutputSignals$ such that (x, y) is a behavior.

We define the set

$$Behaviors \subset InputSignals \times OutputSignals, \quad (3.11)$$

where

$$\begin{aligned} Behaviors = & \{(x, y) \in InputSignals \times OutputSignals \\ & | y \text{ is a possible output sequence for input sequence } x\}. \end{aligned}$$

For a deterministic state machine, the set *Behaviors* is the graph of the function F .

For a nondeterministic machine, for a given $x \in InputSignals$, there may be more than one $y \in OutputSignals$ such that (x, y) is a behavior. The set *Behaviors*, therefore, is no longer the graph of a function. Instead, it defines a **relation**—a generalization of a function where there can be two or more distinct elements in the range corresponding to the same element in the domain. The interpretation is still straightforward, however: if $(x, y) \in Behaviors$, then input sequence x may produce output sequence y .

3.4 Simulation relations

Two different state machines with the same input and output alphabets may be equivalent in the sense that for the same input sequence, they produce the same output sequence. We explore this concept of equivalence in this section.

Example 3.9: The three state machines in Figure 3.7, have the same input and output alphabets:

$$Inputs = \{1, absent\} \text{ and } Outputs = \{0, 1, absent\}.$$

Machine (a) has the most states. However, its behavior is identical to that of (b). Both machines produce an alternating sequence of two 1's and one 0 as they receive a sequence of 1's at the input. The machine in (c) is non-deterministic. It has more behaviors than (a) or (b): it can produce any sequence that has at least one 1 between any two zero's. Thus (c) is more general, or more abstract than the machines (a) or (b).

To study the relationships between the machines in Figure 3.7 we introduce the concept of **simulation**. The machine in (c) is said to **simulate** (b) and (a). Simulation can be viewed as a form of abstraction of state machines.

Example 3.10: In Figure 3.6, the bottom machine can generate any output sequence that the top machine generates, for the same input sequence. The reverse is not true; there are output sequences that the bottom machine can generate that the top machine cannot. The bottom machine is an abstraction of the top one. We will see that the bottom machine simulates the top machine (but not vice versa).

To understand simulation, it is easiest to consider a **matching game** between one machine X and another Y . We wish to determine whether Y simulates X . If it does, Y may be equivalent to X , or it may be an abstraction of X .

The game starts with both machines in their initial states. The first machine X is allowed to react to an input symbol. If this machine is nondeterministic, it may have more than one possible reaction; it is permitted to choose any one of these reactions. The second machine Y must react to the same input symbol such that it produces the same output symbol. If it is non-deterministic, it is free to pick, from among the possible reactions, any one that matches the output symbol of machine X that will permit it to continue to match the output symbols of machine X in future reactions. Machine Y “wins” this matching game (it simulates X) if it can always match the output symbol of machine X . We then say that machine Y simulates X . If X can produce an output symbol that Y cannot match, then Y does not simulate X .

Example 3.11: We wish to determine whether (c) simulates (b) in figure 3.7. The game starts with the two machines in their initial states, which we jointly denote by the pair

$$s_0 = (0 \text{and} 3, 0) \in States_b \times States_c.$$

Machine (b) (the one being simulated) moves first. Given an input symbol, it reacts. If it is nondeterministic, then it is free to react in any way possible, although in this case, (b) is deterministic, so it will have only one possible reaction. Machine (c) then has to **match** the move taken by (b); given the same input symbol, it must react such that it produces the same output symbol.

There are two possible input symbols to machine (b), 1 and *absent*. If the input symbol is *absent*, the machine reacts by stuttering. Machine (c) can match this by stuttering as well. For this example, it will always do to match stuttering moves by stuttering, so we will not consider them further.

Excluding the stuttering input symbol, there is only one possible input symbol to machine (b), 1. The machine reacts by producing the output symbol 1 and changing to state *1and4*. Machine (c) can match this by taking the only possible transition out of its current state, which also produces output symbol 1. The resulting states of the two machines are denoted

$$s_1 = (\text{1and4}, \text{1to5}) \in \text{States}_b \times \text{States}_c.$$

From here, again there is only one non-stuttering input symbol possible, so (b) reacts by moving to *2and5* and producing the output symbol 1. Now (c) has two choices, but in order to match (b), it chooses the (self-loop) transition, which produces 1. The resulting states are

$$s_2 = (\text{2and5}, \text{1to5}) \in \text{States}_b \times \text{States}_c.$$

From here, (b) reacts to the non-stuttering input symbol by moving to *0and3* and producing output symbol 0. To match this move, (c) selects the transition that moves the state to 0, producing 0. The resulting states are s_0 , back to where we started. So we know that (c) can always match (b).

The “winning” strategy of the second machine can be summarized by the set

$$S_{b,c} = \{s_0, s_1, s_2\} \subset \text{States}_b \times \text{States}_c.$$

The set $S_{b,c}$ in this example is called a simulation relation; it shows how (c) simulates (b). A simulation relation associates states of the two machines. Suppose we have two state machines, X and Y , which may be deterministic or nondeterministic. Let

$$X = (\text{States}_X, \text{Inputs}, \text{Outputs}, \text{possibleUpdates}_X, \text{initialState}_X),$$

and

$$Y = (\text{States}_Y, \text{Inputs}, \text{Outputs}, \text{possibleUpdates}_Y, \text{initialState}_Y).$$

The two machines have the same input and output alphabets. If either machine is deterministic, then its *possibleUpdates* function always returns a set with only one element in it.

If Y simulates X , the simulation relation is given as a subset of $States_X \times States_Y$. Note the ordering here; the machine that moves first in the game, X , the one being simulated, is first in $States_X \times States_Y$.

To consider the reverse scenario, if X simulates Y , then the relation is given as a subset of $States_Y \times States_X$. In this version of the game Y must move first.

We can state the “winning” strategy mathematically. We say that Y **simulates** X if there is a subset $S \subset States_X \times States_Y$ such that

1. $(initialState_X, initialState_Y) \in S$, and
2. If $(s_X(n), s_Y(n)) \in S$, then $\forall x(n) \in Inputs$, and
 $\forall (s_X(n+1), y_X(n)) \in possibleUpdates_X(s_X(n), x(n))$,
there is a $(s_Y(n+1), y_Y(n)) \in possibleUpdates_Y(s_Y(n), x(n))$ such that:
 - (a) $(s_X(n+1), s_Y(n+1)) \in S$, and
 - (b) $y_X(n) = y_Y(n)$.

This set S , if it exists, is called the **simulation relation**. It establishes a correspondence between states in the two machines.

Example 3.12: Consider again the state machines in Figure 3.7. The machine in (b) simulates the one in (a). The simulation relation is a subset

$$S_{a,b} \subset \{0, 1, 2, 3, 4, 5\} \times \{0\text{and}3, 1\text{and}4, 2\text{and}5\}.$$

The names of the states in (b) (which are arbitrary) are suggestive of the appropriate simulation relation. Specifically,

$$S_{a,b} = \{(0, 0\text{and}3), (1, 1\text{and}4), (2, 2\text{and}5), (3, 0\text{and}3), (4, 1\text{and}4), (5, 2\text{and}5)\}.$$

The first condition of a simulation relation, that the initial states match, is satisfied because $(0, 0\text{and}3) \in S_{a,b}$. The second condition can be tested by playing the game, starting in each pair of states in $S_{a,b}$.

Start with the two machines in one pair of states in $S_{a,b}$, such as the initial states $(0, 0\text{and}3)$. Then consider the moves that machine (a) can make in a reaction. Ignoring stuttering, if we start with $(0, 0\text{and}3)$, (a) must move to state 1 (given input 1). Given the same input symbol, can (b) match the move? To match the move, it must react to the same input symbol, produce the same output symbol, and move to a state so that the new state of (a) paired with the new state of (b) is in $S_{a,b}$. Indeed, given input symbol 1, (b) produces output symbol 1, and moves to state $1\text{and}4$ which is matched to state 1 of (a).

It is easy (albeit somewhat tedious to do by hand) to check that this matching can be done from any starting point in $S_{a,b}$.

This example shows how to use the game to check that a particular subset of $\text{States}_X \times \text{States}_Y$ is a simulation relation. Thus, the game can be used either to construct a simulation relation or to check whether a particular set is a simulation relation.

For the machines in Figure 3.7, we have shown that (c) simulates (b) and that (b) simulates (a). Simulation is **transitive**, meaning that we can immediately conclude that (c) simulates (a). In particular, if we are given simulation relations $S_{a,b} \subset \text{States}_a \times \text{States}_b$ ((b) simulates (a)) and $S_{b,c} \subset \text{States}_b \times \text{States}_c$ ((c) simulates (b)), then

$$S_{a,c} = \{(s_a, s_c) \in \text{States}_a \times \text{States}_c \mid \text{there exists } s_b \in S_b \text{ where } (s_a, s_b) \in S_{a,b} \text{ and } (s_b, s_c) \in S_{b,c}\} \quad (3.12)$$

is a simulation relation showing that (c) simulates (a).

Example 3.13: For the examples in Figure 3.7, we have already determined that

$$S_{a,b} = \{(0, 0\text{and}3), (1, 1\text{and}4), (2, 2\text{and}5), (3, 0\text{and}3), (4, 1\text{and}4), (5, 2\text{and}5)\}.$$

and

$$S_{b,c} = \{(0\text{and}3, 0), (1\text{and}4, 1\text{to}5), (2\text{and}5, 1\text{to}5)\}.$$

From (3.12) we can conclude that

$$S_{a,c} = \{(0, 0), (1, 1\text{to}5), (2, 1\text{to}5), (3, 0), (4, 1\text{to}5), (5, 1\text{to}5)\},$$

which further supports the suggestive choices of state names.

Simulation relations are not (necessarily) symmetric.

Example 3.14: For the examples in Figure 3.7, (b) does not simulate (c). To see this, we can attempt to construct a simulation relation by playing the game. Starting in the initial states,

$$s_0 = (0 \text{and} 3, 0),$$

we allow (c) to move first. Presented with a nonstuttering input symbol, 1, it produces 1 and moves to *1to5*. Machine (b) can match this by producing 1 and moving to *1and4*. But from state *1to5*, (c) can now produce 0 with input symbol 1, which (b) cannot match. Thus, the game gets stuck, and we fail to construct a simulation relation.

Consider another example, one that illustrates that there may be more than one simulation relation between two machines.

Example 3.15: In Figure 3.8, it is easy to check that (c) simulates (a) and (b). We now verify that (b) simulates (a) and also (a) simulates (b) by determining that not only can (b) match any move (a) makes, but (a) can also match any move (b) makes. Note that (a) is nondeterministic, and in two of its states it has two distinct ways of matching the moves of (b). It can arbitrarily choose from among these possibilities to match the moves of (b).

If from state 1 it always chooses to return to state 0, then the simulation relation is

$$S_{b,a} = \{(0 \text{and} 2, 0), (1 \text{and} 3, 1)\}.$$

Otherwise, if from state 2 it always chooses to return to state 1, then the simulation relation is

$$S_{b,a} = \{(0 \text{and} 2, 0), (1 \text{and} 3, 1), (0 \text{and} 2, 2)\}.$$

Otherwise, the simulation relation is

$$S_{b,a} = \{(0 \text{and} 2, 0), (1 \text{and} 3, 1), (0 \text{and} 2, 2), (1 \text{and} 3, 3)\}.$$

All three are valid simulation relations. Thus, the simulation relation is not unique.

A common use of simulation is to establish a relationship between a more abstract model and a more detailed model. In the example above, (c) is a more abstract model of either (b) or (a). It is more abstract in the sense that it loses detail. For example, it has lost the property that 0's and 1's alternate in the output sequence. We now give a more compelling example of such abstraction, where the abstraction dramatically reduces the number of states while still preserving some properties of interest.

Example 3.16: In the case of the parking meter, the bottom machine in Figure 3.6 simulates the top machine. Let A denote the top machine, and let B denote the bottom machine. We will now identify the simulation relation.

The simulation relation is a subset $S \subset \{0, 1, \dots, 60\} \times \{0, 1, \text{more}\}$. It is intuitively clear that 0 and 1 of the bottom machine correspond to 0 and 1, respectively, of the top machine. Thus, $(0, 0) \in S$ and $(1, 1) \in S$. It is also intuitive that *more* corresponds to all of the remaining states $2, \dots, 60$ of the top machine. So we propose to define the simulation relation as

$$S = \{(0, 0), (1, 1)\} \cup \{(s_A, \text{more}) \mid 2 \leq s_A \leq 60\} \quad (3.13)$$

We now check that S is indeed a simulation relation, as defined above.

The first condition of a simulation relation, that the initial states match, is satisfied because $(0, 0) \in S$. The second condition is more tedious to verify. It says that for each pair of states in S , and for each input symbol, the two machines can transition to a pair of new states that is also in S , and that these two transitions produce the same output symbol. Since machine A is deterministic, there is no choice about which transition it takes and which output symbol it produces. In machine B , there are choices, but all we require is that one of the choices match.

The only state of machine B that actually offers choices is *more*. Upon receiving *tick*, the machine can transition back to *more* or down to 1. In either case, the output symbol is *safe*. It is easy to see that these two choices are sufficient for state *more* to match states 2, 3, ... 60 of machine A .

Thus the bottom machine indeed simulates the top machine with the simulation relation (3.13).

3.4.1 Relating behaviors

A simulation relation establishes a correspondence between two state machines, one of which is typically much simpler than the other. The relation lends confidence that analyzing the simpler machine indeed reveals properties of the more complicated machine.

This confidence rests on a theorem and corollary that we will develop in this section. These results relate the input/output behaviors of state machines that are related by simulation.

Given an input sequence $x = (x(0), x(1), x(2), \dots)$, if a state machine can produce the output sequence $y = (y(0), y(1), y(2), \dots)$, then (x, y) is said to be a behavior of the state machine. The set of all behaviors of a state machine obviously satisfies

$$\text{Behaviors} \subset \text{InputSignals} \times \text{OutputSignals}.$$

Theorem Let B simulate A . Then

$$\text{Behaviors}_A \subset \text{Behaviors}_B.$$

This theorem is easy to prove. Consider a behavior $(x, y) \in \text{Behaviors}_A$. We need to show that $(x, y) \in \text{Behaviors}_B$.

Let the simulation relation be S . Find all possible state responses for A

$$s_A = (s_A(0), s_A(1), \dots)$$

that result in behavior (x, y) . (If A is deterministic, then there will be only one.) The simulation relation assures us that we can find a state response for B

$$s_B = (s_B(0), s_B(1), \dots)$$

where $(s_A(i), s_B(i)) \in S$, such that given input symbol x , B produces y . Thus, $(x, y) \in \text{Behaviors}_B$.

Intuitively, the theorem simply states that B can match every move of A and produce the same output sequence. It also implies that if B cannot produce a particular output sequence, then neither can A . This is stated formally in the following corollary.

Corollary Let B simulate A . Then if

$$(x, y) \notin \text{Behaviors}_B$$

then

$$(x, y) \notin Behaviors_A.$$

The theorem and corollary are useful for analysis. The general approach is as follows. We have a state machine A . We wish to show that its input-output function satisfies some property. That is, every behavior satisfies some condition. We construct a simpler machine B whose input-output relation satisfies the same property, and where B simulates A . Then the theorem guarantees that A will satisfy this property, too. That is, since all behaviors of B satisfy the property, all behaviors of A must also. This technique is useful since it is often easier to understand a simple state machine than a complex state machine with many states.

Conversely, if there is some property that we must assure that no behavior of A has, it is sufficient to find a simpler machine B which simulates A and does not have this property. This scenario is typical of a **safety** problem, where we must show that dangerous outputs from our system are not possible.

Example 3.17: For the parking meter of Figure 3.6, for example, we can use the nondeterministic machine to show that if a coin is inserted at step n , the output symbol at steps n and $n + 1$ is *safe*. By the corollary, this is sufficient to show that the deterministic machine cannot do any differently. We do not have to directly consider the deterministic machine.

It is important to understand what the theorem says, and what it does not say. It does not say, for example, that if $Behaviors_A \subset Behaviors_B$ then B simulates A . In fact, this statement is not true. Consider the two machines in Figure 3.9, where

$$Inputs = \{1, absent\},$$

$$Outputs = \{0, 1, absent\}.$$

These two machines have the same behaviors. The non-stuttering output symbols are $(1, 0)$ or $(1, 1)$, selected nondeterministically, assuming the input sequence has at least two non-stuttering symbols. However, (b) does not simulate (a). The two machines are not equivalent despite the fact that their input/output behaviors are the same.

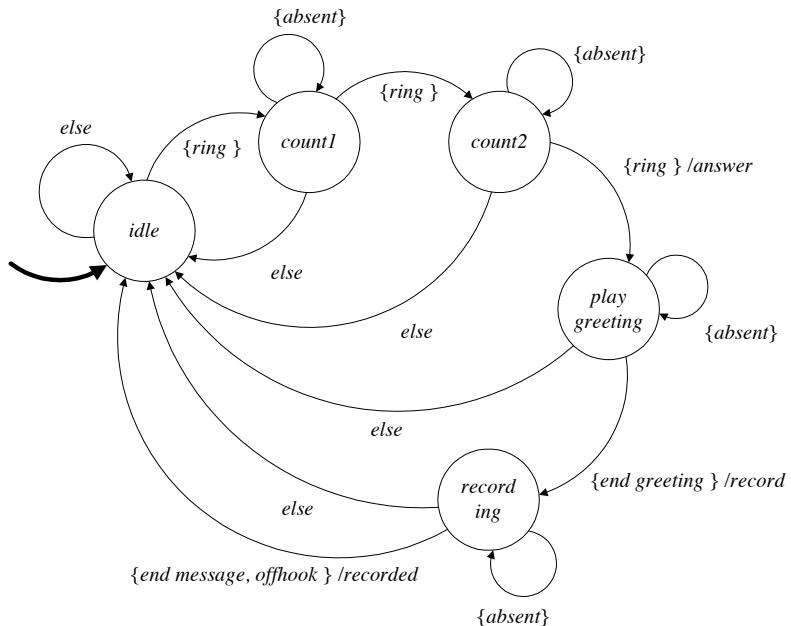
To see this, we play the matching game. Machine (a) is allowed to move first. Ignoring stuttering, it has no choice but to move from a to b and produce output symbol 1. Machine (b) can match this two ways; it has no basis upon which to prefer one way to match it over another, so it picks one, say moving to state f . Now it is the turn of machine (a), which has two choices. If it chooses to move to d , then machine (b) cannot match its move. (A similar argument works if (b) picks state h .) Thus, machine (b) does not simulate machine (a), despite the fact that $Behaviors_A \subset Behaviors_B$.²

3.5 Summary

State machines are models of systems whose input and output signal spaces consist of sequences of symbols. There are three ways of defining state machines: sets and functions, state transition diagram, and the update table. The state machine model gives a step-by-step procedure for evaluating the output signal. This is a state-determined system: once we know the current state, we can tell the future behavior for any future input symbols.

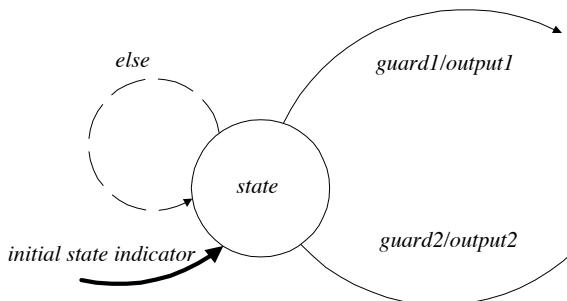
A state machine can be non-deterministic: given the current state and current input symbol, it may have more than one possible next state and current output symbol. Non-deterministic machines typically arise through abstraction of deterministic machines. Two state machines, with the same input and output alphabets, may be related through simulation. Simulation is used to understand properties of the behavior of one machine in terms of the behaviors of another (presumably simpler) machine.

²Recall that in our notation \subset allows the two sets to be equal.



states
<p><i>idle</i>: nothing is happening</p> <p><i>count1</i>: one ring has arrived</p> <p><i>count2</i>: two rings have arrived</p> <p><i>play greeting</i>: playing the greeting message</p> <p><i>recording</i> : recording the message</p>
inputs
<p><i>ring</i> - incoming ringing signal</p> <p><i>offhook</i> - a telephone extension is picked up</p> <p><i>end greeting</i> - greeting message is finished playing</p> <p><i>end message</i> - end of message detected (e.g. dialtone)</p> <p><i>absent</i> - no input of interest.</p>
outputs
<p><i>answer</i> - answer the phone and start the greeting message</p> <p><i>record</i> - start recording the incoming message</p> <p><i>recorded</i>- recorded an incoming message</p> <p><i>absent</i> - default output when there is nothing interesting to say</p>

Figure 3.1: State transition diagram for a telephone answering service.



-0.2in

state machine:

$(States, Inputs, Outputs, update, initialState)$

$update: States \times Inputs \rightarrow States \times Outputs$

$initialState \in States$

elements:

-0.2in $state \in States$

$output1, output2 \in Outputs$

$guard1, guard2 \subset Inputs$

$else = \{i \in Inputs \mid i \notin (guard1 \cup guard2)\}$

determinacy: (There is at most one possible reaction to an input symbol)

$guard1 \cap guard2 = \emptyset$

-0.2in

Figure 3.2: Summary of notation in state transition diagrams, shown for a single state with two outgoing arcs and one self loop.

current state	(next state, output symbol) under specified input symbol				
	ring	offhook	end greeting	end message	absent
idle	(count1, absent)	(idle, absent)	(idle, absent)	(idle, absent)	(idle, absent)
count1	(count2, absent)	(idle, absent)	(idle, absent)	(idle, absent)	(count1, absent)
count2	(play greeting, answer)	(idle, absent)	(idle, absent)	(idle, absent)	(count2, absent)
play greeting	(idle, absent)	(idle, absent)	(recording, record)	(idle, absent)	(play greeting, absent)
recording	(idle, absent)	(idle, recorded)	(idle, absent)	(idle, recorded)	(recording, absent)

Figure 3.3: Update table for the telephone answering service specifies next state and current output symbol as a function of current state and current input symbol.

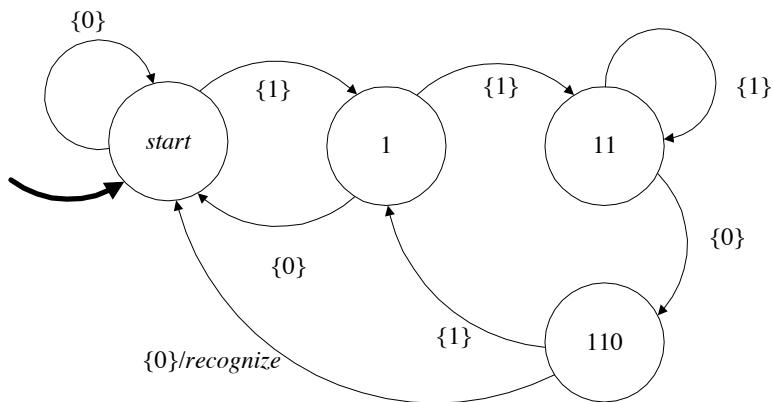


Figure 3.4: A machine that implements *CodeRecognizer*. It outputs *recognize* at the end of every input subsequence 1100, otherwise it outputs *absent*.

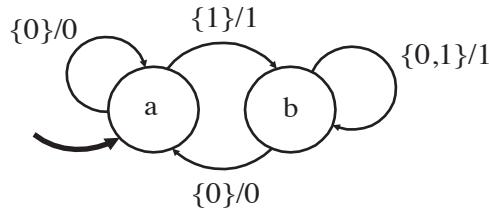


Figure 3.5: A simple nondeterministic state machine.

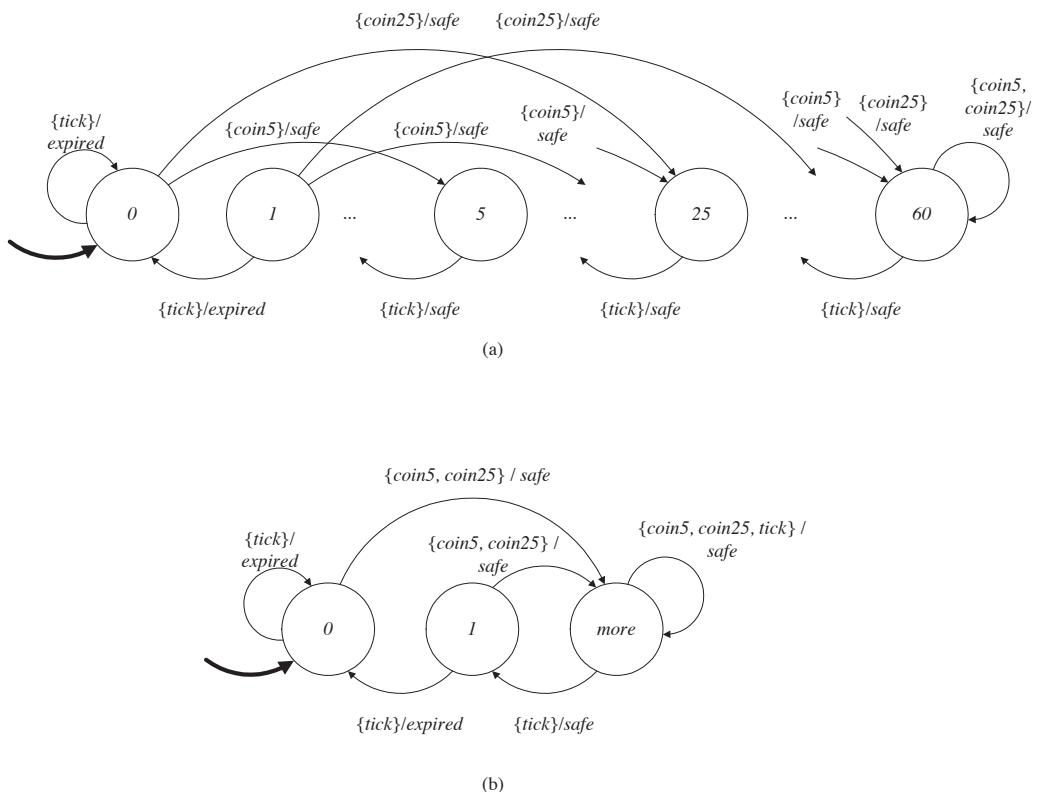


Figure 3.6: Deterministic and nondeterministic models for a 60 minute parking meter.

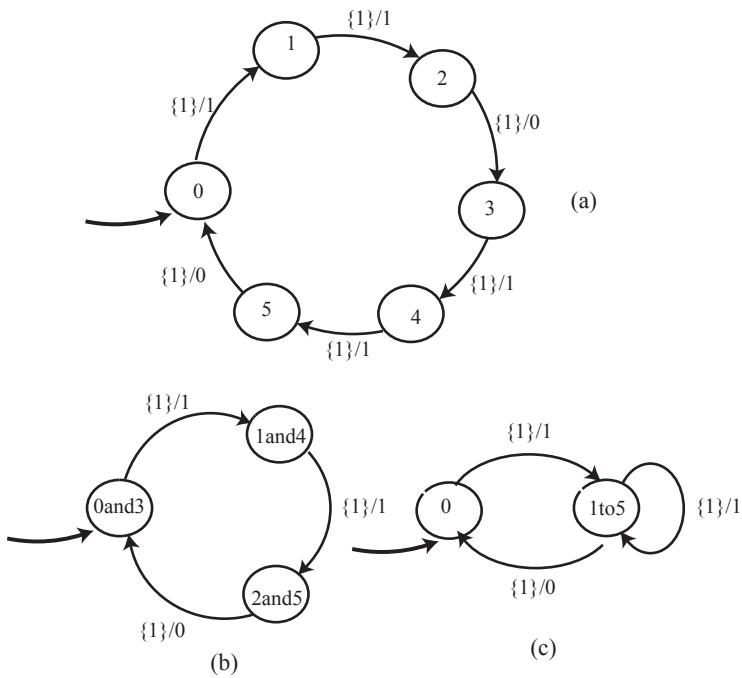


Figure 3.7: Three state machines where (a) and (b) simulate one another and (c) simulates (a) and (b).

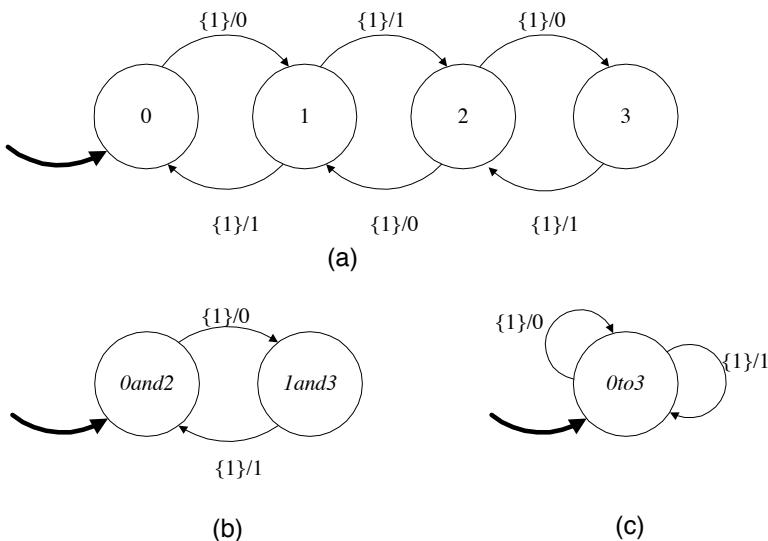


Figure 3.8: Three state machines where (a) and (b) simulate each other and (c) simulates (a) and (b)

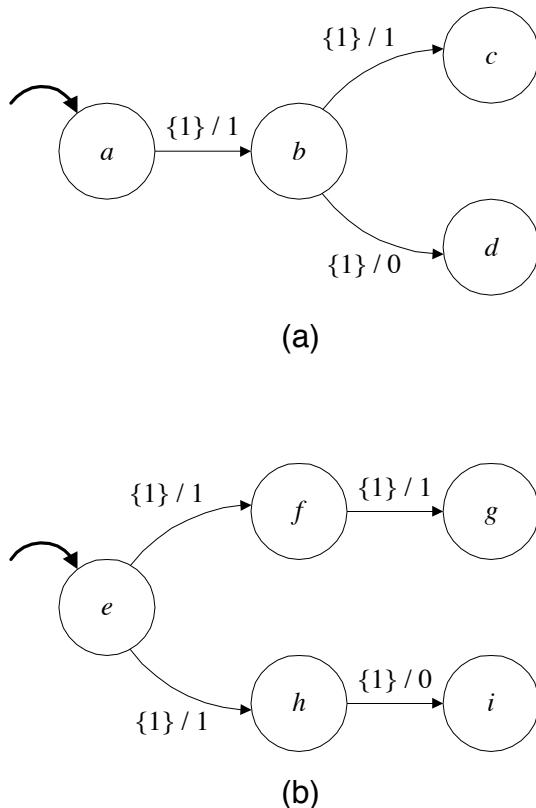


Figure 3.9: Two state machines with the same behaviors where (b) does not simulate (a).

Exercises

In some of the following exercises you are asked to design state machines that carry out a given task. The design is simple and elegant if the state space is properly chosen. Although the state space is not unique, there often is a natural choice. As usual, each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **E** A state machine with

$$\text{Inputs} = \{a, b, c, d, \text{absent}\},$$

has a state s with two emerging arcs with guards

$$\text{guard1} = \{a\}$$

and

$$\text{guard2} = \{a, b, d\}.$$

- (a) Is this state machine deterministic?
- (b) Define the set *else* for state s and specify the source and destination state for the *else* arc.

2. **E** For the answering service example of figure 3.1, assume the input sequence is

$$(offhook, offhook, ring, offhook, ring, ring, ring, offhook, \dots).$$

This corresponds to a user of the answering service making two phone calls, answering a third after the first ring, and answering a second after the third ring.

- (a) Give the state response of the answering service.
- (b) Give the trace of the answering service.
- (c) Give the output sequence.

3. **E** Consider the alphabets

$$\text{Inputs} = \text{Outputs} = \text{Binary} = \{0, 1\}.$$

Note that there is no stuttering input or output symbols here. This simplifies the notation in the problem somewhat.

- (a) Construct a state machine that uses these alphabets such that given any input sequence $(x(0), x(1), \dots)$ without stuttering symbols, the output sequence is given by, $\forall n \in \mathbb{N}_0$,

$$y(n) = \begin{cases} 1 & \text{if } n \geq 2 \wedge (x(n-2), x(n-1), x(n)) = (1, 1, 1) \\ 0 & \text{otherwise} \end{cases}$$

In words, the machine outputs 1 if the current input symbol and the two previous input symbols are all 1's, otherwise it outputs 0. (Had we included a stuttering symbol, the above equation would be a bit more complicated.)

- (b) For the same input and output alphabet, construct a state machine that outputs 1 if the current input symbol and two previous input symbols are either $(1, 1, 1)$ or $(1, 0, 1)$, and otherwise it outputs 0.
4. E A modulo N counter is a device that can output any integer between 0 and $N - 1$. The device has three input symbols, *increment*, *decrement*, and *reset*, plus, as always, a stuttering symbol *absent*; *increment* increases the output integer by 1; *decrement* decreases this integer by 1; and *reset* sets the output symbol to 0. Here *increment* and *decrement* are modulo N operations. Unless otherwise stated, you may assume that the counter begins at 0.

Note: Modulo N numbers work as follows. For any integer m , $m \bmod N = k$ where $0 \leq k \leq N - 1$ is the unique integer such that N divides $(m - k)$. Thus there are only N distinct modulo- N numbers, namely, $0, \dots, N - 1$.

- (a) Give the state transition diagram of this counter for $N = 4$.
- (b) Give the update table of this counter for $N = 4$.
- (c) Give a description of the state machine by specifying the five entities that appear in (3.1); again assume $N = 4$.
- (d) Take $N = 3$. Calculate the state response for the input sequence

$$(increment^4, decrement^3, \dots)$$

starting with initial state 1, where s^n means s repeated n times. You may give the state response for the first seven reactions only.

5. T The state machine *UnitDelay* is defined to behave as follows. On the first non-stuttering reaction (when the first non-stuttering input symbol arrives), the output symbol a is produced. On subsequent reactions (when subsequent input symbols arrive), the input symbol that arrived at the previous non-stuttering reaction is produced as an output symbol.

- (a) Assume the input and output alphabets are

$$\text{Inputs} = \text{Outputs} = \{a, b, c, \text{absent}\}.$$

Give a finite state machine that implements *UnitDelay* for this input set. Give both a state transition diagram and a definition of each of the components in (3.1).

- (b) Assume the input and output sets are

$$\text{Inputs} = \text{Outputs} = \mathbb{N}_0 \cup \{\text{absent}\},$$

and that on the first non-stuttering reaction, the machine produces 0 instead of *a*. Give an (informal) argument that no finite state machine can implement *UnitDelay* for this input set. Give an infinite state machine by defining each of the components in (3.1).

6. **T** Construct an infinite state machine that realizes *Equal*.
7. **C** An elevator connects two floors, 1 and 2. It can go up (if it is on floor 1), down (if it is on floor 2) and stop on either floor. Passengers at any floor may press a button requesting service. Design a controller for the elevator so that (1) every request is served, and (2) if there is no pending request, the elevator is stopped. For simplicity, do not be concerned about responding to requests from passengers inside the elevator.
8. **T** The state machine in Figure 3.10 has the property that it outputs at least one 1 between any two 0's. Construct a two-state nondeterministic state machine that simulates this one and preserves that property.

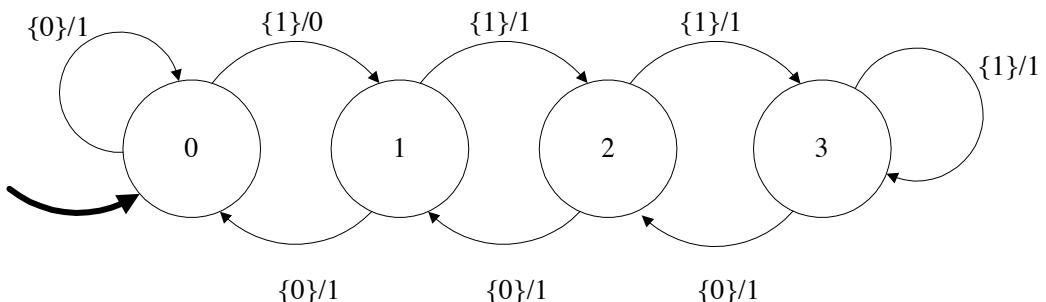


Figure 3.10: Machine that outputs at least one 1 between any two 0's.

9. T For the nondeterministic state machine in Figure 3.11 the input and output alphabets are

$$\text{Inputs} = \text{Outputs} = \{0, 1, \text{absent}\}.$$

- (a) Define the *possibleUpdates* function (3.9) for this state machine.
 - (b) Define the relation *Behaviors* in (3.11) for this state machine. Part of the challenge here is to find a way to describe this relation compactly. For simplicity, ignore stuttering; i.e. assume the input symbol is never *absent*.
10. E The state machine in Figure 3.12 implements *CodeRecognizer*, but has more states than the one in Figure 3.4. Show that the two machines simulate each other by giving simulation relations.
11. E The state machine in Figure 3.13 has input and output alphabets

$$\text{Inputs} = \{1, a\},$$

$$\text{Outputs} = \{0, 1, a\},$$

where *a* (short for *absent*) is the stuttering symbol. State whether each of the following is in the set *Behaviors* for this machine. In each of the following, the ellipsis

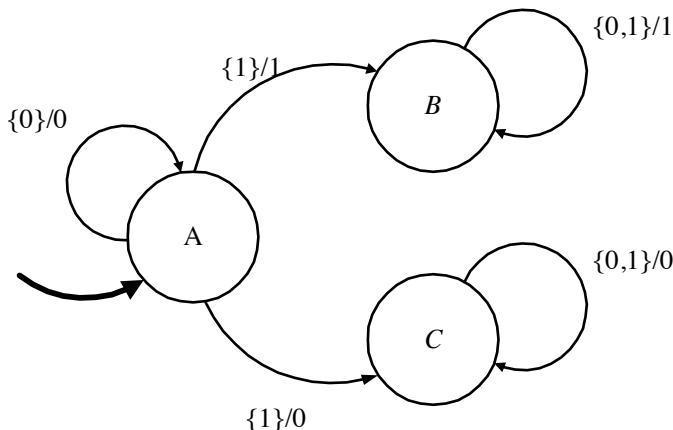


Figure 3.11: Nondeterministic state machine for Exercise 9.

“...” means that the last symbol is repeated forever. Also, in each case, the input and output signals are given as sequences.

- (a) $((1, 1, 1, 1, 1, \dots), (0, 1, 1, 0, 0, \dots))$

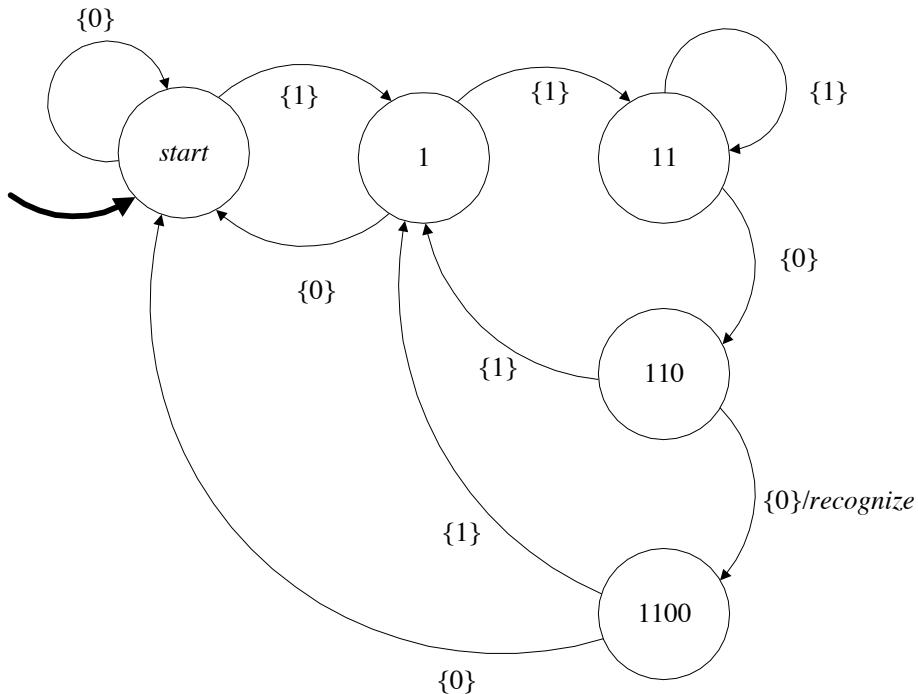


Figure 3.12: A machine that implements *CodeRecognizer*, but has more states than the one in Figure 3.4.

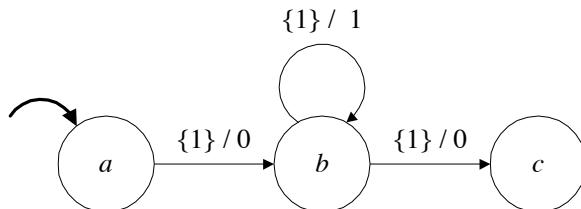


Figure 3.13: State machine for problem 11.

- (b) $((1, 1, 1, 1, 1, \dots), (0, 1, 1, 0, a, \dots))$
- (c) $((a, 1, a, 1, a, \dots), (a, 1, a, 0, a, \dots))$
- (d) $((1, 1, 1, 1, 1, \dots), (0, 0, a, a, a, \dots))$
- (e) $((1, 1, 1, 1, 1, \dots), (0, a, 0, a, a, \dots))$

12. E The state machine in Figure 3.14 has

$$\text{Inputs} = \{1, \text{absent}\},$$

$$\text{Outputs} = \{0, 1, \text{absent}\}.$$

Find a state machine with only two states that simulates the one in Figure 3.14 and that is simulated by the one in Figure 3.14, and give the simulation relations.

13. E You are told that state machine A has

$$\text{Inputs} = \{1, 2, \text{absent}\},$$

$$\text{Outputs} = \{1, 2, \text{absent}\},$$

$$\text{States} = \{a, b, c, d\}.$$

but you are told nothing further. Do you have enough information to construct a state machine B that simulates A? If so, give such a state machine, and the simulation relation.

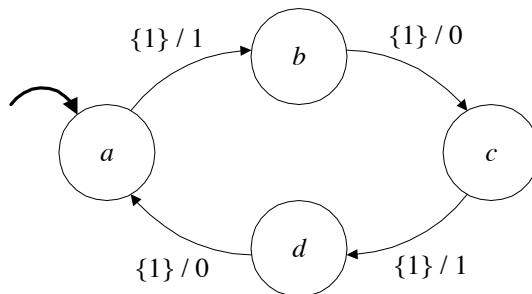


Figure 3.14: A machine that has more states than it needs.

14. **E** Construct a state machine with $Inputs = \{0, 1, absent\}$, $Outputs = \{r, absent\}$, that outputs r whenever the input signal (without stuttering symbols) contains the sequence $(0, 0, 0)$, otherwise it outputs $absent$. More precisely, if $x = (x(0), x(1), \dots)$ is the input sequence then $y = (y(0), y(1), \dots)$ is the output sequence, where

$$y(n) = \begin{cases} r, & \text{if } (x(n-2), x(n-1), x(n)) = (0, 0, 0) \\ absent & \text{otherwise} \end{cases}$$

15. **T** Consider a state machine where

$$Inputs = \{1, absent\},$$

$$Outputs = \{0, 1, absent\},$$

$$States = \{a, b, c, d, e, f\},$$

$$initialState = a,$$

and the *update* function is given by the following table (ignoring stuttering):

$(currentState, inputSymbol)$	$(nextState, outputSymbol)$
$(a, 1)$	$(b, 1)$
$(b, 1)$	$(c, 0)$
$(c, 1)$	$(d, 0)$
$(d, 1)$	$(e, 1)$
$(e, 1)$	$(f, 0)$
$(f, 1)$	$(a, 0)$

- (a) Draw the state transition diagram for this machine.
- (b) Ignoring stuttering, give the *Behaviors* relation for this machine.
- (c) Find a state machine with three states that simulates this one and that is simulated by this one. Draw that state machine, and give the simulation relations.

Composing State Machines

Contents

4.1	Synchrony	138
4.2	Side-by-side composition	139
4.3	Cascade composition	143
4.4	Product-form inputs and outputs	148
4.5	General feedforward composition	151
4.6	Hierarchical composition	154
4.7	Feedback	155
4.7.1	Feedback composition with no inputs	157
4.7.2	State-determined output	163
4.7.3	Feedback composition with inputs	167
4.7.4	Constructive procedure for feedback composition	171
4.7.5	Exhaustive search	175
4.7.6	Nondeterministic machines	175
	<i>Probing Further: Constructive Semantics</i>	176
4.8	Summary	177
	Exercises	179

We design interesting systems by composing simpler components. Since systems are functions, their composition is function composition, as discussed in Section 2.1.5. State machines, however, are not given directly as functions that map input sequences into output sequences. Instead, they are given procedurally, where the *update* function defines

how to progress from one state to the next. This chapter explains how to define a new state machine that describes a composition of multiple state machines.

In Section 2.3.4 we used a block diagram syntax to define compositions of systems. We will use the same syntax here, and we will similarly build up an understanding of composition by first considering easy cases. The hardest cases are those where there is feedback, because the input of one state machine may depend on its own output. It is challenging in this case to come up with a procedure for updating the state of the composite machine. For some compositions, in fact, it isn't even possible. Such compositions are said to be ill-formed.

4.1 Synchrony

We consider a set of interconnected components, where each component is a state machine. By “interconnected” we mean that the outputs of one component may be inputs of another. We wish to construct a state machine model for the composition of components. Composition has two aspects. The first aspect is straightforward: it specifies which outputs of one component are the inputs of another component. These input-output connections are specified using block diagrams.

The second aspect of composition concerns the timing relationships between inputs and outputs. We choose a particular style of composition called **synchrony**. This style dictates that each state machine in the composition reacts *simultaneously* and *instantaneously*. So a reaction of the composite machine consists of a set of simultaneous reactions of each of the component machines.

A reaction of the composite machine is triggered by inputs from the environment. Thus, *when* a reaction occurs is externally determined. This is the same as for a single machine. As with a single state machine, a composite machine may stutter. This simply means that each component machine stutters.

A system that reacts only in response to external stimulus is said to be **reactive**. Because our compositions are synchronous, they are often called **synchronous/reactive** systems.

The reactions of the component machines and of the composite machine are viewed as being instantaneous. That is, a reaction does not take time. In particular, the output symbol from a state machine is viewed as being *simultaneous* with the input symbol, without delay. This creates some interesting subtleties, especially for feedback composition when

the input of a state machine is connected to its own output. We will discuss the ramifications of the synchronous/reactive interpretation below.

Synchrony is a very useful model of the behavior of physical systems. Digital circuits, for example, are almost always designed using this model. Circuit elements are viewed as taking no time to calculate their outputs given their inputs, and time overall is viewed as progressing in a sequence of discrete time steps according to ticks of a clock. Of course, the time that it takes for a circuit element to produce an output cannot ultimately be ignored, but the model is useful because for most circuit elements in a complex design, this time *can* be ignored. Only the time delay of the circuit elements along a **critical path** affects the overall performance of the circuit.

More recently than for circuits, synchrony has come to be used in software as well. Concurrent software modules interact according to the synchronous model. Languages built on this principle are called **synchronous languages**. They are used primarily in real-time embedded system¹ design.

4.2 Side-by-side composition

A simple form of composition of two state machines is shown in figure 4.1. We call this **side-by-side composition**. Side-by-side composition in itself is not useful, but it is useful in combination with other types of composition. The two state machines in Figure 4.1 do not interact with one another. Nonetheless we wish to define a single state machine representing the synchronous operation of the two component state machines.

The state space of the composite state machine is simply

$$\text{States} = \text{States}_A \times \text{States}_B.$$

We could take the cross product in the opposite order, resulting in a *different* but *bisimilar* composite state machine. The initial state is

$$\text{initialState} = (\text{initialState}_A, \text{initialState}_B).$$

¹An **embedded system** is a computing system (a computer and its software) that is embedded in a larger system that is not first and foremost a computer. A digital cellular telephone, for example, contains computers that realize the radio modem and the speech codec. Recent cars contain computers for ignition control, anti-lock brakes, and traction control. Aircraft contain computers for navigation and flight control. In fact, most modern electronic controllers of physical systems are realized as embedded systems.

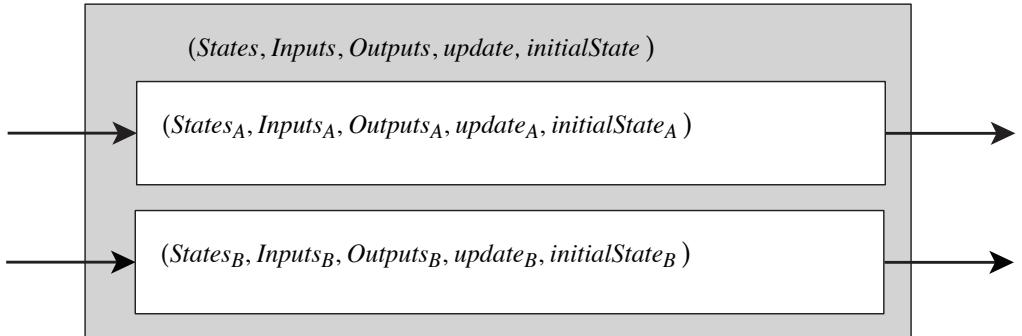
The input and output alphabets are

$$Inputs = Inputs_A \times Inputs_B, \quad (4.1)$$

$$Outputs = Outputs_A \times Outputs_B. \quad (4.2)$$

The update function of the composite machine, *update*, consists of the update functions of the component machines, side-by-side:

$$((s_A(n+1), s_B(n+1)), (y_A(n), y_B(n))) = update((s_A(n), s_B(n)), (x_A(n), x_B(n))),$$



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Definition of the side-by-side composite machine:

$$States = States_A \times States_B$$

$$Inputs = Inputs_A \times Inputs_B$$

$$Outputs = Outputs_A \times Outputs_B$$

$$initialState = (initialState_A, initialState_B)$$

$$((s_A(n+1), s_B(n+1)), (y_A(n), y_B(n)))$$

$$= update((s_A(n), s_B(n)), (x_A(n), x_B(n))),$$

where

$$(s_A(n+1), y_A(n)) = update_A(s_A(n), x_A(n)) \text{ and}$$

$$(s_B(n+1), y_B(n)) = update_B(s_B(n), x_B(n))$$

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Figure 4.1: Summary of side-by-side composition of state machines.

where

$$(s_A(n+1), y_A(n)) = update_A(s_A(n), x_A(n)),$$

and

$$(s_B(n+1), y_B(n)) = update_B(s_B(n), x_B(n)).$$

Recall that $Inputs_A$ and $Inputs_B$ include a stuttering element. This is convenient because it allows a reaction of the composite when we really want only one of the machines to react. Suppose the stuttering elements are $absent_A$ and $absent_B$. Then if the second component of the input symbol is $absent_B$, the reaction of the composite consists only of the reaction of the first machine. The stuttering element of the composite is the pair of stuttering elements of the component machines, $(absent_A, absent_B)$.

Example 4.1: The side-by-side composition in the top of Figure 4.2 has the composite machine with state space

$$States = States_A \times States_B = \{(1,1), (2,1)\},$$

and alphabets

$$Inputs = \{(0,0), (1,0), (absent_A, 0), (0, absent_B), (1, absent_B), (absent_A, absent_B)\},$$

$$Outputs = \{(a,c), (b,c), (absent_A, c), (a, absent_B), (b, absent_B), (absent_A, absent_B)\}.$$

The initial state is

$$initialState = (1,1).$$

The $update$ function can be given as a table, only a part of which is displayed below. The state transition diagram in the lower part of Figure 4.2 gives the same part of the update function.

current state	<i>(next state, output) for input</i>			
	(0,0)	(1,0)	($absent_A, 0$)	...
(1,1)	((1,1), (a,c))	((2,1), (b,c))	((1,1)(($absent_A, c$)))	...
(2,1)	((2,1), (b,c))	((1,1), (a,c))	((2,1), (($absent_A, c$)))	...

Notice that if the second component of the input sequence is always $absent_B$, then the side-by-side composition behaves essentially as machine A, and if the first com-

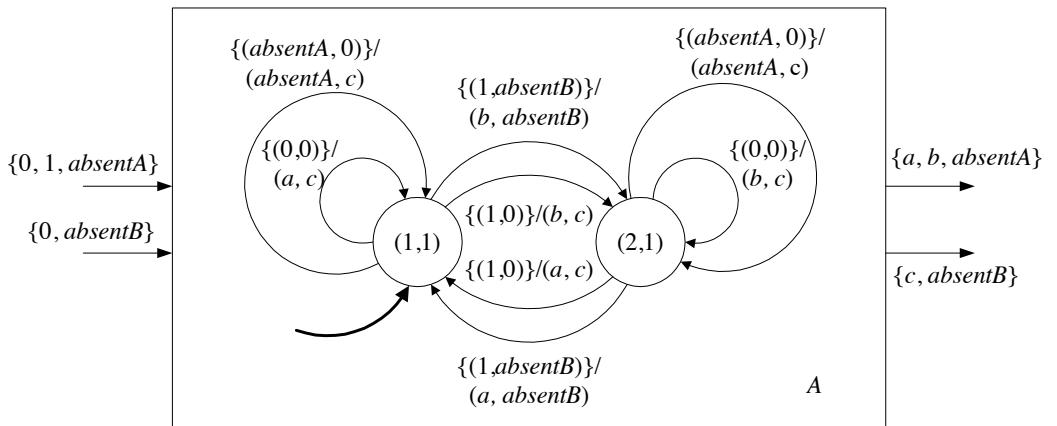
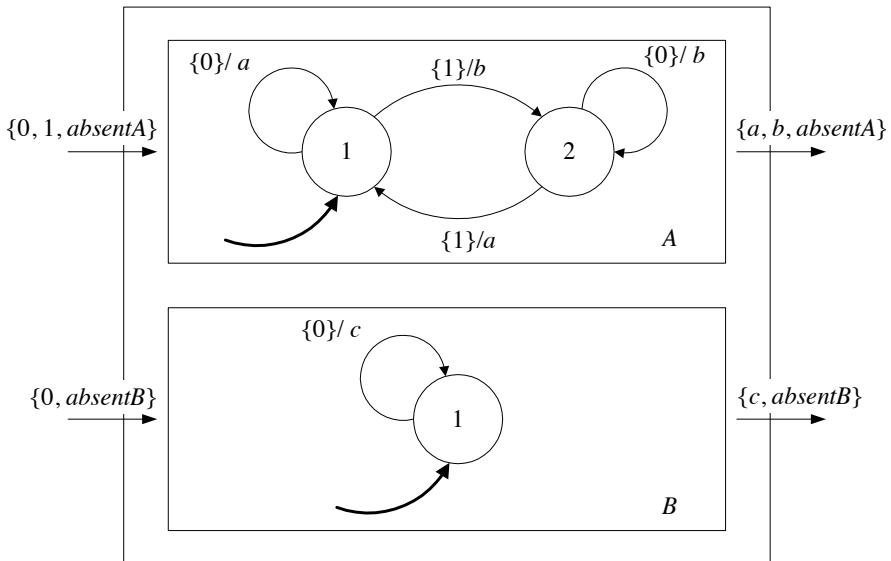


Figure 4.2: Example of a side-by-side composition.

ponent is always absent_A , then it behaves as machine B . The stuttering element of the composite is of course the pair $(\text{absent}_A, \text{absent}_B)$.

4.3 Cascade composition

We now interconnect two state machines as shown in Figure 4.3, where the output of one is the input of the other. This is called a **cascade composition** or a **series connection**. We define the composition so that the component machines react together, synchronously, as one state machine.

Suppose the two state machines are given by

$$\text{StateMachine}_A = (\text{States}_A, \text{Inputs}_A, \text{Outputs}_A, \text{update}_A, \text{initialState}_A)$$

and

$$\text{StateMachine}_B = (\text{States}_B, \text{Inputs}_B, \text{Outputs}_B, \text{update}_B, \text{initialState}_B).$$

Let the composition be given by

$$\text{StateMachine} = (\text{States}, \text{Inputs}, \text{Outputs}, \text{update}, \text{initialState}).$$

Clearly, for a composition like that in Figure 4.3 to be possible we must have

$$\text{Outputs}_A \subset \text{Inputs}_B.$$

Then any output sequence produced by machine A can be an input sequence for machine B . As a result,

$$\text{OutputSignals}_A \subset \text{InputSignals}_B.$$

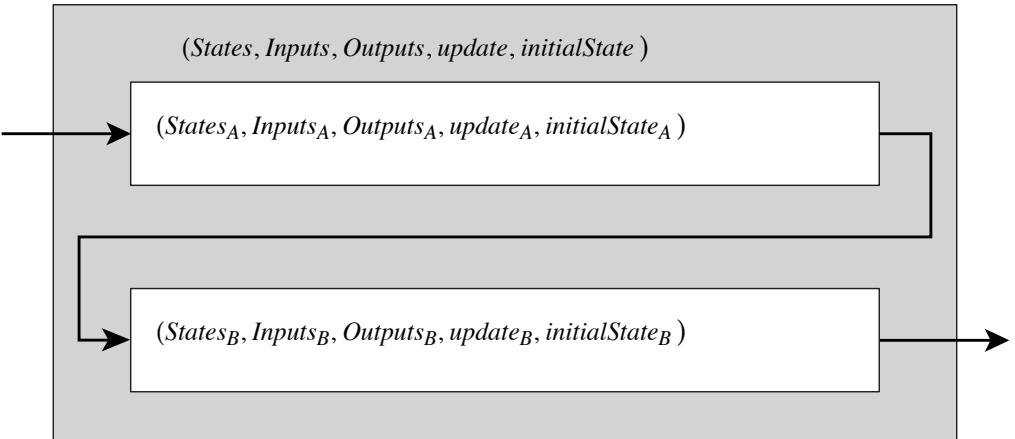
This is analogous to a **type constraint** in programming languages, where in order for two pieces of code to interact, they must use compatible data types. We encountered a similar constraint in discussing function composition, Section 2.1.5.

We are ready to construct a state machine model for this series connection. As noted in the figure, the input alphabet of the composite is

$$\text{Inputs} = \text{Inputs}_A.$$

The stuttering element of $Inputs$, of course, is just the stuttering element of $Inputs_A$. The output alphabet of the composite is

$$Outputs = Outputs_B.$$



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Assumptions about the component machines:

$$Outputs_A \subset Inputs_B$$

Definition of the cascade composite machine:

$$States = States_A \times States_B$$

$$Inputs = Inputs_A$$

$$Outputs = Outputs_B$$

-0.2in $initialState = (initialState_A, initialState_B)$

$$((s_A(n+1), s_B(n+1)), y_B(n)) = update((s_A(n), s_B(n)), x(n)),$$

where

$$(s_A(n+1), y_A(n)) = update_A(s_A(n), x(n)) \text{ and}$$

$$(s_B(n+1), y_B(n)) = update_B(s_B(n), y_A(n)).$$

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Figure 4.3: Summary of cascade composition of state machines.

The state space of the composite state machine is the product set

$$States = States_A \times States_B. \quad (4.3)$$

This asserts that the composite state machine is in state $(s_A(n), s_B(n))$ when the *StateMachine_A* is in state $s_A(n)$ and *StateMachine_B* is in state $s_B(n)$. The initial state is

$$initialState = (initialState_A, initialState_B).$$

We could equally well have defined the states of the composite state machine in the opposite order,

$$States = States_B \times States_A.$$

This would result in a different but bisimilar state machine description (either one simulates the other). Intuitively, it does not matter which of these two choices we make, and we choose (4.3).

To complete the description of the composite machine, we need to define its *update* function in terms of the component machines. Here, a slight subtlety arises. Since we are using synchronous composition, the output symbol of machine *A* is *simultaneous* with its input symbol. Thus, in a reaction, the output symbol of machine *A* in that reaction must be available to machine *B* in the same reaction. This seems intuitive, but it has some counterintuitive consequences. Although the reactions of machine *A* and *B* are simultaneous, we must determine the reaction of *A* before we can determine the reaction of *B*. This apparent paradox is an intrinsic feature of synchronous composition. We will have to deal with it carefully in feedback composition, where it is not immediately evident which reactions need to be determined first.

In the cascade composition, it is intuitively clear what we need to do to define the update function. We first determine the reaction of machine *A*. Suppose that at the n -th reaction the input symbol is $x(n)$ and the state is $s(n) = (s_A(n), s_B(n))$, where $s_A(n)$ is the state of machine *A* and $s_B(n)$ is the state of machine *B*. Machine *A* reacts by updating its state to $s_A(n+1)$ and producing output symbol $y_A(n)$,

$$(s_A(n+1), y_A(n)) = update_A(s_A(n), x(n)). \quad (4.4)$$

Its output symbol $y_A(n)$ becomes the input symbol to machine *B*. Machine *B* reacts by updating its state to $s_B(n+1)$ and producing output symbol $y_B(n)$,

$$(s_B(n+1), y_B(n)) = update_B(s_B(n), y_A(n)). \quad (4.5)$$

The output of the composite machine, of course, is just the output of machine B , and the next state of the composite machine is just $(s_A(n+1), s_B(n+1))$, so the composite machine's *update* is

$$((s_A(n+1), s_B(n+1)), y_B(n)) = \text{update}((s_A(n), s_B(n)), x(n)),$$

where $s_A(n+1)$, $s_B(n+1)$, and $y_B(n)$ are given by (4.4) and (4.5). The definition of the composite machine is summarized in Figure 4.3.

Example 4.2: The cascade composition in Figure 4.4 has the composite machine with state space

$$\text{States} = \text{States}_A \times \text{States}_B = \{(0,0), (0,1), (1,0), (1,1)\}$$

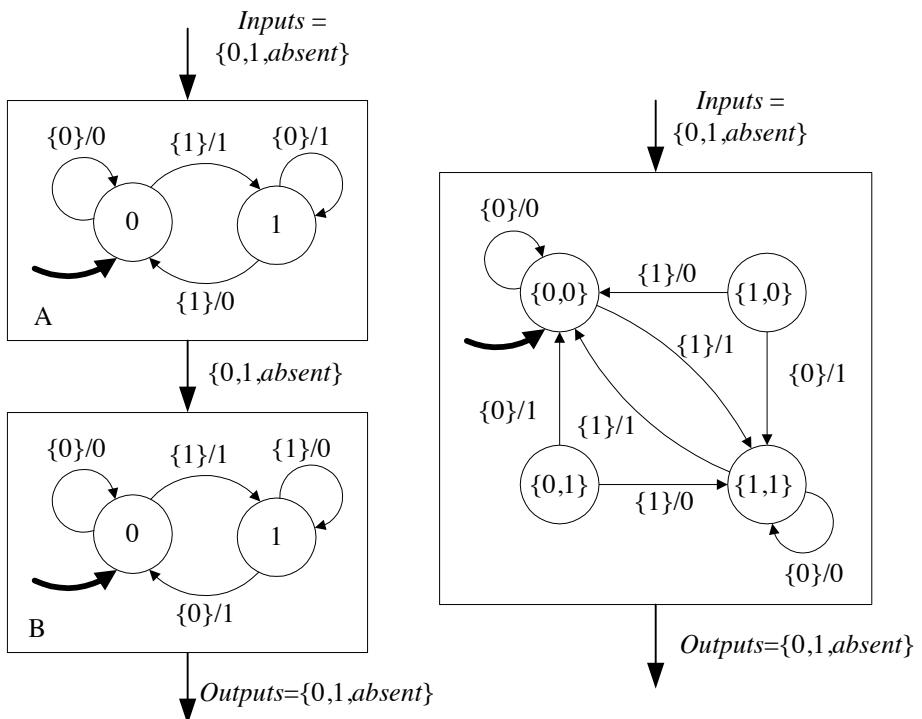


Figure 4.4: Example of a cascade composition. The composed state machine is on the right.

and alphabets

$$\text{Inputs} = \text{Outputs} = \{0, 1, \text{absent}\}.$$

The initial state is

$$\text{initialState} = (0, 0).$$

The *update* function is given by the table:

<i>current state</i>	<i>(next state, output) for input</i>		
	0	1	<i>absent</i>
(0,0)	((0,0),0)	((1,1),1)	((0,0), <i>absent</i>)
(0,1)	((0,0),1)	((1,1),0)	((0,1), <i>absent</i>)
(1,0)	((1,1),1)	((0,0),0)	((1,0), <i>absent</i>)
(1,1)	((1,1),0)	((0,0),1)	((1,1), <i>absent</i>)

The update function is also presented in the state transition diagram of Figure 4.4. The self-loops corresponding to the stuttering input symbol *absent* are not shown in the diagram.

Observe from the table or the diagram that states (0, 1) and (1, 0) are not reachable from the initial state. A state s is said to be **reachable** if some sequence of input symbols can take the state machine from the initial state to s . This suggests that a simpler machine with fewer states would exhibit the same input/output behaviors. In fact, notice from the table that the input is always equal to the output! A trivial one-state machine can exhibit the same input/output behaviors. (Exercise 8 gives a procedure for calculating the reachable states of an arbitrary state machine.)

The simple behavior of the composite machine is not immediately apparent from Figure 4.4. We have to systematically construct the composite machine to derive this simple behavior. In fact, this composite machine can be viewed as an encoder and decoder, because the input bit sequence is encoded by a distinctly different bit sequence (the intermediate signal in Figure 4.4), and then the second machine, given the intermediate signal, reconstructs the original.

This particular encoder is known as a **differential precoder**. It is “differential” in that when the input symbol is 0, the intermediate signal sample is unchanged from the previous sample (whether it was 0 or 1), and when the input symbol is 1, the sample is changed. Thus, the input symbol indicates *change* in the input with a 1, and *no change* with a 0. Differential precoders are used when it is important that

the average number of 1's and 0's is the same, regardless of the input sequence that is encoded.

4.4 Product-form inputs and outputs

In the state machine model of (3.1), at each step the environment selects one input symbol to which the machine reacts and produces one output symbol. Sometimes we wish to model the fact that some input values are selected by one part of the environment, while other input values are simultaneously selected by another part. Also, some output values are sent to one part of the environment, while other output values are simultaneously sent to another part. The product-form composition permits these models.

The machine in Figure 4.5 is shown as a block with two distinct input and output arrows. The figure suggests that the machine receives inputs from two sources and sends outputs to two destinations. In the answering machine example of Chapter 3, for instance, the *end greeting* input value might originate in a physically different piece of hardware in the machine than the *offhook* value.

The distinct arrows into and out of a block are called *ports*. Each port has a set of values called the **port alphabet** associated with it, as shown in figure 4.5. Each port alphabet must include a stuttering element. The set *Inputs* of input values to the state machine is the product of the input sets associated with the ports. Of course, the product can be constructed in any order; each ordering results in a distinct (but bisimilar) state machine model.

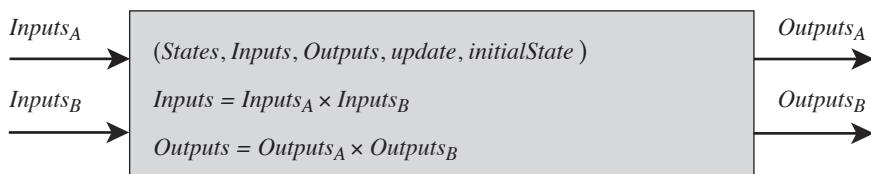


Figure 4.5: State machine with product-form inputs and outputs.

In Figure 4.5 there are two input ports and two output ports. The upper input port can present to the state machine any value in the alphabet $Inputs_A$, which includes *absent*, its stuttering element. The lower port can present any value in the set $Inputs_B$, which also includes *absent*. The input value actually presented to the state machine in a reaction is taken from the set

$$Inputs = Inputs_A \times Inputs_B.$$

The stuttering element for this alphabet is the pair $(\text{absent}, \text{absent})$. The output value produced by a reaction is taken from the set

$$Outputs = Outputs_A \times Outputs_B.$$

If the output of the n -th reaction is $(y_A(n), y_B(n))$, then the upper port shows $y_A(n)$ and the lower port shows $y_B(n)$. These can now be separately presented as inputs to downstream state machines. Again, the stuttering element is $(\text{absent}, \text{absent})$.

Example 4.3: The answering machine of Figure 3.1 has input alphabet

$$Inputs = \{\text{ring}, \text{offhook}, \text{end greeting}, \text{end message}\}.$$

In a typical realization of an answering machine, *ring* and *offhook* come from a subsystem (often an **ASIC**, or **application-specific integrated circuit**) that interfaces to the telephone line. The value *end greeting* comes from another subsystem, such as a magnetic tape machine or digital audio storage device, that plays the answer message. The value *end message* comes from a similar, but distinct, subsystem that records incoming messages. So a more convenient model will show three separate factors for the inputs, as in figure 4.6. That figure also shows the outputs in product form, anticipating that the distinct output values will need to be sent to distinct subsystems.

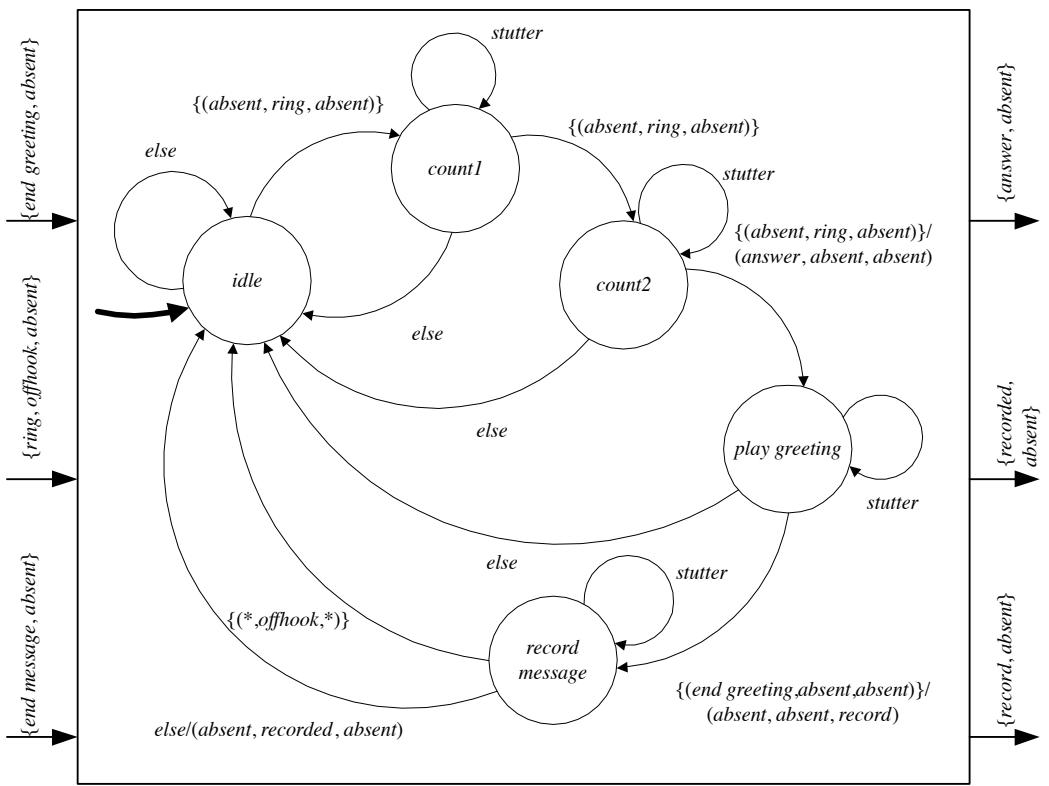
Several features distinguish the diagram in Figure 4.6 from that of Figure 3.1. Each state except the *idle* state has acquired a self-loop labeled *stutter*, which is a name for the guard

$$stutter = \{(\text{absent}, \text{absent}, \text{absent})\}.$$

This self loop prevents the state machine from returning to the idle state (via the *else* transition) when nothing interesting is happening on the inputs. Usually, there will not be a reaction if nothing interesting is happening on the inputs, but because

of synchrony, this machine may be composed with others, and all machines have to react at the same time. So if anything interesting is happening elsewhere in the system, then this machine has to react even though nothing interesting is happening here. Recall that such a reaction is called a stutter. The state does not change, and the output symbol produced is the stuttering element of the output alphabet.

Each guard now consists of a set of triples, since the product-form input has three components. The shorthand “ $(*, \text{offhook}, *)$ ” on the arc from the *record message*



NOTE: *stutter* = $\{(absent, absent, absent)\}$

Figure 4.6: Answering machine with product-form inputs and outputs has three input ports and three output ports.

state to the *idle* state represents a set,

$$(*, \text{offhook}, *) = \{ \quad (\text{absent}, \text{offhook}, \text{absent}), \\ (\text{end greeting}, \text{offhook}, \text{absent}), \\ (\text{absent}, \text{offhook}, \text{end message}), \\ (\text{end greeting}, \text{offhook}, \text{end message}) \}.$$

The “*” is a **don’t care** or **wildcard** notation. Anything in its position will trigger the guard.

Because there are three output ports, the output symbols are also triples, but most of them are implicitly $(\text{absent}, \text{absent}, \text{absent})$.

4.5 General feedforward composition

Given that state machines can have product-form inputs and outputs, it is easy to construct a composition of state machines that combines features of both the cascade composition of Figure 4.3 and the side-by-side composition of Figure 4.1. An example is shown in

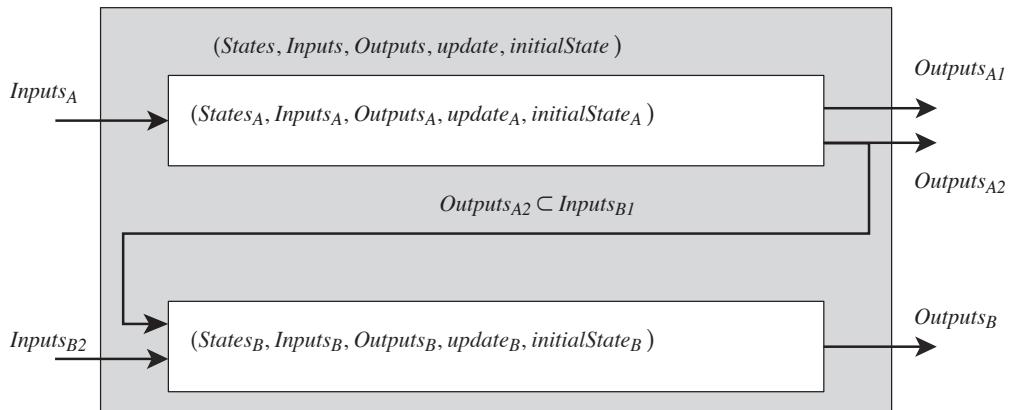


Figure 4.7: More complex composition.

Figure 4.7. In that figure,

$$\begin{aligned} Outputs_A &= Outputs_{A1} \times Outputs_{A2} \\ Inputs_B &= Inputs_{B1} \times Inputs_{B2}. \end{aligned}$$

Notice that the bottom port of machine A goes both to the output of the composite machine and to the top port of machine B. Sending a value to multiple destinations like this is called **forking**. In Exercise 1 at the end of this chapter you are asked to define the composite machine for this example.

Example 4.4: We compose the answering machine of figure 4.6 with a playback system, shown in Figure 4.8, which plays messages that have been recorded by the answering machine. The playback system receives the *recorded* input symbol from the answering machine whenever the answering machine is done recording a message. Its task is to light an indicator that a message is pending, and to wait for a user to press a play button on the answering machine to request that pending messages be played back. When that button is pressed, all pending messages are played back. When they are done being played back, then the indicator light is turned off.

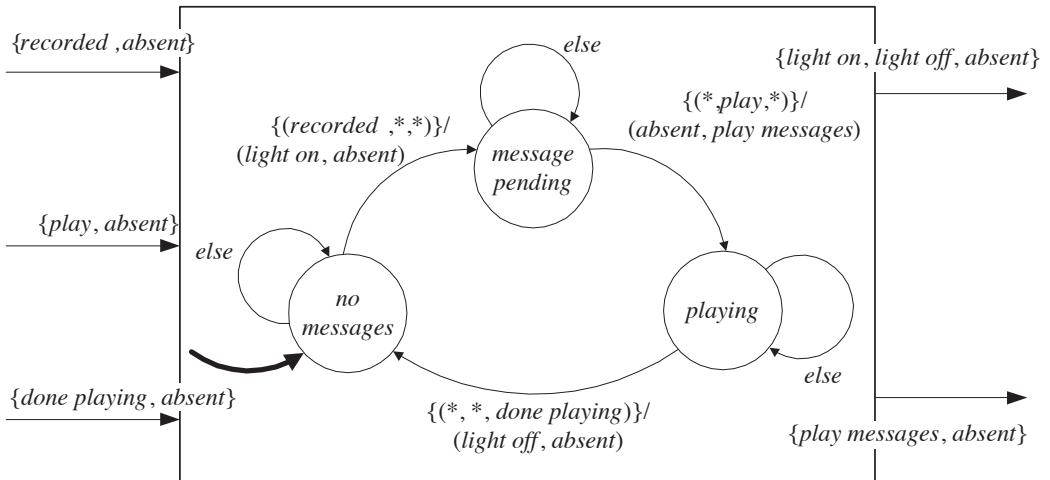


Figure 4.8: Playback system for composing with the answering machine.

The composition is shown in Figure 4.9. The figure shows a number of other components, not modeled as state machines, to help understand how everything works in practice. These other components are shown as three-dimensional objects, to emphasize their physicality. We have simplified the figure by omitting the *absent* elements of all the sets. They are implicit.

A telephone line interface provides *ring* and *offhook* when these are detected. Detection of one of these can trigger a reaction of the composite machine. In fact, any output symbol from any of the physical components can trigger a reaction of the composite machine. When *AnsweringMachine* generates the *answer* output sym-

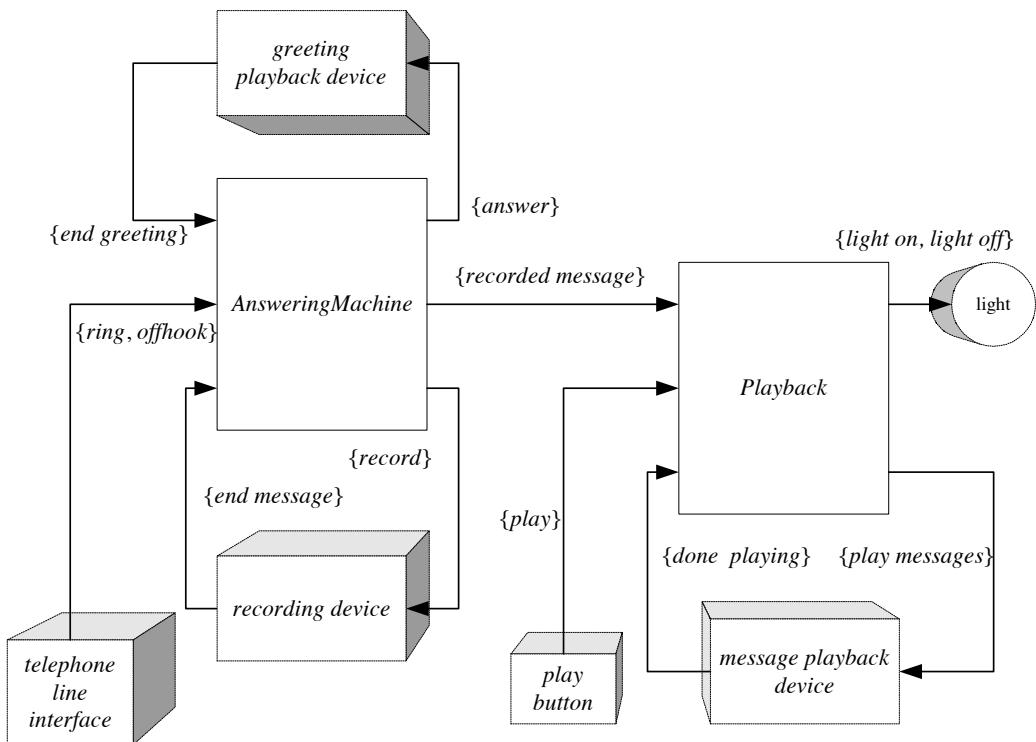


Figure 4.9: Composition of an answering machine with a message playback machine. The three-dimensional boxes are physical components that are not modeled as state machines. They are the sources of some inputs and the destinations of some outputs.

bol, then the “greeting playback device” plays back the greeting. From the perspective of the state machine model, all that happens is that time passes (during which some reactions may occur), and then an *end greeting* input symbol is received. The recording device works similarly. When *AnsweringMachine* generates a *recorded* output symbol, then the *Playback* machine will respond by lighting the indicator light. When a user presses the play button the input symbol *play* is generated, the composite machine reacts, and the *Playback* machine issues a *play messages* output symbol to the “message playback device.” This device also allows time to pass, then generates a *done playing* input symbol to the composite state machine.

If we wish to model the playback or recording subsystem in more detail using finite state machines, then we need to be able to handle feedback compositions. These are considered below.

4.6 Hierarchical composition

By using the compositions discussed above, we can now handle any interconnection of state machines that does not have feedback. Consider for example the cascade of three state machines shown in Figure 4.10. The composition techniques we have discussed so far involved only two state machines. It is easy to generalize the composition in Figure 4.3 to handle three state machines (see Exercise 2), but a more systematic method might be to apply the composition of Figure 4.3 to compose two of the state machines, and then apply it again to compose the third state machine with the result of the first composition. This is called **hierarchical composition**.

In general, given a collection of interconnected state machines, there are several ways to hierarchically compose them. For example, in Figure 4.10, we could first compose machines *A* and *B* to get, say, machine *D*, and then compose *D* with *C*. Alternatively, we could first compose *B* and *C* to get, say, machine *E*, and then compose *E* and *A*. These two procedures result in different but bisimilar state machine models (each simulates the other).

4.7 Feedback

In simple feedback systems, an output from a state machine is fed back as an input to the same state machine. In more complicated feedback systems, several state machines might be connected in a loop; the output of one eventually affects its own input through some intervening state machines.

Feedback is a subtle form of composition in the synchronous model. In synchronous composition, in a reaction, the output symbol of a state machine is simultaneous with the input symbol. So the output symbol of a machine in feedback composition depends on an input symbol that depends on its own output symbol!

We frequently encounter such situations in mathematics. A common problem is to find x such that

$$x = f(x) \quad (4.6)$$

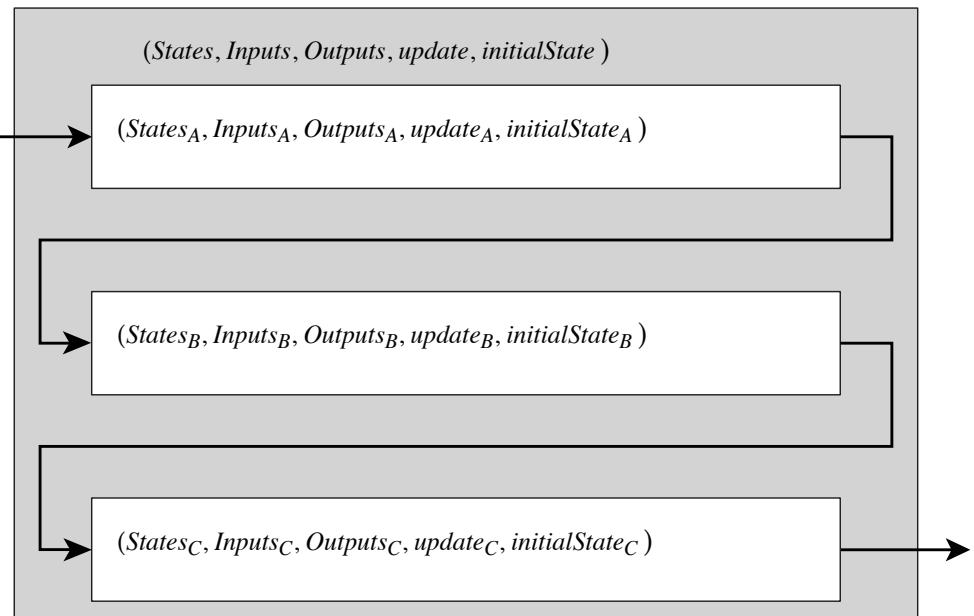


Figure 4.10: Cascade composition of three state machines. They can be composed in different ways into different, but bisimilar, state machines.

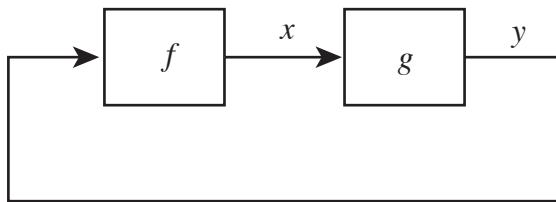


Figure 4.11: Illustration of a fixed point problem.

for a given function f . A solution to this equation, if it exists, is called a **fixed point** in mathematics. It is analogous to feedback because the ‘output’ $f(x)$ of f is equal to its ‘input’ x , and vice versa. The top diagram in Figure 4.12 illustrates a similar relationship: the state machine’s output symbol is the same as its (simultaneous) input symbol.

A more complicated problem, involving two equations, is to find x and y so that

$$x = f(y), \text{ and } y = g(x).$$

The analogous feedback composition has two state machines in feedback, with the structure of Figure 4.11.²

A fixed-point equation like (4.6) may have no fixed point, a unique fixed point, or multiple fixed points. Take for example the function $f: \mathbb{R} \rightarrow \mathbb{R}$ where $\forall x \in \mathbb{R}, f(x) = 1 + x^2$. In this case, (4.6) becomes $x = 1 + x^2$, which has no fixed point in the reals. If $f(x) = 1 - x$, (4.6) becomes $x = 1 - x$, which has a unique fixed point, $x = 0.5$. Lastly, if $f(x) = x^2$, (4.6) becomes $x = x^2$, which has two fixed points, $x = 0$ and $x = 1$.

In the context of state machines, a feedback composition with no fixed point in some reachable state is a defective design; we call such a composition **ill-formed**. We can not evaluate an ill-formed composition. Usually, we also wish to exclude feedback compositions that have more than one non-stuttering fixed point in some reachable state. So these too are ill-formed. A feedback composition with a unique non-stuttering fixed point in all reachable states is **well-formed**. Fortunately, it is easy to construct well-formed feedback compositions, and they prove surprisingly useful. We explore this further, beginning with a somewhat artificial case of feedback composition with no inputs.

²Figure 4.9 would be a feedback composition if any of the three recording or playback devices were modeled as state machines. In the figure, however, these devices are part of the environment.

4.7.1 Feedback composition with no inputs

The upper state machine in Figure 4.12 has an output port that feeds back to its input port. We wish to construct a state machine model that hides the feedback, as suggested by the figure. The result will be a state machine with no input. This does not fit our model, which requires the environment to provide inputs to which the machine reacts. So we artificially provide an input alphabet

$$\text{Inputs} = \{\text{react}, \text{absent}\},$$

as suggested in the lower machine in Figure 4.12. We interpret the input symbol *react* as a command for the internal machine to react, and the input symbol *absent* as a command for the internal machine to stutter. The output alphabet is

$$\text{Outputs} = \text{Outputs}_A.$$

This is an odd example of a synchronous/reactive system because of the need for this artificial input alphabet. Typically, however, such a system will be composed with others, as suggested in Figure 4.13. That composition does have an external input. So the overall composition, including the component with no external input, reacts whenever an external

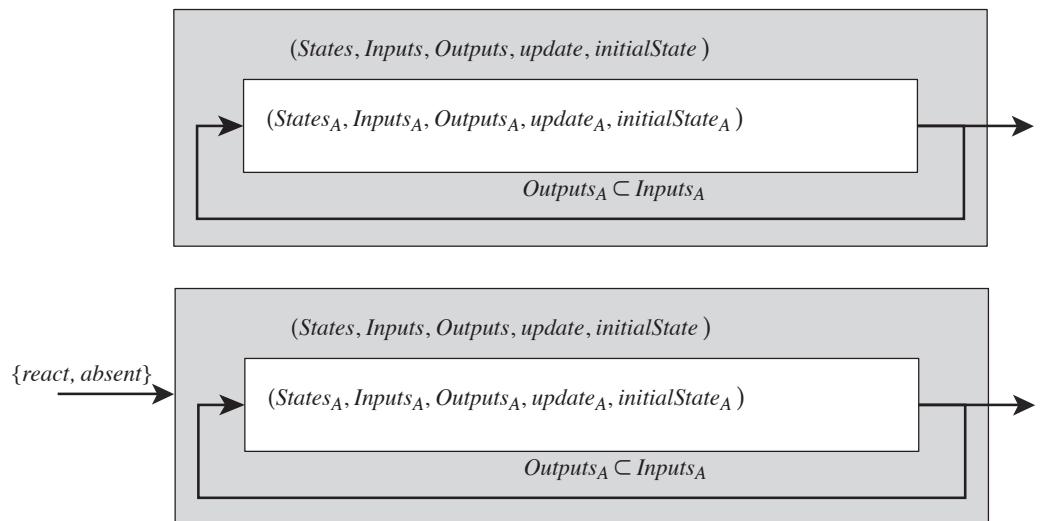


Figure 4.12: Feedback composition with no inputs.

input symbol is presented, and there is no need for the artificial inputs. Of course when a stuttering element is provided to the composite, all components stutter.

Although it is not typical, we first consider the example in Figure 4.12 because the formulation of the composition is simplest. We will augment the model to allow inputs after this.

In Figure 4.12, for the feedback connection to be possible, of course, we must have

$$Outputs_A \subset Inputs_A.$$

Suppose the current state at the n -th reaction is $s(n) \in States_A$. The problem is to find the output symbol $y(n) \in Outputs_A$. Since $y(n)$ is also the input symbol, it must satisfy

$$(s(n+1), y(n)) = update_A(s(n), y(n)),$$

where $s(n+1)$ is the next state. The difficulty here is that the “unknown” $y(n)$ appears on both sides. Once we find $y(n)$, $s(n+1)$ is immediately determined by the $update_A$ function. To simplify the discussion, we get rid of $s(n+1)$ by working with the function

$$output_A : States_A \times Inputs_A \rightarrow Outputs_A$$

This function gives the output symbol as a function of the current state and the current input symbol, as we saw in Section 3.1.1. So our problem is: given the current state $s(n)$

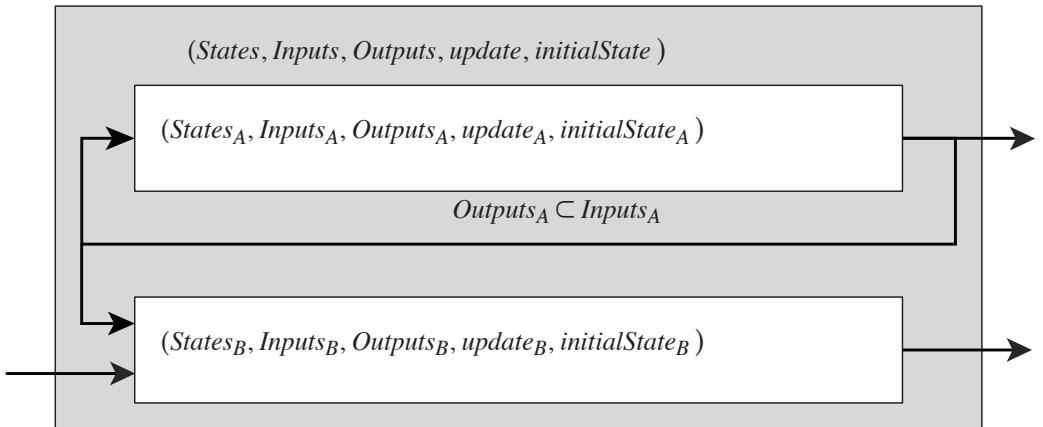


Figure 4.13: Feedback composition composed with another state machine.

and the known function $output_A$, find $y(n)$ such that

$$y(n) = output_A(s(n), y(n)). \quad (4.7)$$

Here $s(n)$ is a known constant, so the equation is of the form (4.6), and its solution, if it exists, is a fixed point.

One solution that is always available is to stutter, i.e.,

$$y(n) = absent, \text{ (and then } s(n+1) = s(n)\text{)},$$

since $absent = output_A(s(n), absent)$, assuming that $absent$ is the stuttering input symbol for machine A . But this is not an interesting solution, since the state does not change. We want to find a non-stuttering solution for $y(n)$.

We say that the composition of Figure 4.12 is **well-formed** if for every reachable $s(n) \in States_A$, there is a unique non-stuttering output symbol $y(n)$ that solves (4.7); otherwise, the composition is **ill-formed**. If the composition is well-formed, the composite machine definition is:

$$\begin{aligned} States &= States_A \\ Inputs &= \{react, absent\} \\ Outputs &= Outputs_A \\ initialState &= initialState_A \\ update(s(n), x(n)) &= \begin{cases} update_A(s(n), y(n)), \\ \quad \text{where } y(n) \neq absent \text{ uniquely satisfies (4.7)} \\ \quad \text{if } x(n) = react \\ (s(n), x(n)) \\ \quad \text{if } x(n) = absent \end{cases} \end{aligned}$$

Notice that the composite machine is defined only if the composition is well-formed, i.e., there is a unique $y(n)$ that satisfies (4.7). If there is no such $y(n)$, the composition is ill-formed and the composite machine is not defined.

The next example illustrates the difference between well-formed and ill-formed compositions. It will suggest a procedure to solve (4.7) in the important special case of systems with state-determined output.

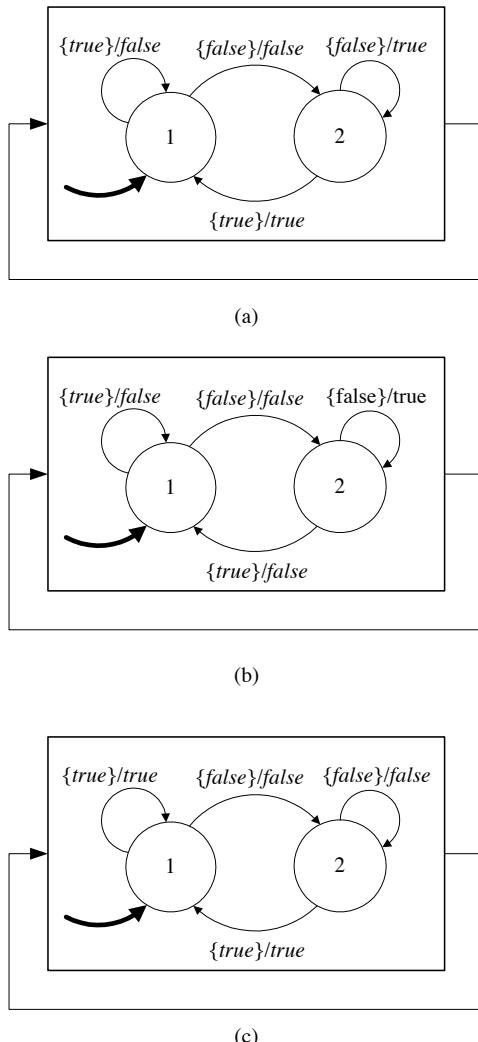


Figure 4.14: Three examples of feedback composition. Examples (b) and (c) are ill-formed. Composition (b) has no non-stuttering fixed point in state 2, while composition (c) has two non-stuttering fixed points in either state.

Example 4.5: Consider the three feedback compositions in Figure 4.14. In all cases, the input and output alphabets of the component machines are

$$\text{Inputs}_A = \text{Outputs}_A = \{\text{true}, \text{false}, \text{absent}\}.$$

The input alphabet to the *composite* machine is $\{\text{react}, \text{absent}\}$, as in Figure 4.12, but we do not show this (to reduce clutter in the figure). We want to find a non-stuttering solution $y(n)$ of (4.7). Since the output symbol is also the input symbol, we are looking for a non-stuttering input symbol.

Consider the top machine first. Suppose the current state is the initial state, $s(n) = 1$. There are two outgoing arcs, and for a non-stuttering input symbol, both produce $y(n) = \text{false}$, so we can conclude that the output symbol of the machine is *false*. Since the output symbol is *false*, then the input symbol is also *false*, and the non-stuttering fixed point of (4.7) is unique,

$$\text{output}_A(1, \text{false}) = \text{false}.$$

The state transition taken by the reaction goes from state 1 to state 2.

Suppose next that the current state is $s(n) = 2$. Again, there are two outgoing arcs. Both arcs produce output symbol *true* for a non-stuttering input symbol, so we can

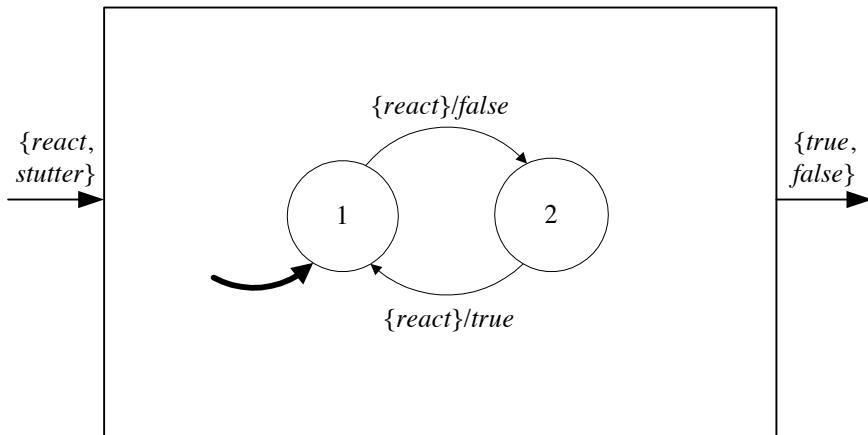


Figure 4.15: Composite machine for Figure 4.14(a).

conclude that the output symbol is *true*. Since the output symbol is *true*, then the input symbol is also *true*, there is a unique non-stuttering fixed point,

$$\text{output}_A(2, \text{true}) = \text{true},$$

and the state transition taken goes from 2 to 1. Since there is a unique non-stuttering fixed point in every reachable state, the feedback composition is well-formed.

The composite machine alternates states on each reaction, and produces the output sequence

$$(\text{false}, \text{true}, \text{false}, \text{true}, \text{false}, \text{true}, \dots)$$

for the input sequence

$$(\text{react}, \text{react}, \text{react}, \dots).$$

The composite machine is shown in Figure 4.15.

Now consider the second machine in Figure 4.14. If the initial state is 1 the analysis is the same as above. There is a unique non-stuttering fixed point, the output and input symbols are both *false*, and the state transition goes from 1 to 2. But if the initial state is 2 and the unknown input symbol is *true*, the output symbol is *false*; and if the unknown input symbol is *false*, the output symbol is *true*. Thus there is no non-stuttering fixed point $y(n)$ that solves,

$$\text{output}_A(2, y(n)) = y(n).$$

The feedback composition is not well-formed.

Consider the third machine in Figure 4.14. This feedback composition is also ill-formed but for a different reason. If the initial state is 1 and the unknown input symbol is *true*, the output symbol is also *true*, so *true* is a fixed point, and the output symbol can be *true*. However, the output symbol can also be *false*, since if it is, then a transition will be taken that produces the input symbol *false*. So *false* is also a fixed point. Thus, the problem here is that there is more than one non-stuttering solution, not that there are none!

Our conclusion is that with machines like the second and third, you cannot connect them in a feedback composition as shown. The second is rejected because it has no solution and the third because it has more than one. We only accept feedback compositions where there is exactly one non-stuttering solution in each reachable state.

4.7.2 State-determined output

In the first machine of Figure 4.14, in each state, all outgoing arcs produce the *same* output symbol, independent of the input symbol. In other words, the output symbol $y(n)$ depends only on the state; in the example, $y(n) = \text{false}$ if $s(n) = 1$, and $y(n) = \text{true}$ if $s(n) = 2$. The unique fixed point of (4.7) is this output symbol, and we can immediately conclude that the feedback composition is well-formed.

We say that a machine A has **state-determined output** if in every reachable state $s(n) \in \text{States}_A$, there is a unique output symbol $y(n) = b$ (which depends on $s(n)$) independent of the non-stuttering input symbol; i.e. for every $x(n) \neq \text{absent}$,

$$\text{output}_A(s(n), x(n)) = b.$$

In this special case of state-determined output, the composite machine is:

$$\begin{aligned} \text{States} &= \text{States}_A \\ \text{Inputs} &= \{\text{react}, \text{absent}\} \\ \text{Outputs} &= \text{Outputs}_A \\ \text{initialState} &= \text{initialState}_A \\ \text{update}(s(n), x(n)) &= \begin{cases} \text{update}_A(s(n), b), \\ \quad \text{where } b \text{ is the unique output symbol in} \\ \quad \text{state } s(n) \text{ if } x(n) = \text{react} \\ (s(n), x(n)) \\ \quad \text{if } x(n) = \text{absent} \end{cases} \end{aligned}$$

When a machine with state-determined output is combined with any other state machines in a feedback composition, the resulting composition is also well-formed, as illustrated in the next example.

Example 4.6:

In Figure 4.16 the machine A is combined with machine B in a feedback composition. A is the same as the first machine, and B is the same as the second machine in Figure 4.14. (The output port of B is drawn on the left and the input port on the right so that the block diagram looks neater.) A has state-determined output, but B does not. The composition is well-formed.

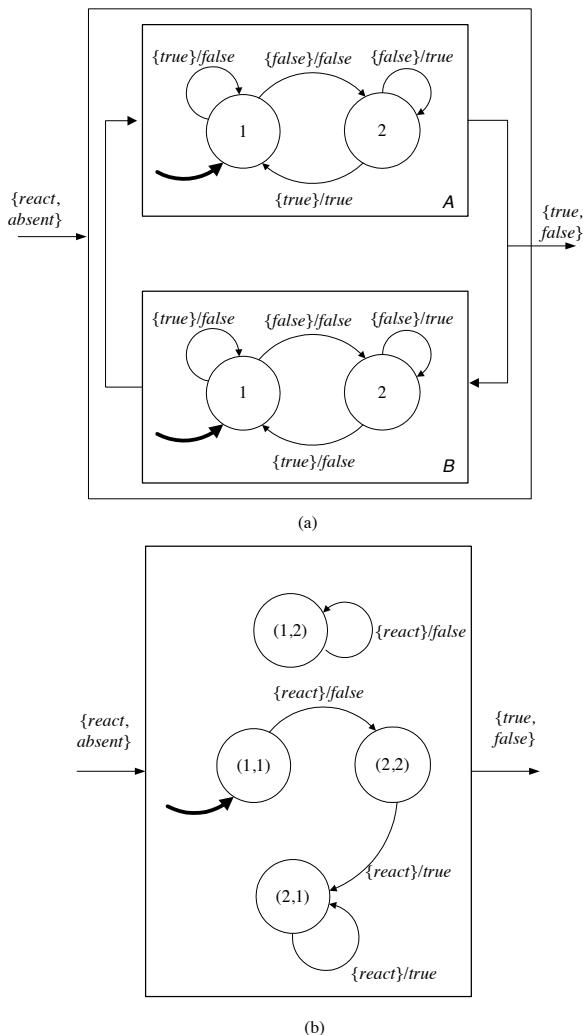


Figure 4.16: Machine A has state-determined output, but B does not. The feedback composition is well-formed, and the composite machine is shown on the bottom. Note that state $(1, 2)$ is not reachable.

To see this, suppose both machines are in their initial states 1. A produces output symbol *false*, independent of its input symbol. This output is the input of B which then produces output symbol *false* and makes the transition to state 2. The output symbol *false* of B is the input to A which makes the transition to its state 2. (A and B make their state transitions together in our synchronous/reactive model.) We can determine the output symbol and transition in the same way for all other states. The state diagram of the composite machine is shown in the figure on the right. Note that state (1, 2) is not reachable from the initial state (1, 1), so we could have ignored it in determining whether the composition is well-formed.

The input alphabet of the composite machine is $\{react, absent\}$, taking *absent* as the stuttering input symbol. The output alphabet is the same as the output alphabet of A, $\{true, false, absent\}$. The state space is $States_A \times States_B$. The *update* function is given by the table:

current state	(next state, output) for input	
	react	absent
(1,1)	((2,2), <i>false</i>)	((1,1), <i>absent</i>)
(2,2)	((2,1), <i>true</i>)	((2,2), <i>false</i>)
(1,2)	((1,2), <i>false</i>)	((1,2), <i>false</i>)
(2,1)	((2,1), <i>true</i>)	((2,1), <i>false</i>)

It is possible for a machine without state-determined outputs to be placed in a well-formed feedback composition as illustrated in the next example.

Example 4.7: Consider the example in Figure 4.17. For the component machine, the output alphabet is $Outputs_A = \{true, false, maybe, absent\}$, and the input alphabet is $Inputs_A = \{true, false, absent\}$. The stuttering element is *absent*. The machine does not have state-determined output because, for instance, the outgoing arcs from state 1 can produce both *maybe* and *false*. Nevertheless, equation (4.7) has a unique non-stuttering fixed point in each state:

$$output_A(1, \textit{false}) = \textit{false}, \text{ and } output_A(2, \textit{true}) = \textit{true}.$$

So the feedback composition is well-formed. The composite machine is shown on the bottom.

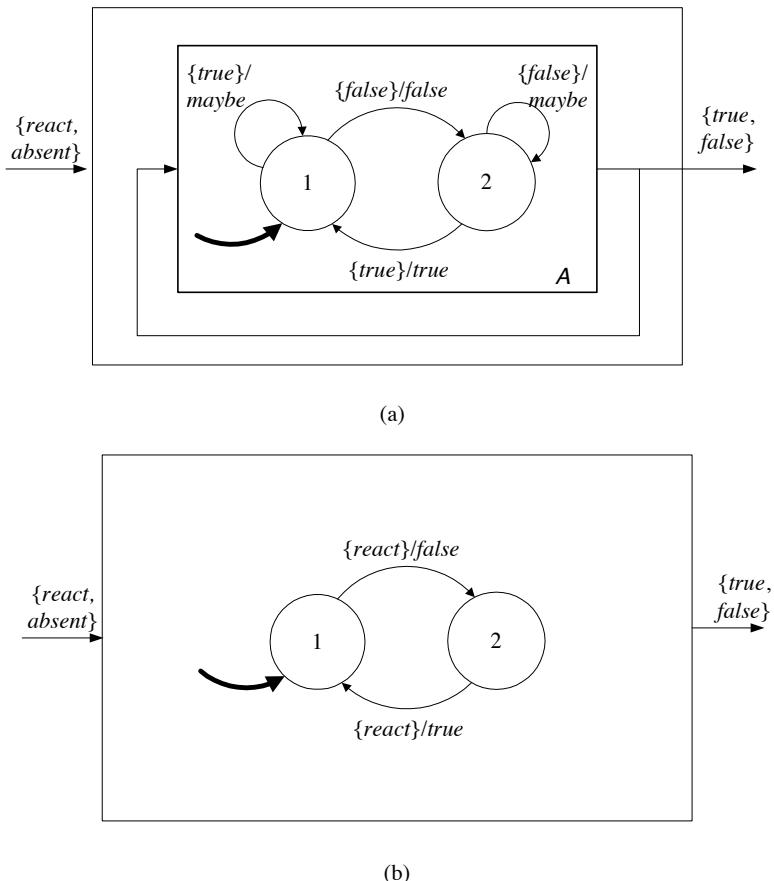


Figure 4.17: Machine A does not have state-determined outputs, but the feedback composition is well-formed. The machine on the bottom is the composite machine.

It can be considerably harder to find the behavior of a feedback composition without state-determined outputs, even if the composition is well-formed. Below, in Section 4.7.4, we give a constructive procedure that often works to quickly find a fixed point, and to determine whether it is unique. However, even that procedure does not always work (and in fact, will fail on example 4.7). If the input alphabet is finite, the only strategy that always works is to try all possible output values $y(n)$ in (4.7) for each reachable state $s(n)$. Before discussing this procedure, we generalize to more interesting feedback compositions.

4.7.3 Feedback composition with inputs

Now consider the state machine in Figure 4.18. It has two input and output ports. The second output port feeds back to the second input port. We wish to construct a state machine model that hides the feedback, as suggested by the figure, and becomes a simple input/output state machine. This is similar to the example in Figure 4.12, but now there is an additional input and an additional output. The procedure for finding the composite machine is similar, but the notation is more cumbersome. Given the current state and the current external input symbol, we must determine the “unknown” output symbol.

The inputs and outputs of machine A are in product form:

$$\begin{aligned} \text{Inputs}_A &= \text{Inputs}_{A1} \times \text{Inputs}_{A2}, \\ \text{Outputs}_A &= \text{Outputs}_{A1} \times \text{Outputs}_{A2}. \end{aligned}$$

For the feedback composition to be possible we must have

$$\text{Outputs}_{A2} \subset \text{Inputs}_{A1}.$$

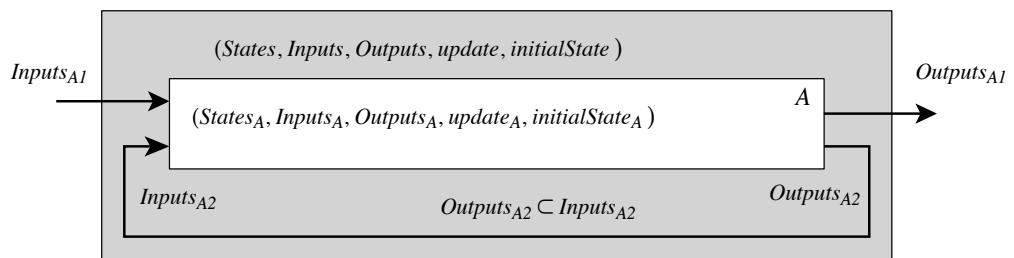


Figure 4.18: Feedback composition of a state machine.

The output function of A is

$$\text{output}_A : \text{States}_A \times \text{Inputs}_A \rightarrow \text{Outputs}_A.$$

It is convenient to write it in product form as,

$$\text{output}_A = (\text{output}_{A1}, \text{output}_{A2}),$$

where

$$\text{output}_{A1} : \text{States}_A \times \text{Inputs}_A \rightarrow \text{Outputs}_{A1},$$

gives the output symbol at the first output port and

$$\text{output}_{A2} : \text{States}_A \times \text{Inputs}_A \rightarrow \text{Outputs}_{A2},$$

gives the output symbol at the second output port.

Suppose we are given that at the n -th reaction, the current state of A is $s(n)$ and the current external input symbol is $x_1(n) \in \text{Inputs}_{A1}$. Then the problem is to find the “unknown” output symbol $(y_1(n), y_2(n)) \in \text{Outputs}_A$ such that

$$\text{output}_A(s(n), (x_1(n), y_2(n))) = (y_1(n), y_2(n)). \quad (4.8)$$

The symbol $y_2(n)$ appears on both sides because the second input $x_2(n)$ to machine A is equal to $y_2(n)$. In terms of the product form, (4.8) is equivalent to two equations:

$$\text{output}_{A1}(s(n), (x_1(n), y_2(n))) = y_1(n), \quad (4.9)$$

$$\text{output}_{A2}(s(n), (x_1(n), y_2(n))) = y_2(n). \quad (4.10)$$

In these equations, $s(n)$ and $x_1(n)$ are known, while $y_1(n)$ and $y_2(n)$ are unknown. Observe that if (4.10) has a unique solution $y_2(n)$, then the input symbol to A is $(x_1(n), y_2(n))$ and the next state $s(n+1)$ and output symbol $y_1(n)$ are determined. So the fixed point equation (4.10) plays the same role as (4.7).

We say that the composition of Figure 4.18 is well-formed if for every reachable state $s(n) \in \text{States}_A$ and for every external input symbol $x_1(n) \in \text{Inputs}_{A1}$, there is a unique non-stuttering output symbol $y_2(n) \in \text{Outputs}_{A2}$ that solves (4.10). If the composition is well-formed, the composite machine definition is:

$$\text{States} = \text{States}_A$$

$$\text{Inputs} = \text{Inputs}_{A1}$$

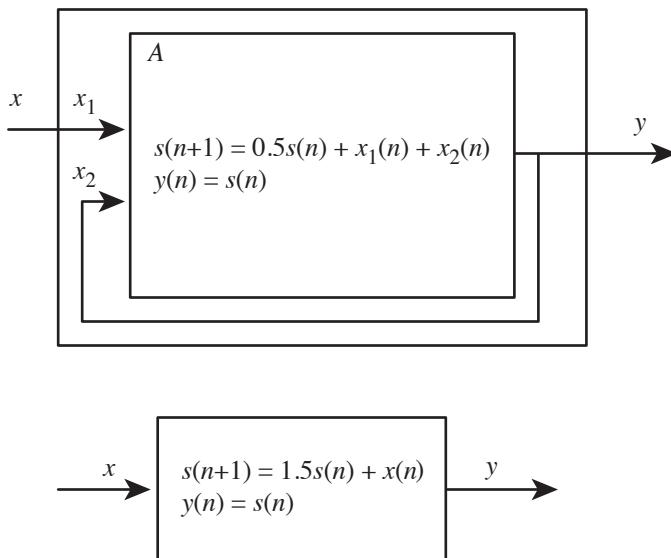


Figure 4.19: Machine A has two input ports and one output port. The output port is connected to the second input port. The composition is well-formed. The composite machine is shown at the bottom.

$$\text{Outputs} = \text{Outputs}_{A1}$$

$$\text{initialState} = \text{initialState}_A$$

$$\text{update}(s(n), x(n)) = (\text{nextState}(s(n), x(n)), \text{output}(s(n), x(n))):$$

$$\text{nextState}(s(n), x(n)) = \text{nextState}_A(s(n), (x(n), y_2(n))) \text{ and}$$

$$\text{output}(s(n), x(n)) = \text{output}_A(s(n), (x(n), y_2(n))), \text{ where } y_2(n) \text{ is the unique solution of (4.10).}$$

(The nextState function is defined in Section 3.1.1.)

In the following example, we illustrate the procedure for defining the composition machine given a sets and functions description (3.1) for the component machine A .

Example 4.8: Figure 4.19 shows a feedback composition, where component machine A has two input ports and one output port,

$$\text{Inputs}_A = \mathbb{R} \times \mathbb{R}, \text{ Outputs}_A = \mathbb{R},$$

and states $States_A = \mathbb{R}$. Thus A has infinite input and output alphabets and infinitely many states. At the n -th reaction, the pair of input values is denoted by $(x_1(n), x_2(n))$, the current state by $s(n)$, the next state by $s(n+1)$, and the output symbol by $y(n)$. In terms of these, the update function is given by

$$\begin{aligned}(s(n+1), y(n)) &= update_A(s(n), (x_1(n), x_2(n))) \\ &= (0.5s(n) + x_1(n) + x_2(n), s(n)).\end{aligned}$$

Equivalently,

$$\begin{aligned}s(n+1) &= nextState_A(s(n), (x_1(n), x_2(n))) \\ &= 0.5s(n) + x_1(n) + x_2(n) \\ y(n) &= output_A(s(n), (x_1(n), x_2(n))) = s(n).\end{aligned}$$

Thus, the component machine A has state-determined output. The feedback connects the output port to the second input port, so $x_2(n) = y(n)$. Given the current state $s(n)$ and the external input symbol $x(n)$ at the first input port, (4.10) becomes,

$$output_A(s(n), (x_1(n), x_2(n))) = x_2(n),$$

which gives

$$s(n) = x_2(n).$$

So the composite machine is defined by

$$Inputs = \mathbb{R}, \quad Outputs = Reals, \quad States = \mathbb{R}$$

$$\begin{aligned}update(s(n), x(n)) &= (0.5s(n) + x(n) + s(n), s(n)) \\ &= (1.5s(n) + x(n), s(n)).\end{aligned}$$

Note that the input to the composite machine is a scalar. The composite machine is shown in the lower part of the figure.

4.7.4 Constructive procedure for feedback composition

Our examples so far involve one or two state machines and a feedback loop. If any machine in the loop has state determined output, then finding the fixed point is easy. Most interesting designs are more complicated, involving several state machines and several feedback loops, and the loops do not necessarily include machines with state-determined output.

In this section, we describe a constructive procedure for finding the fixed point that often (but not always) works. It is “constructive” in the sense that it can be applied mechanically, and will, in a finite number of steps, either identify a fixed point or give up. The approach is simple. At each reaction, begin with all unspecified signals having value *unknown*. Then with what is known about the input symbols, try each state machine to determine as much as possible about the output symbols. You can try the state machines in any order. Given what you learn about the output symbols, then update what you know about the feedback input symbols, and repeat the process, trying each state machine again. Repeat this process until all signal values are specified, or until you learn nothing more about the output symbols. We illustrate the procedure in an example involving only one machine, but keep in mind that the procedure works for any number of machines.

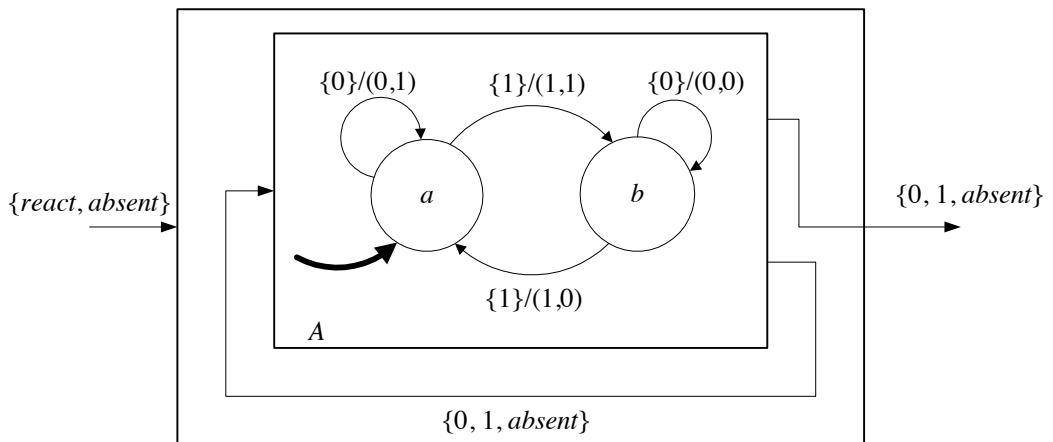


Figure 4.20: Feedback composition without state-determined output.

Example 4.9: Figure 4.20 shows a feedback composition without state-determined output. Nonetheless, our constructive procedure can be used to find a unique fixed point for each reaction. Suppose that the current state is a , and that the input to the composition is *react*. Begin by assuming that the symbol on the feedback connection is *unknown*. Try component machine A (this is the only component machine in this example, but if there were more, we could try them in any order). Examining machine A , we see that in its current state, a , the output symbol cannot be fully determined. Thus, this machine does not have state-determined output. However, more careful examination reveals that in state a , the second element of the output tuple *is* determined. That second element has value 1. Fortunately, this changes the value on the feedback connection from *unknown* to 1.

Now we repeat the procedure. We choose a state machine to try. Again, there is only one state machine in this example, so we try A . This time, we know that the input symbol is 1, so we know that the machine must take the transition from a to b and produce the output tuple $(1, 1)$. This results in all symbols being known for the reaction, so we are done evaluating the reaction.

Now assume the current state is b . Again, the feedback symbol is initially *unknown*, but once again, trying A , we see that the second element of the output tuple must be 0. Thus, we change the feedback symbol from *unknown* to 0 and try the machine again. This time, its input is 0, so it must take the self loop back to b and produce the output tuple $(0, 0)$.

Recall that the set *Behaviors* is the set of all (x, y) such that x is an input sequence and y is an output sequence. For this machine, ignoring stuttering, the only possible input sequence is $(\text{react}, \text{react}, \text{react}, \dots)$. We have just determined that the resulting output sequence is $(1, 0, 0, 0, \dots)$. Thus, ignoring stuttering,

$$\text{Behaviors} = \{((\text{react}, \text{react}, \text{react}, \dots), (1, 0, 0, 0, \dots))\}.$$

Of course, we should take into account stuttering, so this set needs to be augmented with all (x, y) pairs that look like the one above but have stuttering symbols inserted.

This procedure can be applied in general to any composition of state machines. If the procedure can be applied successfully (nothing remains *unknown*) for all reachable states

of the composition, then the composition is well-formed. The following example applies the procedure to a more complicated example.

Example 4.10: We add more detail to the message recorder in Figure 4.9. In particular, as shown in Figure 4.21, we wish to model the fact that the message recorder stops recording when either it detects a dialtone or when a timeout period is

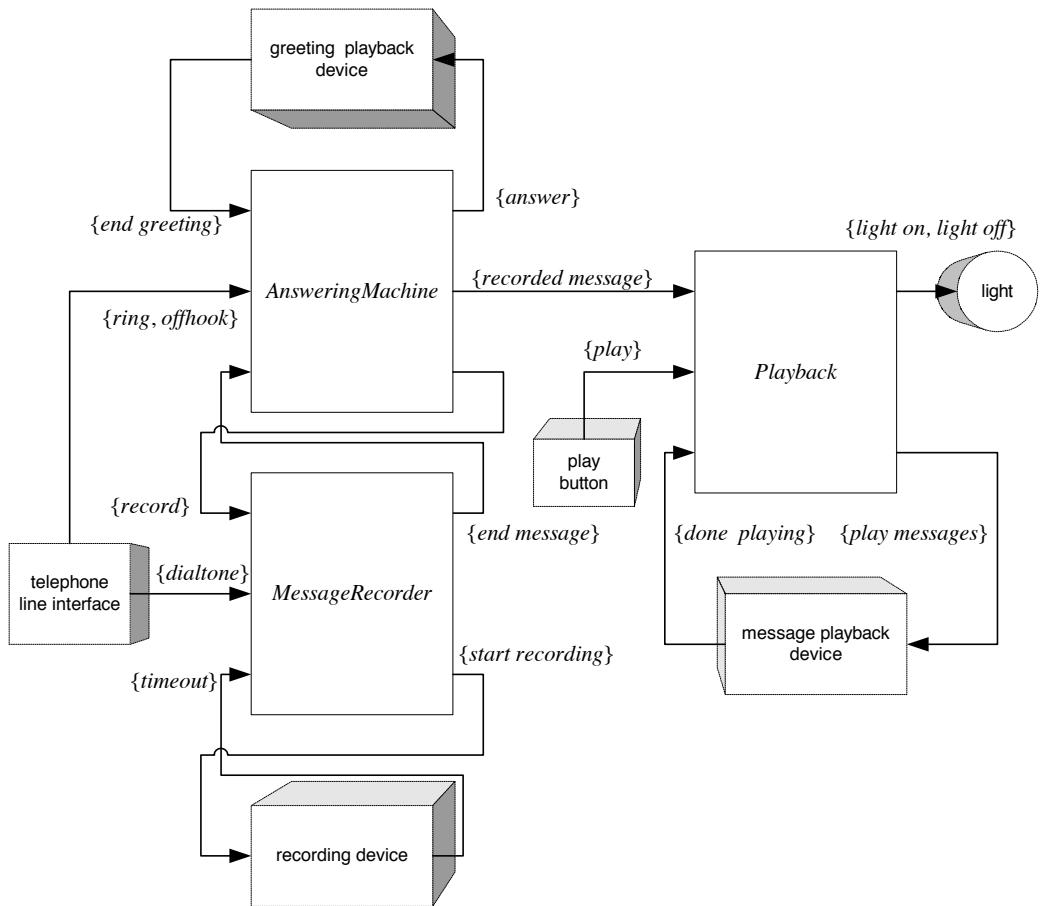


Figure 4.21: Answering machine composition with feedback. The *absent* elements are not shown (to reduce clutter).

reached. This is modeled by a two-state finite state machine, shown in Figure 4.22. Note that this machine does not have state-determined output. For example, in state *idle*, the output could be (*absent*, *start recording*) or it could be (*absent*, *absent*) when the input is not the stuttering input.

The *MessageRecorder* and *AnsweringMachine* state machines form a feedback loop. Let us verify that composition is well-formed. First, note that in the *idle* state of the *MessageRecorder*, the upper output symbol is known to be *absent* (see Figure 4.22). Thus, only in the *recording* state is there any possibility of a problem that would lead to the composition being ill-formed. In that state, the output symbol is not known unless the input symbols are known. However, notice that the *recording* state is entered only when a *record* input symbol is received. In Figure 4.6, you can see that the *record* value is generated only when entering state *record message*. But in all arcs emerging from that state, the lower output symbol of *AnsweringMachine* will always be *absent*; the input symbol does not need to be known to know that. Continuing this reasoning by considering all possible state transitions from this point, we can convince ourselves that the feedback loop is well-formed.

The sort of reasoning in this more complicated example is difficult and error-prone for even moderate compositions of state machines. It is best automated. Compilers for synchronous languages do exactly this. Successfully compiling a program involves proving that feedback loops are well-formed.

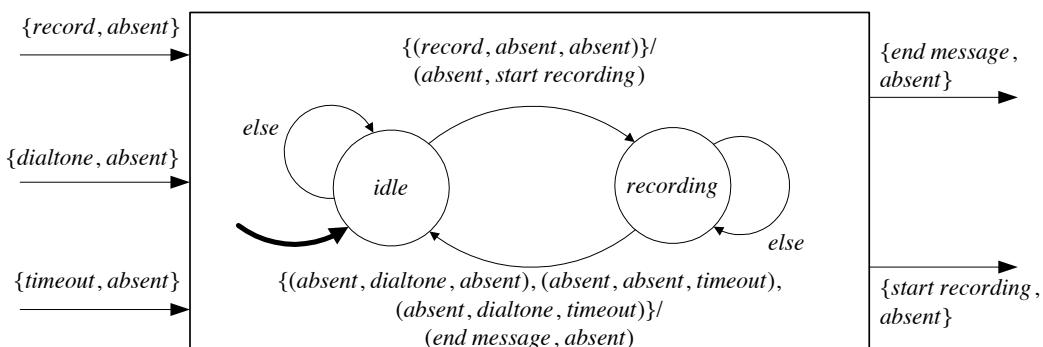


Figure 4.22: Message recorder subsystem of the answering system.

4.7.5 Exhaustive search

If a feedback composition has one or more machines with state-determined output, then finding a unique fixed point is easy. Without such state-determined output, we can apply the procedure in the previous section. Unfortunately, if the procedure fails, we cannot conclude that the composition is ill-formed. The procedure fails for example 4.7, shown in Figure 4.17, despite the fact that this example is well-formed. For that example, we can determine the unique fixed point by exhaustive search. That is, for each reachable state of the composition, and for each possible input to the composition, we try all possible transitions out of the current states of the component machines. We reject those that lead to a contradiction. For example, in Figure 4.17, assuming the current state is 1, the output of the component machine cannot be *maybe* because then the input would have to be *maybe*, which would result in the output being *absent*. If after rejecting all contradictions there remains exactly one possibility in each reachable state, then the composition is well-formed.

Exhaustive search works in Figure 4.17 only because the number of reachable states is finite and the number of transitions out of each state is finite. If either of these conditions is violated, then exhaustive search will not work. Thus, there are state machine that when put in a feedback loop are well-formed, but where there is no constructive procedure for evaluating a reaction (see box on page 176). Even when exhaustive search is theoretically possible, in practice the number of possibilities that must be tried grows extremely fast.

4.7.6 Nondeterministic machines

Nondeterministic state machines can be composed just as deterministic state machines are composed. In fact, since deterministic state machines are a special case, the two types of state machines can be mixed in a composition. Compositions without feedback are straightforward, and operate almost exactly as described above (see exercises 14 and 15). Compositions with feedback require a small modification to our evaluation process.

Recall that to evaluate the reaction of a feedback composition, we begin by setting to *unknown* any input symbols that are not initially known. We then proceed through a series of rounds where in each round, we attempt to determine the output symbols of the state machines in the composition given what we know about the input symbols. After some number of rounds, no more information is gained. At this point, if all of the input and

Probing Further: Constructive Semantics

The term “**semantics**” means meaning. We have defined the meaning of compositions of state machines using the notion of synchrony, which makes feedback compositions particularly interesting. When we define “well-formed,” we are, in effect, limiting the compositions that are valid. Compositions that are not well-formed fall outside our synchronous semantics. They have no meaning.

One way to define the semantics of a composition is to give a procedure for evaluating the composition (the resulting procedure is called an **operational semantics**). We have given three successively more difficult procedures for evaluating a reaction of a composition of state machines with feedback. If at least one machine in each directed loop has state-determined output, then it is easy to evaluate a reaction. If not, we can apply the constructive procedure of section 4.7.4. However, that procedure may result in some feedback connections remaining *unknown* even though the composition is well-formed. The ultimate procedure is exhaustive search, as described in section 4.7.5. However, exhaustive search is not always possible, and even when it is theoretically possible, the number of possibilities to explore may be so huge that it is not practical. There are state machines that when put in a feedback loop are well-formed, but where there is no constructive procedure for evaluating a reaction, and no constructive way to demonstrate that they are well-formed. Thus, there is no operational semantics for our feedback compositions.

This situation is not uncommon in computing and in mathematics. Kurt Gödel’s famous incompleteness theorem (1931), for example, states (loosely) that in any formal logical system, there are statements that are true but not provable. This is analogous in that we can have feedback compositions that are well-formed, but we have no procedure that will always work to demonstrate that they are well-formed. Around the same time, Alan Turing and Alonzo Church demonstrated that there are functions that cannot be computed by any procedure.

To deal with this issue, Gerard Berry has proposed that synchronous composition have a **constructive semantics**, which means precisely that well-formed compositions are defined to be those for which the constructive procedure of Section 4.7.4 works. When that procedure fails, we simply declare the composition to be unacceptable. This is pragmatic solution, and in many situations, it is adequate. See G. Berry, *The Constructive Semantics of Pure Esterel*, Book Draft, <http://www-sop.inria.fr/meije/esterel/doc/main-papers.html>.

output symbols are known, then the composition is well-formed. This procedure works for most (but not all) well-formed compositions.

This process needs to be modified slightly for nondeterministic machines because in each reaction, a machine may have several possible output symbols and several possible next states. For each machine, at each reaction, we define the sets $PossibleInputs \subset Inputs$, $PossibleNextStates \subset States$ and $PossibleNextOutputs \subset Outputs$. If the inputs to a particular machine in the composition are known completely, then $PossibleInputs$ has exactly one element. If they are completely unknown, then $PossibleInputs$ is empty.

The rounds proceed in a similar fashion to before. For each state machine in the composition, given what is known about the input symbols, i.e. given $PossibleInputs$, determine what you can about the next state and output symbols. This may result in elements being added to $PossibleNextStates$ and $PossibleNextOutputs$. When a round results in no such added elements, the process has converged. If none of the $PossibleInputs$ or $PossibleOutputs$ sets is empty, then the composition is well-formed.

4.8 Summary

Many systems are designed as state machines. Usually the design is structured by composing component state machines. In this chapter, we considered synchronous composition. Feedback composition proves particularly subtle because the input symbol of a state machine in a reaction may depend on its own output symbol in the same reaction. We call a feedback composition well-formed if every signal has a unique non-stuttering symbol in each reaction.

Describing systems as compositions of state machines helps in many ways. It promotes understanding. The block diagram syntax that describes the structure often shows that individual components are responsible for distinct functions of the overall system. Some components may already be available and so we can reuse their designs. The design of the answering machine in Figure 4.9 takes into account the availability of the telephone line interface, recording device, etc. Composition also simplifies description; once we specify the component state machines and the composition, the overall state machine is automatically defined by the rules of composition. Compilers for synchronous programming languages and tools for verification do this automatically.

We have three successively more difficult procedures for evaluating a reaction of a composition of state machines with feedback. If at least one machine in each directed loop

has state-determined output, then it is easy to evaluate a reaction. If not, we can apply the constructive procedure of section 4.7.4. But that procedure may be inconclusive. The ultimate procedure is exhaustive search, as described in section 4.7.5. However, exhaustive search is not always possible, and even when it is theoretically possible, the number of possibilities to explore may be so huge that it is not practical.

Exercises

In some of the following exercises you are asked to design state machines that carry out a given task. The design is simplified and elegant if the state space is properly chosen. Although the state space is not unique, there often is a natural choice. Each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **E** Define the composite state machine in Figure 4.7 in terms of the component machines, as done for the simpler compositions in figures 4.3 and 4.1. Be sure to state any required assumptions.
2. **E** Define the composite state machine in Figure 4.10 in terms of the component machines, as done for the simpler compositions in figures 4.3 and 4.1. Be sure to state any required assumptions. Give the definition in two different ways:
 - (a) Directly form a product of the three state spaces.
 - (b) First compose the A and B state machines to get a new D state machine, and then compose D with C .
 - (c) Comment on the relationship between the models in part (a) and (b).
3. **T** Consider the state machine *UnitDelay* studied in part (a) of exercise 5 at the end of the previous chapter.
 - (a) Construct a state machine model for a cascade composition of two such machines. Give the sets and functions model (it is easier than the state transition diagram or table).
 - (b) Are all of the states in the state space of your model in part (a) reachable? If not, give an example of an unreachable state.
 - (c) Give the state space (only) for cascade compositions of three and four unit delays. How many elements are there in each of these state spaces?
 - (d) Give an expression for the size of the state space as function of the number N of cascaded delays in the cascade composition.
4. **C** Consider the parking meter example of the previous chapter, example 3.1, and the modulo N counter of Exercise 4 at the end of the previous chapter. Use these

two machines to model a citizen that parks at the meter when the machines start, and inserts 25 cents every 30 minutes, and a police officer who checks the meter every 45 minutes, and issues a ticket if the meter is expired. For simplicity, assume that the police office issues a new ticket each time he finds the meter expired, and that the citizen remains parked forever.

You may construct the model at the block diagram level, as in Figure 4.9, but describe in words any changes you need to make to the designs of the previous chapter. Give state transition diagrams for any additional state machines you need. How long does it take for the citizen to get the first parking ticket?

Assume you have an eternal clock that emits an event *tick* every minute.

Note that the output alphabet of the modulo N counter does not match the input alphabet of the parking meter. Neither does its input alphabet match the output alphabet of the parking meter. Thus, one or more intermediate state machines will be needed to translate these alphabets. You should fully specify these state machines (i.e., don't just give them at the block diagram level). **Hint:** These state machines, which perform an operation called **renaming**, only need one state.

5. C Consider a machine with

$$\begin{aligned} States &= \{0, 1, 2, 3\}, \\ Inputs &= \{\text{increment}, \text{decrement}, \text{reset}, \text{absent}\}, \\ Outputs &= \{\text{zero}, \text{absent}\}, \\ initialState &= 0, \end{aligned}$$

such that *increment* increases the state by 1 (modulo 4), *decrement* decreases the state by 1 (modulo 4), *reset* resets the state to 0, and the output symbol is *absent* unless the next state is 0, in which case the output symbol is *zero*. So, for example, if the current state is 3 and the input is *increment*, then the new state will be 0 and the output will be *zero*. If the current state is 0 and the input is *decrement*, then the new state will be 3 and the output will be *absent*.

- Give the *update* function for this machine, and sketch the state transition diagram.
- Design a cascade composition of two state machines, each with two states, such that the composition has the same behaviors as the one above. Give a diagram of the state machines and their composition, and carefully define all the input and output alphabets.

- (c) Give a simulation relation from the single machine and the cascade composition, and a simulation relation from the cascade composition to the single machine.
6. C A road has a pedestrian crossing with a traffic light. The light is normally green for vehicles, and the pedestrian is told to wait. However, if a pedestrian presses a button, the light turns yellow for 30 seconds and then red for 30 seconds. When it is red, the pedestrian is told “cross now.” After the 30 seconds of red, the light turns back to green. If a pedestrian presses the button again while the light is red, then the red is extended to a full minute.

Construct a composite model for this system that has at least two state machines, *TrafficLight* for the traffic light seen by the cars, and *WalkLight* for the walk light seen by the pedestrians. The state of machine should represent the state of the lights. For example, *TrafficLight* should have at least three states, one for green, one for yellow, and one for red. Each color may, however, have more than one state associated with it. For example, there may be more than one state in which the light is red. It is typical in modeling systems for the states of the model to represent states of the physical system.

Assume you have a timer available such that if you emit an output *start timer*, then 30 seconds later an input symbol *timeout* will appear. It is sufficient to give the state transition graphs for the machines. State any assumptions you need to make.

7. E Suppose you are given two state machines *A* and *B*, Suppose the sizes of the input alphabets are i_A, i_B , respectively, the sizes of the output alphabets are o_A, o_B respectively, and the numbers of states are s_A, s_B , respectively. Give the sizes of the input and output alphabets and the number of states for the following compositions:
- side-by-side,
 - cascade,
 - and feedback, where the structure of the feedback follows the pattern in Figure 4.16(a).
8. T Example 4.2 shows a state machine in which a state is not reachable from the initial state. Here is a recursive algorithm to calculate the reachable states for any nondeterministic machine,

$$\text{StateMachine} = (\text{States}, \text{Inputs}, \text{Outputs}, \text{possibleUpdates}, \text{initialState}).$$

Recursively define subsets $\text{ReachableStates}(n)$, $n = 0, 1, \dots$ of States by:

$$\begin{aligned}\text{ReachableStates}(0) &= \{\text{initialState}\}, \text{ and for } n \geq 0 \\ \text{ReachableStates}(n+1) &= \{s(n+1) \mid \exists s(n) \in \text{ReachableStates}(n), \\ &\quad \exists x(n) \in \text{Inputs}, \\ &\quad \exists y(n) \in \text{Outputs}, \\ &\quad (s(n+1), y(n)) \\ &\quad \in \text{possibleUpdates}(s(n), x(n))\} \\ &\quad \cup \text{ReachableStates}(n).\end{aligned}$$

In words: $\text{ReachableStates}(n+1)$ is the set of states that can be reached from $\text{ReachableStates}(n)$ in one step using any input symbol, together with $\text{ReachableStates}(n)$.

- (a) Show that for all n , $\text{ReachableStates}(n) \subset \text{ReachableStates}(n+1)$.
- (b) Show that $\text{ReachableStates}(n)$ is the set of states that can be reached in n or fewer steps, starting in *initialState*. Now show that if for some n ,

$$\text{ReachableStates}(n) = \text{ReachableStates}(n+1), \quad (4.11)$$

then $\text{ReachableStates}(n) = \text{ReachableStates}(n+k)$ for all $k \geq 0$.

- (c) Suppose (4.11) holds for $n = N$. Show that $\text{ReachableStates}(N)$ is the set of all reachable states, i.e. this set comprises all the states that can be reached using any input sequence starting in *initialState*.
- (d) Suppose there are N states. Show that (4.11) holds for $n = N$.
- (e) Compute $\text{ReachableStates}(n)$ for all n for the machine in Figure 4.4.
- (f) Suppose States is infinite. Show that the set of reachable states is given by

$$\bigcup_{n=0}^{\infty} \text{ReachableStates}(n).$$

9. T The algorithm in Exercise 8 has a fixed point interpretation. For a nondeterministic state machine,

$$\text{StateMachine} = (\text{States}, \text{Inputs}, \text{Outputs}, \text{possibleUpdates}, \text{initialState}),$$

define the function $\text{nextStep} : \wp(\text{States}) \rightarrow \wp(\text{States})$ that maps subsets of States into subsets of States (recall that $\wp(A)$ is the powerset of A) as follows: for any

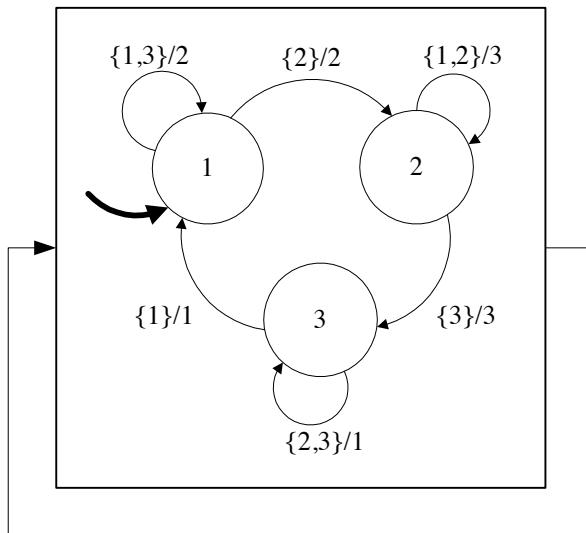
$$S(n) \subset States$$

$$\begin{aligned} nextStep(S(n)) &= \{s(n+1) \mid \exists s(n) \in S(n), \\ &\quad \exists x(n) \in Inputs, \\ &\quad \exists y(n) \in Outputs, \\ &\quad (s(n+1), y(n)) \\ &\quad \in possibleUpdates(s(n), x(n))\} \cup S(n). \end{aligned}$$

By definition, a fixed point of *nextStep* is any subset $S \subset States$ such that $nextStep(S) = S$.

- (a) Show that \emptyset and *States* are both fixed points of *nextState*.
 - (b) Let *ReachableStates* be the set of all states that can be reached starting in *initialState*. Show that *ReachableStates* is also a fixed point.
 - (c) Show that *ReachableStates* is the least fixed point of *nextStep* containing *initialState*.
10. C Recall the playback machine of Figure 4.8 and the *CodeRecognizer* machine of Figure 3.4. Enclose *CodeRecognizer* in a block and compose it with the playback machine so that someone can play back the recorded messages only if she correctly enters the code 1100. You will need to modify the playback machine appropriately.
11. E Consider the following state machine in a feedback composition, where the input and output alphabets for the state machine is

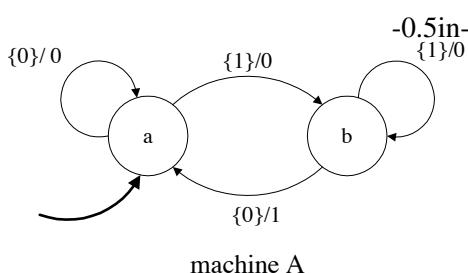
$$\{1, 2, 3, absent\} :$$



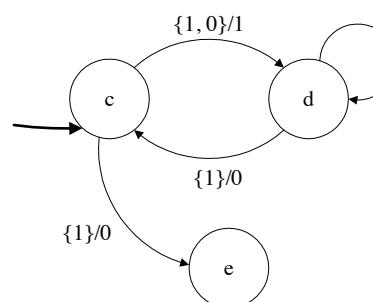
Is it well-formed? If so, then find the output symbols for the first 10 reactions.

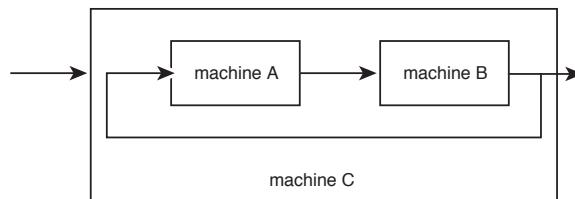
12. **E** In this problem, we will explore the fact that a carefully defined delay in a feed-back composition always makes the composition well-formed.
- For an input and output alphabet
- $$\text{Inputs} = \text{Outputs} = \{\text{true}, \text{false}, \text{absent}\}$$
- design a state machine that outputs *false* on the first reaction, and then in subsequent reactions, outputs the value observed at the input in the previous reaction. This is similar to *UnitDelay* of problem 5 at the end of Chapter 3, with the only difference being that it outputs an initial *false* instead of *absent*.
- Compose the machine in Figure 4.14 (b) with the delay from part (a) of this problem in a feedback loop (as in Figure 4.16). Give an argument that the composition is well-formed. Then do the same for Figure 4.14 (c) instead of (b).
13. **C** Construct a feedback state machine with the structure of figure 4.12 that outputs the periodic sequence $a, b, c, a, b, c \dots$ (with, as usual, any number of intervening stuttering outputs between the non-stuttering outputs).

14. **E** Modify Figure 4.1 as necessary so that the machines in the side-by-side composition are both nondeterministic.
15. **E** Modify Figure 4.3 as necessary so that the machines in the cascade composition are both nondeterministic.
16. **C,T** Data packets are to be reliably exchanged between two computers over communication links that may lose packets. The following protocol has been suggested. Suppose computer *A* is sending and *B* is receiving. Then *A* sends a packet and starts a timer. If *B* receives the packet it sends back an acknowledgment. (The packet or the acknowledgment or both may be lost.) If *A* does not receive the acknowledgment before the timer expires, it retransmits the packet. If the acknowledgment arrives before the timer expires, *A* sends the next packet.
- Construct two state machines, one for *A* and one for *B*, that implement the protocol.
 - Construct a two-state nondeterministic machine to model the link from *A* to *B*, and another copy to model the link from *B* to *A*. Remember that the link may correctly deliver a packet, or it may lose it.
 - Compose the four machines to model the entire system.
 - Suppose the link correctly delivers a packet, but after a delay that exceeds the timer setting. What will happen?
17. **T** Consider the following three state machines:



0.5in





Machines *A* and *B* have input and output alphabets

$$\text{Inputs} = \text{Outputs} = \{0, 1, \text{absent}\}.$$

Machine *C* has the same output alphabet, but input alphabet

$$\text{Inputs}_C = \{\text{react}, \text{absent}\}.$$

- (a) Which of these machines is deterministic?
 - (b) Draw the state transition diagram for the composition (machine C), showing only states that are reachable from the initial state.
 - (c) Give the *Behaviors*_{*C*} relation for the composition of machine C, ignoring stuttering.
18. T The feedback composition in Figure 4.14(c) is ill-formed because it has two non-stuttering fixed points in each of the two states of the component machine. Instead of declaring it to be ill-formed, we could have interpreted the composition as representing a nondeterministic state machine. That is, in each state, we accept either of the two possible fixed points as possible reactions of the machine. Using this interpretation, give the nondeterministic machine for the feedback composition by giving its sets and functions model and a state transition diagram.

5

Linear Systems

Contents

5.1	Operation of an infinite state machine	189
5.1.1	Time	191
5.2	Linear functions	192
5.3	The $[A, B, C, D]$ representation of a system	195
5.3.1	Impulse response	198
5.3.2	One-dimensional SISO systems	199
5.3.3	Zero-state and zero-input response	205
5.3.4	Multidimensional SISO systems	208
5.3.5	Multidimensional MIMO systems	216
5.3.6	Linear input-output function	217
5.4	Continuous-time state-space models	218
5.5	Summary	219
<i>Basics: Functions yielding tuples</i>		220
<i>Basics: Matrices and vectors</i>		221
<i>Basics: Vectors</i>		222
<i>Basics: Matrix arithmetic</i>		223
<i>Basics: Matrix arithmetic (continued from page 223)</i>		224
<i>Probing Further: Impulse Responses of MIMO Systems</i>		225
<i>Probing Further: Approximating continuous-time</i>		226
Exercises		227

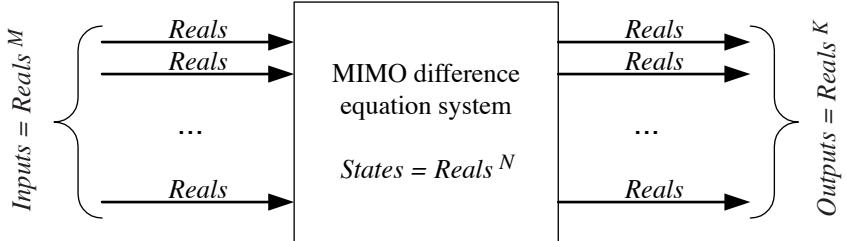


Figure 5.1: Block representing a multiple-input, multiple output (MIMO) system.

Recall that the [state](#) of a system is a summary of its past. It is what the system needs to remember about the past in order to react at the present and move into the future. In previous chapters, systems typically had a finite number of possible states. Many useful and interesting systems are not like that, however. They have an infinite number of states. The analytical approaches used to analyze finite-state systems, such as [simulation](#), get more difficult when the number of states is not finite.

In this chapter, we begin considering infinite-state systems. We impose two key constraints. First, we require that the state space and input and output alphabets be numeric sets. That is, we must be able to do arithmetic on members of these sets. (Contrast this with the answering machine example, where the states are symbolic names, and no arithmetic makes sense.) Second, we require that the *update* function be linear. We will define what this means precisely. In exchange for these two constraints, we gain a very rich set of analytical methods for designing and understanding systems. In fact, most of the remaining chapters are devoted to developing these methods.

In particular, we study state machines with

$$\begin{aligned} \text{States} &= \mathbb{R}^N \\ \text{Inputs} &= \mathbb{R}^M \\ \text{Outputs} &= \mathbb{R}^K. \end{aligned} \tag{5.1}$$

Such state machines are shown schematically in Figure 5.1. The inputs and outputs are in product form, as discussed for general state machines in Section 4.4. The system, therefore, can be viewed as having M distinct inputs and K distinct outputs. So the input

is a tuple with M real numbers, and the output is a tuple with K real numbers. Such a system is called a **multiple-input, multiple-output (MIMO)** system. When $M = K = 1$, it is called a **single-input, single-output (SISO)** system. The state is a tuple with N real numbers. N (rather than M or K) is called the **dimension of the system**.

Example 5.1: A stereo audio system processes two channels of audio, and therefore has $M = K = 2$. "Surround sound," used in movie theaters and some home audio systems, has five channels, so $M = K = 5$.

Example 5.2: Some modern cars have **traction control** systems, where the torque applied to each wheel is controlled individually to avoid skidding. The key input comes from the accelerator pedal, which specifies a desired acceleration. The output is the torque applied to each of four wheels. Hence, $M = 1$ and $K = 4$. A more sophisticated traction control system might also use as input the steering angle, in which case $M = 2$.

5.1 Operation of an infinite state machine

Recall that a deterministic state machine is a 5-tuple

$$M = (\text{States}, \text{Inputs}, \text{Outputs}, \text{update}, \text{initialState}) \quad (5.2)$$

where *States* is the state space, *Inputs* is the input space, *Outputs* is the output space, *update*: $\text{States} \times \text{Inputs} \rightarrow \text{States} \times \text{Outputs}$ is the update function, and *initialState* is the initial state.

In this chapter, the *update* function has the form

$$\text{update}: \mathbb{R}^N \times \mathbb{R}^M \rightarrow \mathbb{R}^N \times \mathbb{R}^K.$$

The result of evaluating this function is an N -tuple (the next state) and a K -tuple (the current output). It will be useful in this chapter to break this function into two parts, as

done in Section 3.1.1, one giving the new state and one giving the output,

$$update = (nextState, output),$$

where

$$nextState: \mathbb{R}^N \times \mathbb{R}^M \rightarrow \mathbb{R}^N,$$

$$output: \mathbb{R}^N \times \mathbb{R}^M \rightarrow \mathbb{R}^K,$$

such that

$$\forall s \in \mathbb{R}^N, \forall x \in \mathbb{R}^M, \quad update(s, x) = (nextState(s, x), output(s, x)).$$

These two functions separately give the next state and the current output as a function of the current state and input. Given an input sequence $x(0), x(1), \dots$ of M -tuples in \mathbb{R}^M , the system recursively generates a **state response**

$$s(0), s(1), \dots$$

of N -tuples in \mathbb{R}^N and an **output response** $y(0), y(1), \dots$ of K -tuples in \mathbb{R}^K as follows:

$$\begin{aligned} s(0) &= initialState, \\ (s(n+1), y(n)) &= update(s(n), x(n)), \quad n \geq 0. \end{aligned} \tag{5.3}$$

The second equation can be rewritten as a separate **state update equation**,

$$\boxed{\forall n \in \mathbb{Z}, n \geq 0, \quad s(n+1) = nextState(s(n), x(n))} \tag{5.4}$$

and an **output equation**,

$$\boxed{\forall n \in \mathbb{Z}, n \geq 0, \quad y(n) = output(s(n), x(n))}. \tag{5.5}$$

Equations (5.4) and (5.5) together are called a **state-space model** of the system, because instead of giving the output directly as a function of the input, the state is explicitly described. The equations suggest a detailed procedure for calculating the response of a system. We start with a given initial state $s(0) = initialState$, and an input sequence $x(0), x(1), \dots$. At step $n = 0$, we evaluate the right-hand side of (5.4) at the known values of $s(0), x(0)$ and we assign the result to $s(1)$. At step $n = 1$, we evaluate the right-hand side at the known values of $s(1), x(1)$ and we assign the result to $s(2)$. To proceed from step n to step $n + 1$, we only need to remember $s(n)$ and know the new input $x(n)$. At each

step n , we evaluate the output $y(n)$ using (5.5). This procedure is no different from that used for state machines in previous chapters. However, starting with Section 5.2, we will specialize the *nextState* and *output* functions so that they are linear, which will then lead to a powerful set of analytical tools.

5.1.1 Time

The index n in the equations above denotes the **step** number, the count of reactions, as with any state machine. For general state machines, it is rare to associate a fixed time interval with a step. So there is normally no simple relation between the step number and the real time at which the corresponding reaction occurs. For example, in the answering machine, if the initial state is *idle*, there may be an arbitrary amount of time before *ring* occurs and the state moves to *count1*.

The systems we study in this and the next several chapters, however, usually evolve with a fixed time interval between updates. Suppose this interval is δ seconds. Then step n occurs at time $n\delta$ seconds, relative to time 0. Such systems are **discrete-time systems**, and the index n is called the **time index**.

We will require that for each time index n , the input $x(n)$ be in \mathbb{R}^M and the output $y(n)$ be in \mathbb{R}^K . We *disallow* stuttering input or output values such as *absent*. This is consistent with the interpretation of n as a real (physical) time index: the system's input and output must take some physical value at each n , and *absent* is not such a value.

Example 5.3: Compact discs store digital audio signals as discrete-time signals. For each channel of audio, there are 44,100 numbers (samples) representing each second of sound. The n -th number, therefore, represents the sound value at time $n\delta$ from the beginning of the CD, where $\delta = 1/44,100$, about 23 microseconds. By contrast, the telephone network transmits speech signals by sending only 8,000 samples per second, so the sampling interval is $\delta = 1/8,000$, or 125 microseconds. We will see in Chapter 11 that this difference (partly) accounts for the lower audio quality over the telephone network, compared to CDs.

The systems in this chapter will be **time-invariant** systems, meaning that the *nextState* and *output* functions do not change with the time index n . It is, therefore, a matter of convention to have time start at 0 rather than, say, at -10 or 50. We will stick to convention

and so the set of input signals in this chapter will be

$$InputSignals = [\mathbb{Z}_+ \rightarrow \mathbb{R}^M],$$

where $\mathbb{Z}_+ = \mathbb{N}_0 = \{0, 1, 2, \dots\}$. Correspondingly,

$$OutputSignals = [\mathbb{Z}_+ \rightarrow \mathbb{R}^K].$$

The state response, then, is a function

$$s: \mathbb{Z}_+ \rightarrow \mathbb{R}^N$$

where $s(0) = initialState$.

5.2 Linear functions

A function $f: \mathbb{R} \rightarrow \mathbb{R}$ is a **linear function** if $\forall u \in \mathbb{R}$ and $a \in \mathbb{R}$,

$$f(au) = af(u),$$

and $\forall u, v \in \mathbb{R}$,

$$f(u+v) = f(u) + f(v).$$

The first property is called **homogeneity** and the second property is called **additivity**. When its domain and range both are \mathbb{R} , a linear function can be represented as

$$\forall x \in \mathbb{R}, \quad f(x) = ax, \tag{5.8}$$

for some constant a . The term “linear” comes from the fact that the graph of this function is a straight line through the origin, with slope a . (If the line did not pass through the origin, the function is said to be **affine**. It would satisfy neither homogeneity nor additivity.) We need a more general notion of linear function, one that operates on tuples.

A function $f: \mathbb{R}^N \rightarrow \mathbb{R}^M$ is a linear function if $\forall u, v \in \mathbb{R}^N$ and $\forall a \in \mathbb{R}$,

$$f(au) = af(u), \tag{5.10}$$

$$f(u+v) = f(u) + f(v). \tag{5.11}$$

As before, (5.10) is the **homogeneity** property and (5.11) is the **additivity** property. The two properties can be combined into the **superposition** property:

$$\boxed{\begin{aligned} f \text{ is linear if } \forall u, v \in \mathbb{R}^N \text{ and } \forall a, b \in \mathbb{R}, \\ f(au + bv) = af(u) + bf(v) \end{aligned}} \quad (5.12)$$

Above, superposition is defined by considering a linear combination $au + bv$ of two elements u and v in the domain of f . In fact, for linear functions, superposition holds for a linear combination of any number of elements. That is, $\forall u_1, \dots, u_n \in \mathbb{R}^N$ and $\forall a_1, \dots, a_n \in \mathbb{R}$,

$$f(a_1u_1 + \dots + a_nu_n) = a_1f(u_1) + \dots + a_nf(u_n). \quad (5.13)$$

In (5.13) u_1, \dots, u_n are vectors in \mathbb{R}^N , $f(u_1), \dots, f(u_n)$ are vectors in \mathbb{R}^M , and a_1, \dots, a_n are scalars (numbers).

Every matrix defines a linear function in the following way. Let A be an $M \times N$ matrix. Then the function $f: \mathbb{R}^N \rightarrow \mathbb{R}^M$ defined by

$$\forall x \in \mathbb{R}^N, \quad f(x) = Ax. \quad (5.14)$$

is a linear function, as can be checked using the basics of matrix arithmetic.

More interestingly, every linear function can be represented by such a matrix multiplication, similarly to the scalar case (5.8). To show this, we show how to find the appropriate matrix given any linear function. Define the vectors

$$e_1 = \begin{bmatrix} 1 \\ 0 \\ \dots \\ 0 \end{bmatrix}, e_2 = \begin{bmatrix} 0 \\ 1 \\ \dots \\ 0 \end{bmatrix}, \dots, e_N = \begin{bmatrix} 0 \\ 0 \\ \dots \\ 1 \end{bmatrix}.$$

Then note that we can express any vector $x \in \mathbb{R}^N$ as a sum

$$x = x_1e_1 + \dots + x_Ne_N,$$

where x_i is the i -th element of the vector x (a scalar). Now consider a linear function $f: \mathbb{R}^N \rightarrow \mathbb{R}^M$. Then, by (5.13),

$$y = f(x) = x_1f(e_1) + \dots + x_Nf(e_N). \quad (5.15)$$

Write the column vector $f(e_j) \in \mathbb{R}^M$ as

$$f(e_j) = \begin{bmatrix} a_{1,j} \\ a_{2,j} \\ \dots \\ a_{M,j} \end{bmatrix}.$$

Then we can rewrite (5.15) as

$$\begin{aligned} y &= \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_M \end{bmatrix} = x_1 \begin{bmatrix} a_{1,1} \\ a_{2,1} \\ \dots \\ a_{M,1} \end{bmatrix} + x_2 \begin{bmatrix} a_{1,2} \\ a_{2,2} \\ \dots \\ a_{M,2} \end{bmatrix} + \dots + x_N \begin{bmatrix} a_{1,N} \\ a_{2,N} \\ \dots \\ a_{M,N} \end{bmatrix} \\ &= \begin{bmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,N} \\ a_{2,1} & a_{2,2} & \dots & a_{2,N} \\ \dots & \dots & \dots & \dots \\ a_{M,1} & a_{M,2} & \dots & a_{M,N} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_N \end{bmatrix}. \end{aligned}$$

More compactly,

$$y = Ax,$$

where A is the $M \times N$ matrix

$$A = [a_{i,j}, 1 \leq i \leq M, 1 \leq j \leq N].$$

Thus, there is a straightforward association between linear functions with domain \mathbb{R}^N and range \mathbb{R}^M and $M \times N$ matrices. This association will be very important for us.

Example 5.4: The function $g: \mathbb{R}^3 \rightarrow \mathbb{R}$ given by

$$\forall x \in \mathbb{R}^3, \quad g(x_1, x_2, x_3) = 0.5x_1 - 0.4x_3$$

is linear, as can be checked by verifying (5.12). Here, x_i refers to the i -th element of the vector x . The matrix representation is

$$g(x) = [0.5, 0, -0.4] \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}.$$

The function $f: \mathbb{R}^N \rightarrow \mathbb{R}^N$ given by

$$\forall x \in \mathbb{R}^N, \quad f(x)_n = \begin{cases} x_{n+1}, & \text{if } n < N \\ x_1, & \text{if } n = N \end{cases}$$

is linear. Here $f(x)_n$ refers to the n -th element of the vector $f(x)$. The matrix representation is

$$f(x) = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 1 & 0 & 0 & \cdots & 0 \end{bmatrix} x.$$

5.3 The $[A, B, C, D]$ representation of a system

We consider an arbitrary system with

$$\text{States} = \mathbb{R}^N, \text{Inputs} = \mathbb{R}^M, \text{Outputs} = \mathbb{R}^K.$$

Its state-space model is given by the state update and output equations: $\forall n \in \mathbb{Z}_+$,

$$\begin{aligned} s(n+1) &= \text{nextState}(s(n), x(n)), \\ y(n) &= \text{output}(s(n), x(n)). \end{aligned}$$

This system is said to be a **linear system** if the initial state is an N -tuple of zeros, and the *nextState* and *output* functions are linear. If it is also time invariant (the *nextState* and *output* functions do not change with time), then we have a **linear time-invariant system**, or **LTI system**. We can then represent the *nextState* function by a $N \times (N + M)$ matrix and the *output* function by a $K \times (N + M)$ matrix.

Consider the $N \times (N + M)$ matrix representing the *nextState* function. This matrix has $N + M$ columns. We denote the $N \times N$ matrix comprising the first N columns by A , and the $N \times M$ matrix comprising the last M columns as B , so that

$$\text{nextState}(s(n), x(n)) = As(n) + Bx(n).$$

We similarly partition the $K \times (N + M)$ matrix representing the *output* function into the $K \times N$ matrix C comprising the first N columns and the $K \times M$ matrix D comprising the

last M columns. Then

$$\text{output}(s(n), x(n)) = Cs(n) + Dx(n).$$

With this notation, the state-space model is represented as

$$\begin{aligned} s(n+1) &= As(n) + Bx(n), \\ y(n) &= Cs(n) + Dx(n). \end{aligned} \tag{5.16}$$

This is the $[A, B, C, D]$ representation of the LTI system. This compact representation is very powerful. All the results in this chapter and the next are in terms of these four matrices. The A matrix is the most important, since it characterizes the system dynamics as we will see in the sections below.

Example 5.5: Take $[A, B, C, D]$ as

$$\begin{aligned} A &= \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}, & B &= \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, \\ C &= [1 \ 0 \ 0], & D &= [1]. \end{aligned}$$

So $N = 3, M = 1, K = 1$. (This is a 3-dimensional, SISO system.) Using these in (5.16) gives the state-space model in tuple form,

$$\begin{aligned} s_1(n+1) &= s_1(n) + s_2(n), \\ s_2(n+1) &= s_2(n) + s_3(n), \\ s_3(n+1) &= s_3(n) + x(n), \\ y(n) &= s_1(n) + x(n). \end{aligned}$$

The first three equations together give the *nextState* function, the fourth equation gives the *output* function.

Observe in (5.16) that if *initialState* is zero, $s(0) = 0$, and the input $x(n) = 0$, for all $n \geq 0$, then the state is unchanged, $s(n) = 0$. That is why we say that 0 is an **equilibrium** or **rest** state of the $[A, B, C, D]$ system.

Example 5.6: An echo effect can be obtained for audio signals by realizing the following difference equation,

$$y(n) = x(n) + \alpha y(n - N),$$

where the (discrete-time) audio input is x , the output is y , $0 \leq \alpha < 1$ is a real constant, and $N \in \mathbb{N}$ is an integer constant. Together, α and N determine how long the echo lasts and what it sounds like. Once again, this is a SISO system, with $M = 1, K = 1$. This works simply because the output sample at n is a combination of the current input $x(n)$ and a scaled old output $\alpha y(n - N)$, called the **echo term**. Typically, N needs to be a large number to hear this as an echo. For example, if the sample rate is 8,000 samples per second, then if $N = 8000$, the echo term $\alpha y(n - N)$ is the previous output one second earlier. This will be heard as a distinct echo.

To construct a state-space model, we need to figure out what will work as the state. Since the output depends on $y(n - N)$, which is past history, the state will have to yield $y(n - N)$. The following state definition will work,

$$s(n) = \begin{bmatrix} y(n-1) \\ y(n-2) \\ \vdots \\ y(n-N) \end{bmatrix}.$$

It is easy to check that with this state definition, $[A, B, C, D]$ are given by

$$A = \begin{bmatrix} 0 & 0 & \cdots & 0 & 0 & \alpha \\ 1 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 & 0 \\ 0 & 0 & \cdots & 0 & 1 & 0 \end{bmatrix}, \quad B = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix},$$

$$C = [0 \ 0 \ \cdots \ 0 \ \alpha], \quad D = [1],$$

5.3.1 Impulse response

The $[A, B, C, D]$ representation provides a complete description of an LTI system. It is a complete in the sense that given any input sequence, we can calculate the output sequence using the state and output equations of (5.16) (or (5.19) and (5.20) for the scalar case). We will discover that there are several other descriptions of LTI systems that are also complete. The first of these that we will consider is the **impulse response**. For systems that are initially at rest, the impulse response gives enough information to calculate the output sequence given any input sequence. The calculation is performed using what is known as a **convolution sum**.

Suppose that $M = 1$, and the input sequence x is given by $x = \delta$, where

$$\forall n \in \mathbb{Z}, \quad \delta(n) = \begin{cases} 1, & \text{if } n = 0 \\ 0, & \text{if } n \neq 0 \end{cases}. \quad (5.17)$$

This function $\delta: \mathbb{Z} \rightarrow \mathbb{R}$ is called an **impulse**, or a **Kronecker delta function** (this function figures prominently in chapters 8 and 9). Remarkably, the response of an LTI system to this particular input is a complete description of the LTI system.

Assuming the system is initially at rest, we can use (5.16) to write the state response to input δ as

$$\begin{aligned} s(0) &= 0 \\ s(1) &= B \\ s(2) &= AB \\ s(3) &= A^2B \\ &\dots \\ s(n) &= A^{n-1}B \\ &\dots \end{aligned}$$

This is because if $x = \delta$, then $x(0) = 1$ and $x(n) = 0$ for all $n \neq 0$.

To avoid confusion, we will use the name h instead of y for the output of a system when the input is the impulse δ . In other words, while y is the output for any input x , h is the output for the specific input δ . This output is called the **impulse response**. Using (5.16),

it can be written as

$$\begin{aligned}
 h(0) &= D \\
 h(1) &= CB \\
 h(2) &= CAB \\
 h(3) &= CA^2B \\
 &\dots \\
 h(n) &= CA^{n-1}B
 \end{aligned}$$

Of course, since the system is initially at rest, $h(n) = 0$ for all $n < 0$. We can recognize the pattern and write the impulse response as

$$\forall n \in \mathbb{Z}, \quad h(n) = \begin{cases} 0, & \text{if } n < 0 \\ D, & \text{if } n = 0 \\ CA^{n-1}B, & \text{if } n \geq 1 \end{cases} . \quad (5.18)$$

This formula is rarely the right way to compute an impulse response (usually it is easier to directly determine the output when the input is an impulse), but it does relate the impulse response to the $[A, B, C, D]$ representation. The remarkable fact, developed below, is that knowing the impulse response is sufficient to calculate the output given *any* input (assuming the system is initially at rest).

The impulse response only makes sense if the dimension M of the input is one (otherwise the input could not be an impulse as defined above). We can gain insight by considering even more special systems where $N = K = 1$, as done in the next section.

5.3.2 One-dimensional SISO systems

The simplest LTI system is the one-dimensional, **SISO** system. Since $N = M = K = 1$, the $[A, B, C, D]$ representation is simply $[a, b, c, d]$ where a, b, c, d are scalar constants. The state-space model (5.16) is $\forall n \in \mathbb{Z}_+$,

$$s(n+1) = as(n) + bx(n), \quad (5.19)$$

$$y(n) = cs(n) + dx(n). \quad (5.20)$$

The initial state $s(0) = \text{initialState}$. For this system, the state at a given time index is a real number, as are the input and the output.

Let us consider an example where we construct a state-space model from an input-output description of a system.

Example 5.7: In Section 2.3.3 we considered a simple moving average example, where the output y is given in terms of the input x by

$$\forall n \in \mathbb{Z}_+, \quad y(n) = (x(n) + x(n-1))/2. \quad (5.21)$$

This is not a state-space model because it gives the output directly in terms of the current and *past* input. To construct a state-space model for it, we first need to decide what the state is. Usually, there are multiple answers, so we face a choice. The state is a summary of the past. Examining (5.21), it is evident that we need to remember the previous input, $x(n-1)$, in order to produce an output $y(n)$ (of course, we also need the current input, $x(n)$, but that is not part of the past; that is the present). So we can define the state to be

$$\forall n \in \mathbb{Z}_+, \quad s(n) = x(n-1).$$

We assume that the system is initially at rest, i.e., $s(0) = 0$. (If we knew $x(-1)$, we would take that to be the initial state.) With this choice of state, we need to choose a , b , c , and d so that (5.19) and (5.20) are equivalent to (5.21). Let us look first at (5.20), which reads

$$y(n) = cs(n) + dx(n).$$

Observing that $s(n) = x(n-1)$, can you determine c and d ? From (5.21), it is obvious that $c = d = 1/2$.

Next, we determine a and b in

$$s(n+1) = as(n) + bx(n).$$

Since $s(n) = x(n-1)$, it follows that $s(n+1) = x(n)$, and this becomes

$$x(n) = ax(n-1) + bx(n),$$

from which we can see that $a = 0$ and $b = 1$.

Note that we could have chosen the state differently. For example,

$$\forall n \in \mathbb{Z}_+, \quad s(n) = x(n-1)/2$$

would work fine. How would that change a , b , c , and d ?

In the preceding example, we started with an input-output description and obtained a state-space model. The next example shows we can also go the other way.

Example 5.8: Consider a one-dimensional SISO system

$$\begin{aligned}s(n+1) &= as(n) + bx(n), \\ y(n) &= cs(n) + dx(n).\end{aligned}$$

From these equations we get

$$\begin{aligned}y(n) &= c[as(n-1) + bx(n-1)] + dx(n), \\ y(n-1) &= cs(n-1) + dx(n-1).\end{aligned}$$

Multiplying the second equation by a and subtracting from the first eliminates the state to yield a difference equation description of the system,

$$y(n) - ay(n-1) = dx(n) + (cb - ad)x(n-1).$$

There is a generalization of this example that works for state-space models of any dimension.

In the following example, we use a state-space model to calculate the output of a system given an input sequence.

Example 5.9: Suppose the state $s(n)$ is your bank balance at the beginning of day n , and $x(n)$ is the amount you deposit or withdraw during day n . If $x(n) > 0$, it means that you are making a deposit of $x(n)$ dollars, and if $x(n) < 0$, it means that you are withdrawing $x(n)$ dollars. The output of the system at time index n is the bank balance on day n . Thus,

$$\text{States} = \text{Inputs} = \text{Outputs} = \mathbb{R}.$$

Note that these sets are probably not, strictly speaking, equal to \mathbb{R} , since deposits and withdrawals can only be a whole number of cents. Using \mathbb{R} is a considerable simplification.

Suppose that the daily interest rate is r . Then your balance at the beginning of day $n + 1$ is given by

$$\forall n \in \mathbb{Z}, \quad s(n+1) = (1+r)s(n) + x(n). \quad (5.22)$$

The output of the system is your current balance,

$$\forall n \in \mathbb{Z}, \quad y(n) = s(n).$$

Comparing to (5.19)-(5.20), we have $a = 1 + r$, $b = 1$, $c = 1$, and $d = 0$. The initial condition is *initialState*, your bank balance at the beginning of day 0. Suppose the daily interest rate is 0.01, or one percent (this would only be reasonable in an economy with hyperinflation). Suppose that *initialState* = 100, and you deposit 1,000 dollars on day 0 and withdraw 30 every subsequent day for the next 30 days. What is your balance $s(31)$ on day 31? You can compute $s(31)$ recursively from

$$\begin{aligned} s(0) &= 100, \\ s(1) &= 1.01s(0) + 1000, \\ &\dots \\ s(n+1) &= 1.01s(n) - 30, \quad n = 1, \dots, 30, \end{aligned}$$

but this would be tedious. We can develop a formula that is easier to use. We will do this for a general one-dimensional $[a, b, c, d]$ system.

Suppose we are given an input sequence $x(0), x(1), \dots$ for an $[a, b, c, d]$ system. As in example 5.9, if we repeatedly use (5.19) we obtain the first few terms of a sequence,

$$\begin{aligned}
 s(0) &= \text{initialState}, \\
 s(1) &= as(0) + bx(0), \\
 s(2) &= as(1) + bx(1) \\
 &= a\{as(0) + bx(0)\} + bx(1) \\
 &= a^2s(0) + abx(0) + bx(1), \\
 s(3) &= as(2) + bx(2) \\
 &= a\{a^2s(0) + abx(0) + bx(1)\} + bx(2) \\
 &= a^3s(0) + a^2bx(0) + abx(1) + bx(2), \\
 &\dots
 \end{aligned} \tag{5.23}$$

From this it is not difficult to guess the general pattern for the state response and the output response. The state response of (5.19) is given by

$$s(n) = a^n \text{initialState} + \sum_{m=0}^{n-1} a^{n-1-m} bx(m) \tag{5.24}$$

for all $n \geq 0$, and the output response of (5.20) is given by

$$y(n) = ca^n \text{initialState} + \left\{ \sum_{m=0}^{n-1} ca^{n-1-m} bx(m) \right\} + dx(n) \tag{5.25}$$

for all $n \geq 0$.

We use induction to show that these are correct. Induction is where we show that these are correct for some fixed n , and then show that if it is correct for any n , then it is correct for $n+1$. For $n = 0$, (5.24) gives $s(0) = a^0 \text{initialState} = \text{initialState}$, which matches (5.23), and hence is correct.¹ Now suppose that the right-hand side of (5.24) gives the correct value of the response for some $n \geq 0$. We must show that it gives the correct value of the response for $n+1$. From (5.19) and using the hypothesis that (5.24) is the correct

¹For any real number a , $a^0 = 1$ by definition of exponentiation.

expression for $s(n)$, we get

$$\begin{aligned}s(n+1) &= as(n) + bx(n) \\&= a\{a^n \text{initialState} + \sum_{m=0}^{n-1} a^{n-1-m} bx(m)\} + bx(n) \\&= a^{n+1} \text{initialState} + \sum_{m=0}^{n-1} a^{n-m} bx(m) + bx(n) \\&= a^{n+1} \text{initialState} + \sum_{m=0}^n a^{n-m} bx(m),\end{aligned}$$

which is the expression on the right-hand side of (5.24) for $n+1$. It follows by induction that the response is indeed given by (5.24) for all $n \geq 0$. The fact that the output response is given by (5.25) follows immediately from (5.20) and (5.24).

Example 5.10: We use formula (5.24) in example 5.9 to figure out the monthly payment of w on a \$10,000, 32-month loan with a monthly interest of 0.01. So in (5.24) we substitute $n = 32, a = 1.01, b = 1, s(0) = -10,000, s(32) = 0$, and $x(0) = \dots = x(31) = w$, to get

$$0 = -1.01^{32} \times 10000 + \sum_{m=0}^{31} 1.01^{31-m} w.$$

Using the identity (valid for $\rho \neq 1$)

$$\sum_{m=0}^M \rho^m = \frac{\rho^{1+M} - 1}{\rho - 1},$$

we get

$$\sum_{m=0}^{31} 1.01^{31-m} w = \frac{1.01^{32} - 1}{0.01} w.$$

So the monthly payment is

$$w = 0.01 \times \frac{10000 \times 1.01^{32}}{1.01^{32} - 1} = 366.7.$$

In the next example we identify the unknown parameter a of an $[a, b, c, d]$ representation given input-output data.

Example 5.11: Financial analysts compare alternative investment opportunities using a measure called the **internal rate of return**. Suppose an investment of \$10,000 at the beginning of year 0 yields an income stream of \$2,000 for each of 10 successive years, and nothing thereafter. By definition, the investment's internal rate of return is the annual interest rate r that a bank should give so that you can get the same income stream. So we need to find r such that

$$s(n+1) = (1+r)s(n) + x(n),$$

with $s(0) = 10,000$, $s(10) = 0$, and $x(0) = \dots = x(9) = -2000$. We recognize this as a state update with $a = 1+r$ and $b = 1$. Substituting in (5.24) gives

$$\begin{aligned} 0 &= (1+r)^{10}10000 - \sum_{m=0}^9 (1+r)^{9-m} \times 2000 \\ &= (1+r)^{10}10000 - \frac{(1+r)^{10} - 1}{r} \times 2000, \end{aligned}$$

so

$$1 - (1+r)^{-10} = 5r,$$

which we can solve by trial-and-error to obtain $r \approx 0.15$ or 15 percent. Suppose there is another investment opportunity for the same \$10,000 investment that yields an internal rate of return smaller than 15 percent. Then, all else being equal, one would choose the first opportunity.

5.3.3 Zero-state and zero-input response

The expressions (5.24) for the state response and (5.25) for the output are each the sum of two terms. The role of these two terms will be better understood if we consider them in isolation.

If the system is initially at rest, $initialState = 0$, the first term vanishes, and only the second term is left. This second term is called the **zero-state response**. It gives the response of

the system to an input sequence when the initial state is zero. For many applications, particularly when modeling a physical system, the zero-state response is what we are interested in.

If the input sequence is zero, i.e. $0 = x(0) = x(1) = \dots$, the second term vanishes, and only the first term is left. The first term is called the **zero-input response**. It gives the response of the system to some initial condition, with zero input stimulus applied. Of course, if the system is initially at rest and the input is zero, then the state remains at zero. So the zero-input response is only interesting if the system is not initially at rest.

So the right-hand side of both equations (5.24) and (5.25) are a sum of a zero-state response and a zero-input response. To make it clear which equation we are talking about, we use the following terminology:

zero-state state response	The state sequence $s(n)$ when the initial state is zero.
zero-input state response	The state sequence $s(n)$ when the input is zero.
zero-state output response	The output sequence $y(n)$ when the initial state is zero.
zero-input output response	The output sequence $y(n)$ when the input is zero.

Note that “zero-state” really means that the *initial* state is zero, while “zero input” means that the input is *always* zero.

Let us focus on the zero-state output response. First, note from (5.18) that in this scalar case, the impulse response can be written

$$\forall n \in \mathbb{Z}, \quad h(n) = \begin{cases} 0, & \text{if } n < 0 \\ d, & \text{if } n = 0 \\ ca^{n-1}b, & \text{if } n \geq 1 \end{cases}. \quad (5.26)$$

We can use this sequence in (5.25) to simplify its form. This simplified form will show us how to calculate the response to an arbitrary input given only the response to an impulse.

Combining (5.25) and (5.26), the zero-state output response can be written as

$$\forall n \geq 0, \quad y(n) = \sum_{m=0}^n h(n-m)x(m). \quad (5.27)$$

Thus, we see that h is a complete description of the system, in the sense that it is all we need to know to find the output given any input x (assuming zero initial state).

Let $x(n) = 0$ for all $n < 0$, and, noting that $h(n) = 0$ for all $n < 0$, we can write this as

$$\boxed{\forall n \in \mathbb{Z}, \quad y(n) = \sum_{m=-\infty}^{\infty} h(n-m)x(m).} \quad (5.28)$$

The additional terms in the summation are harmless because they all have value zero. A summation of this form is called a **convolution** sum. We say that y is the convolution of h and x , and write it using the shorthand

$$\boxed{y = h * x.}$$

The ‘ $*$ ’ symbol represents convolution. By changing variables, defining $k = n - m$, one can see that the convolution sum can also be written in the equivalent form

$$\boxed{\forall n \in \mathbb{Z}, \quad y(n) = \sum_{k=-\infty}^{\infty} h(k)x(n-k).} \quad (5.29)$$

That is, $h * x = x * h$. Convolution sums will be studied in much more detail in Chapter 9.

The impulse response of a system is simply the output when the input is an impulse. If -0.5 in the system is initially at rest, then its output is given by the convolution of the input and the impulse response.

Example 5.12: For our bank example, $a = 1 + r$, $b = 1$, $c = 1$, and $d = 0$ in (5.20). The impulse response of the bank system is given by (5.18),

$$h(n) = \begin{cases} 0, & \text{if } n \leq 0 \\ (1+r)^{n-1}, & \text{if } n \geq 1 \end{cases}.$$

This represents the balance of a bank account with daily interest rate r if an initial deposit of one dollar is put in on day 0, and no further deposits or withdrawals are made. Notice that since $1 + r > 1$, the balance continues to increase forever; see

Figure 5.2. This system is said to be **unstable** because even though the input is always bounded, the output grows without bound. The system is also an **infinite impulse response (IIR)** system.

Writing the output as a convolution, using (5.27), we see that

$$\forall n \geq 0, \quad y(n) = \sum_{m=0}^{n-1} (1+r)^{n-m-1} x(m).$$

This gives a simple formula that we can use to calculate the bank balance on any given day (although it will be tedious for large n , and you will want to use a computer).

The zero-input state response of the $[a, b, c, d]$ system is

$$s(n) = a^n s(0), n \geq 0.$$

This is a geometric or **exponential sequence**. If $s(0) \neq 0$, the response will eventually die out, i.e. $s(n) \rightarrow 0$ as $n \rightarrow \infty$, if and only if $|a| < 1$, in which case we say the system is **stable**.

5.3.4 Multidimensional SISO systems

In the previous section we considered the simplest systems of the form of Figure 5.1 with $M = K = N = 1$. Systems with larger dimension, $N > 1$, occur more frequently in practice. In this section, we allow the dimension N to be arbitrarily large, but keep the simplification that $M = K = 1$, so the system is still SISO (single-input, single-output). In the $[A, B, C, D]$ representation, A is $N \times N$, B is $N \times 1$, C is $1 \times N$ and D is 1×1 . So for an SISO system we may write $B = b$, $C = c^T$, $D = d$, where b, c are N -dimensional column vectors and d is a scalar. Thus, SISO systems have an $[A, b, c, d]$ representation, and their **state-space model** is

$$s(n+1) = As(n) + bx(n), \quad (5.30)$$

$$y(n) = c^T s(n) + dx(n). \quad (5.31)$$

The result of evaluating the *nextState* function (5.30) is an N -dimensional vector, $s(n+1)$. The $N \times N$ matrix A defines the linear combination of the N elements of $s(n)$ that are used

to calculate the N elements $s(n+1)$. The N -dimensional column vector b defines the weights used to include $x(n)$ in the linear combination for each element of $s(n+1)$.

The result of evaluating the *output* function (5.31) is a scalar, $y(n)$. The row vector c^T (which is N -dimensional) defines the linear combination of elements of $s(n)$ and d defines the weight used to include $x(n)$ in the output $y(n)$.

Example 5.13: Above we constructed a state-space model for a length-two moving average. The general form of this is the M -point moving average, given by

$$\forall n \in \mathbb{Z}, \quad y(n) = \frac{1}{M} \sum_{k=0}^{M-1} x(n-k). \quad (5.32)$$

To be specific, let's take $M = 3$. Equation (5.32) becomes

$$\forall n \in \mathbb{Z}, \quad y(n) = \frac{1}{3}(x(n) + x(n-1) + x(n-2)). \quad (5.33)$$

We can construct a state-space model for this in a manner similar to what we did for the length-two moving average. First, we need to decide what is the state. Recall that the state is the summary of the past. Equation (5.33) tells us that we need to remember $x(n-1)$ and $x(n-2)$, the two past inputs. We could define these to be the state, collected as a column vector,

$$s(n) = \begin{bmatrix} x(n-1) \\ x(n-2) \end{bmatrix}.$$

(Of course, we could have equally well put the elements in the other order; see Exercise 9.)

Consider the output equation (5.31). We need to determine c^T and d . The vector c^T is a row vector with dimension $N = 2$, so we must fill in the blanks in the output equation below:

$$y(n) = [_, _] \begin{bmatrix} x(n-1) \\ x(n-2) \end{bmatrix} + [_]x(n)$$

It is easy to see that each of the three blanks must be filled with $1/M = 1/3$ in order to get (5.33). Thus,

$$c = \begin{bmatrix} 1/3 \\ 1/3 \end{bmatrix}, \quad d = 1/3.$$

Consider next the state equation (5.30). We need to determine A and b . The matrix A is 2×2 . The vector b is dimension 2 column vector. So we can fill in the blanks in the output equation below:

$$s(n+1) = \begin{bmatrix} x(n) \\ x(n-1) \end{bmatrix} = \begin{bmatrix} \text{--} & \text{--} \\ \text{--} & \text{--} \end{bmatrix} \begin{bmatrix} x(n-1) \\ x(n-2) \end{bmatrix} + \begin{bmatrix} \text{--} \\ \text{--} \end{bmatrix} x(n).$$

From this, we can fill in the blanks, getting

$$A = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \text{ and } b = \begin{bmatrix} 1 \\ 0 \end{bmatrix}.$$

Note that once the state is specified, there is only one way to fill in the blanks and obtain the $[A, b, c, d]$ representation.

The state response of the SISO system (5.30)-(5.31) is given by an expression similar to (5.24), but involving matrices and vectors rather than just scalars,

$$s(n) = A^n \text{initialState} + \sum_{m=0}^{n-1} A^{n-1-m} b x(m) \quad (5.34)$$

for all $n \geq 0$. The state response is also sometimes called the **state trajectory**. The output response of (5.39) is given by

$$y(n) = c^T A^n \text{initialState} + \left\{ \sum_{m=0}^{n-1} c^T A^{n-1-m} b x(m) \right\} + d x(n) \quad (5.35)$$

for all $n \geq 0$. (Exercise 13 asks you to derive these equations.)

Notice again that the state response (5.34) and the output response (5.35) are each the sum of two terms. The first term is the **zero-input response** and the second term is the **zero-state response**.

The impulse response, in terms of the state-space model, is the sequence of real numbers

$$h(n) = \begin{cases} 0, & \text{if } n < 0 \\ d, & \text{if } n = 0 \\ c^T A^{n-1} b, & \text{if } n \geq 1 \end{cases} \quad (5.36)$$

This is just like (5.18) except that b and c are vectors, and d is a scalar. This formula can be quite tedious to apply. It is usually easier to simply let $x = \delta$, the Kronecker delta function, and observe or calculate the output. The zero-state output response is given by convolution of this impulse response with the input, (5.29).

Example 5.14: We can find the impulse response h of the moving average system of (5.32) by letting $x = \delta$, where δ is given by (5.17). That is,

$$\forall n \in \mathbb{Z}, \quad h(n) = \frac{1}{M} \sum_{k=0}^{M-1} \delta(n-k).$$

Now, $\delta(n-k) = 0$ except when $n = k$, at which point it equals one. Thus,

$$h(n) = \begin{cases} 0 & \text{if } n < 0 \\ 1/M & \text{if } 0 \leq n < M \\ 0 & \text{if } n \geq M \end{cases}.$$

This function, therefore, is the impulse response of an M -point moving average system. This result could also have been obtained by comparing (5.32) to (5.29), the output as a convolution. Or it could have been obtained by constructing a state-space model for the general length- M moving average, and applying (5.36). However, this latter method would have proved the most tedious in this case.

Notice that in the previous example, the impulse response is finite in extent (it starts at 0 and stops at $M - 1$). For this reason, such a system is called a **finite impulse response system** or **FIR** system.

Example 5.15: The M -point moving average can be viewed as a special case of the more general FIR system given by

$$\forall n \in \mathbb{Z}, \quad y(n) = \sum_{k=0}^{M-1} h(k)x(n-k).$$

Letting $h(k) = 1/M$ for $0 \leq k < M$, we get the M -point moving average. Choosing other values for $h(k)$, however, we can get other responses (this will be explored in chapter 8).

A state-space model for the FIR system is constructed by again deciding on the state. A reasonable choice is the $M - 1$ past samples of the input,

$$s(n) = [x(n-1), x(n-2), \dots, x(n-M+1)]^T,$$

a column vector. The state-space model is then given by (5.30) and (5.31) with

$$A = \begin{bmatrix} 0 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 1 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 1 & 0 & 0 & \cdots & 0 & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & 0 & 0 & \cdots & 1 & 0 \end{bmatrix}, \quad b = \begin{bmatrix} 1 \\ 0 \\ \cdots \\ 0 \\ 0 \end{bmatrix},$$

$$c = \begin{bmatrix} h(1) \\ h(2) \\ \cdots \\ h(M-2) \\ h(M-1) \end{bmatrix}, \quad d = h(0).$$

Notice that the model that we found in example 5.13 has this form. The $(M-1) \times (M-1)$ matrix A has coefficients $a_{i+1,i} = 1$, while all other coefficients are zero. This is a rather special form of the A matrix, limited to FIR systems. The vector b has the first coefficient equal to 1, while all others are zero. The vector c contains the coefficients of the impulse response.

Many interesting systems, unlike this example, have an **infinite impulse response**, and are referred to as **IIR systems**.

Example 5.16: Recall from example 5.6 that an echo effect can be obtained for audio signals by realizing the following difference equation,

$$\forall n \in \mathbb{Z}, \quad y(n) = x(n) + \alpha y(n-N).$$

The impulse response h can be obtained by simply letting the input be an impulse, $x = \delta$, and finding the output $y = h$. That is

$$\forall n \in \mathbb{Z}, \quad h(n) = \delta(n) + \alpha h(n-N). \quad (5.37)$$

But of course, this means that

$$h(n - N) = \delta(n - N) + \alpha h(n - 2N).$$

Substituting this back into (5.37), we get

$$h(n) = \delta(n) + \alpha\delta(n - N) + \alpha^2 h(n - 2N).$$

But of course,

$$h(n - 2N) = \delta(n - 2N) + \alpha h(n - 3N),$$

so

$$h(n) = \delta(n) + \alpha\delta(n - N) + \alpha^2\delta(n - 2N) + \alpha^3 h(n - 3N).$$

Continuing in this fashion, we see that the impulse response of the echo system is the original impulse and an infinite set of echos (delayed and scaled impulses). This can be written compactly as follows,

$$\forall n \in \mathbb{Z}, \quad h(n) = \sum_{k=0}^{\infty} \alpha^k \delta(n - kN).$$

This impulse response is plotted in Figure 5.3 for $N = 4$ and $\alpha = 0.7$. In that figure, you can see that the original impulse gets through the system at $n = 0$, while the first echo is scaled by 0.7 and delayed to $n = 4$, and the second echo is scaled by 0.7^2 and delayed to $n = 8$.

We can check this impulse response using the state-space representation of example 5.6 in (5.36). From example 5.6, we have that $d = 1$, so (5.36) is obviously correct for $n < 0$ and $n = 0$. Checking it for $n > 0$ is somewhat more involved. Assuming $N = 4$, we have from example 5.6

$$A = \begin{bmatrix} 0 & 0 & 0 & \alpha \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, \quad b = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad c = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \alpha \end{bmatrix}, \quad d = [1].$$

To use (5.36) we need to know A^{n-1} . It is easy to check that

$$A^2 = \begin{bmatrix} 0 & 0 & \alpha & 0 \\ 0 & 0 & 0 & \alpha \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, \quad A^3 = \begin{bmatrix} 0 & \alpha & 0 & 0 \\ 0 & 0 & \alpha & 0 \\ 0 & 0 & 0 & \alpha \\ 1 & 0 & 0 & 0 \end{bmatrix},$$

$$A^4 = \begin{bmatrix} \alpha & 0 & 0 & 0 \\ 0 & \alpha & 0 & 0 \\ 0 & 0 & \alpha & 0 \\ 0 & 0 & 0 & \alpha \end{bmatrix} = \alpha I,$$

where I is the 4×4 identity matrix. Thus,

$$A^5 = \alpha A, A^6 = \alpha A^2, A^7 = \alpha A^3, A^8 = \alpha A^4 = \alpha^2 I.$$

The pattern continues. Note that because of the particular structure of b , $A^{n-1}b$ is simply the first column of A^{n-1} . Thus,

$$h(1) = c^T A^0 b = [0 \ 0 \ 0 \ \alpha] \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} = 0.$$

Similarly,

$$h(2) = c^T A^1 b = [0 \ 0 \ 0 \ \alpha] \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} = 0,$$

and

$$h(3) = c^T A^2 b = [0 \ 0 \ 0 \ \alpha] \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = 0.$$

Only when we get to $h(4)$ do we get a non-zero result,

$$h(4) = c^T A^3 b = [0 \ 0 \ 0 \ \alpha] \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} = \alpha.$$

Continuing in this fashion, we can determine that 3 of every four samples of the impulse response are zero, and the non-zero ones have the form $\alpha^{n/4}$ where n is a multiple of four, in perfect agreement with figure 5.3.

The echo system of the previous example is an example of an **infinite impulse response (IIR)** system because the response to an impulse never completely dies out. Here is another example of an IIR system.

Example 5.17: An audio **oscillator** is a system that produces a sinusoidal signal of a given frequency. We can construct one with the two-dimensional system given by

$$A = \begin{bmatrix} \cos(\omega) & -\sin(\omega) \\ \sin(\omega) & \cos(\omega) \end{bmatrix}, b = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, c = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, d = 0,$$

where ω is a constant that will turn out to be the oscillation frequency. It can be shown (see Exercise 14) that for all $n = 0, 1, 2, \dots$

$$A^n = \begin{bmatrix} \cos(n\omega) & -\sin(n\omega) \\ \sin(n\omega) & \cos(n\omega) \end{bmatrix},$$

Suppose the initial state is

$$\text{initialState} = [0, 1]^T.$$

Then the **zero-input state response** is

$$\begin{aligned} s_{\text{zero-input}}(n) &= A^n \text{initialState} \\ &= \begin{bmatrix} \cos(n\omega) & -\sin(n\omega) \\ \sin(n\omega) & \cos(n\omega) \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} \\ &= \begin{bmatrix} -\sin(n\omega) \\ \cos(n\omega) \end{bmatrix}, \end{aligned}$$

and the **zero-input response** is

$$\begin{aligned} y_{\text{zero-input}}(n) &= c^T A^n \text{initialState} \\ &= [1 \ 0] \begin{bmatrix} -\sin(n\omega) \\ \cos(n\omega) \end{bmatrix} \\ &= -\sin(n\omega). \end{aligned}$$

Notice that without any input, as long as the initial state is non-zero, the system will produce a sinusoidal output in perpetuity.

If we instead consider the situation where the system is initially at rest, then we find that the impulse response is

$$h(n) = \begin{cases} d, & \text{if } n = 0 \\ c^T A^{n-1} b, & \text{if } n \geq 1 \end{cases}.$$

For the values of A, b, c in this example we obtain

$$h(n) = \begin{cases} 0, & \text{if } n = 0 \\ -\sin((n-1)\omega), & \text{if } n \geq 1 \end{cases}.$$

Thus, if the oscillator is initially at rest, it can be started with an impulse, and its output will henceforth be sinusoidal, similar to the zero-input response. Thus, if the oscillator is initially at rest, it can be started with an impulse at the input.

5.3.5 Multidimensional MIMO systems

In the preceding sections, the input and output were both scalars. A **MIMO** system is only slightly more complicated. A state-space model for such a system is

$$\forall n \in \mathbb{Z}_+, \quad s(n+1) = As(n) + Bx(n) \quad (5.38)$$

$$y(n) = Cs(n) + Dx(n) \quad (5.39)$$

where, $s(n) \in \mathbb{R}^N$, $x(n) \in \mathbb{R}^M$ and $y(n) \in \mathbb{R}^K$, for any integer n . In the $[A, B, C, D]$ representation, A is an $N \times N$ (square) matrix, B is an $N \times M$ matrix, C is a $K \times N$ matrix, and D is a $K \times M$ matrix. Now that these are all matrices, it is conventional to write them with capital letters.

Let $initialState \in \mathbb{R}^N$ be a given initial state. Let $x(0), x(1), x(2), \dots$, be a sequence of inputs in \mathbb{R}^M (each input is a vector of dimension M). The state response of (5.38) is given by

$$s(n) = A^n initialState + \sum_{m=0}^{n-1} A^{n-1-m} Bx(m) \quad (5.40)$$

for all $n \geq 0$, and the output sequence of (5.39) is given by

$$y(n) = CA^n initialState + \left\{ \sum_{m=0}^{n-1} CA^{n-1-m} Bx(m) \right\} + Dx(n) \quad (5.41)$$

for all $n \geq 0$ (each output is a vector of dimension K).

The right-hand sides of these equations are the sum of a zero-input response and a zero-state response. Consider the zero-state output response,

$$y(n) = \sum_{m=0}^{n-1} CA^{n-1-m} Bx(m) + Dx(n) \quad (5.42)$$

for all $n \geq 0$. Define the sequence $h(0), h(1), h(2), \dots$ of $K \times M$ matrices by

$$h(n) = \begin{cases} D, & \text{if } n = 0 \\ CA^{n-1}B, & \text{if } n \geq 1 \end{cases} \quad (5.43)$$

This can no longer be called an impulse response, because the input cannot be an impulse; it has the wrong dimension (see box).

From (5.42) it follows that the zero-state output response is given by

$$y(n) = \sum_{m=0}^n h(n-m)x(m), \quad n \geq 0 \quad (5.44)$$

This is once again a **convolution sum**.

The i, j th element of the matrix sequence $h(0), h(1), \dots$, namely

$$h_{i,j}(0), h_{i,j}(1), \dots,$$

is indeed the impulse response of the SISO system whose input is x_j and whose output is y_i . In terms of Figure 5.1, this is the SISO system obtained by setting all inputs except the j th input to zero, and considering only the i th output. If B^j denotes the j th column of B and C_i^T denotes the i th row of C , then $h_{i,j}$ is the impulse response of the SISO system $[A, B^j, C_i, D_{i,j}]$. All these SISO systems have the same A matrix.

5.3.6 Linear input-output function

In the systems that this chapter considers, the *nextState* and *output* functions are linear. Recall that a function $f: X \rightarrow Y$ is linear if (and only if) it satisfies the superposition property: for all $x_1, x_2 \in X$, and $w, u \in \mathbb{R}$,

$$f(wx_1 + ux_2) = wf(x_1) + uf(x_2).$$

What does it mean for a *system* to be linear? Recall that a system S is a function $S: X \rightarrow Y$, where X and Y are signal spaces. For a MIMO system, $X = [\mathbb{Z} \rightarrow \mathbb{R}^M]$, and $Y = [\mathbb{Z} \rightarrow \mathbb{R}^K]$. The function S is defined by (5.41), which gives $y = S(x)$, given x . So the answer is obvious. S is a **linear system** if S is a linear function. (It is an **LTI** system if it is also time invariant).

Examining (5.41), or its simpler SISO versions, (5.25) or (5.35), it is easy to see that superposition is satisfied if *initialState* is zero. This is because with zero initial state, the output $y(n)$ is a linear combination of the input samples $x(n)$. Hence, a system given by a state-space model that is initially at rest is a linear system. The superposition property turns out to be an extremely useful property, as we will discover in the next chapters.

5.4 Continuous-time state-space models

A continuous-time state-space model for an LTI SISO system has the form

$$\forall t \in \mathbb{R}_+, \quad \dot{z}(t) = Az(t) + bv(t) \quad (5.45)$$

$$w(t) = c^T z(t) + dv(t) \quad (5.46)$$

where

- $z: \mathbb{R}_+ \rightarrow \mathbb{R}^N$ gives the state response;
- $\dot{z}(t)$ is the derivative with respect to time of z evaluated at $t \in \mathbb{R}_+$;
- $v: \mathbb{R}_+ \rightarrow \mathbb{R}$ is the input signal; and
- $w: \mathbb{R}_+ \rightarrow \mathbb{R}$ is the output signal.

As with the discrete-time SISO model, A is an $N \times N$ matrix, b and c are $N \times 1$ column vectors, and d is a scalar. As before, this is the $[A, b, c, d]$ representation of the system, but the equations are different.

Continuous-time systems are no longer state machines, since inputs, outputs, and state transitions do not occur at discrete instances. Nevertheless, they share many properties of discrete systems. The major difference between this model and that of (5.30) and (5.31) is that instead of giving new state as a function of the input and the old state, (5.45) gives the derivative of the state. The derivative of a vector z is simply the vector consisting of the derivative of each element of the vector. A derivative, of course, gives the trend of the state at any particular time. Giving a trend makes more sense than giving a new state for a continuous-time system, because the state evolves continuously.

All of the methods that we have developed for discrete-time systems can also be developed for continuous-time systems. However, they get somewhat more challenging mathematically because the summations become integrals. We leave it to a more advanced text to explore this.

A continuous-time state-space model may be approximated by a discrete-time state-space model (see box). In fact, this approximation forms the basis for most computer simulations of continuous-time systems.

5.5 Summary

This chapter has begun the exploration of state machines whose state update and output functions are linear. The number of possible states for such systems is typically infinite, so brute-force methods that enumerate the states will be ineffective. Instead, powerful mathematical tools leverage the linearity of the key functions. This chapter barely begins an exploration of the very rich set of tools that engineers have developed for such systems. Subsequent chapters will continue that exploration.

Basics: Functions yielding tuples

The ranges of the *nextState* and *output* functions are tuples. It helps if we break them down further into an N -tuple and K -tuple of functions, one for each element of the result tuple. That is, we define the functions

$$\text{nextState}_i: \mathbb{R}^N \times \mathbb{R}^M \rightarrow \mathbb{R}, i = 1, \dots, N,$$

such that $\forall s \in \mathbb{R}^N, \forall x \in \mathbb{R}^M$,

$$\text{nextState}(s, x) = (\text{nextState}_1(s, x), \dots, \text{nextState}_N(s, x)).$$

We write simply

$$\text{nextState} = (\text{nextState}_1, \dots, \text{nextState}_N).$$

The output function can be given similarly as

$$\text{output} = (\text{output}_1, \dots, \text{output}_K),$$

where

$$\text{output}_i: \mathbb{R}^N \times \mathbb{R}^M \rightarrow \mathbb{R}, i = 1, \dots, K.$$

Using these, the **state update equation** and **output equation** can be written as follows. For all $n \in \mathbb{Z}, n \geq 0$,

$$\begin{aligned} s_1(n+1) &= \text{nextState}_1((s_1(n), \dots, s_N(n)), (x_1(n), \dots, x_M(n))), \\ s_2(n+1) &= \text{nextState}_2((s_1(n), \dots, s_N(n)), (x_1(n), \dots, x_M(n))), \\ &\dots \\ s_N(n+1) &= \text{nextState}_N((s_1(n), \dots, s_N(n)), (x_1(n), \dots, x_M(n))), \end{aligned} \tag{5.6}$$

and

$$\begin{aligned} y_1(n) &= \text{output}_1((s_1(n), \dots, s_N(n)), (x_1(n), \dots, x_M(n))), \\ y_2(n) &= \text{output}_2((s_1(n), \dots, s_N(n)), (x_1(n), \dots, x_M(n))), \\ &\dots \\ y_K(n) &= \text{output}_K((s_1(n), \dots, s_N(n)), (x_1(n), \dots, x_M(n))). \end{aligned} \tag{5.7}$$

This system of equations shows the structure of the operation of such a machine.

Basics: Matrices and vectors

An $M \times N$ matrix A is written as

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,N} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,N} \\ \cdots & \cdots & \cdots & \cdots \\ a_{M,1} & a_{M,2} & \cdots & a_{M,N} \end{bmatrix}.$$

The **dimension of the matrix** is said to be $M \times N$, where the number of rows is always given first, and the number of columns is given second. In general, the coefficients of the matrix are real or complex numbers, so they support all the standard arithmetic operations. We write the matrix more compactly as

$$A = [a_{i,j}, 1 \leq i \leq M, 1 \leq j \leq N],$$

or, even more simply as $A = [a_{i,j}]$ when the dimension of A is understood. The matrix entries $a_{i,j}$ are called the coefficients of the matrix.

Basics: Vectors

A **vector** is a matrix with only one row or only one column. An N -dimensional **column vector** s is written as an $N \times 1$ matrix

$$s = \begin{bmatrix} s_1 \\ s_2 \\ \dots \\ s_N \end{bmatrix}.$$

An N -dimensional **row vector** z^T is written as a $1 \times N$ matrix

$$z^T = [z_1, z_2, \dots, z_N].$$

The **transpose** of a $M \times N$ matrix $A = [a_{i,j}]$ is the $N \times M$ matrix $A^T = [a_{j,i}]$. Therefore, the transpose of an N -dimensional column vector s is the N -dimensional row vector s^T , and the transpose of an N -dimensional row vector z is the N -dimensional column vector z^T .

From now on, unless explicitly stated otherwise, all vectors denoted s, x, y, b, c etc. *without* the transpose notation are column vectors, and vectors denoted s^T, x^T, y^T, b^T, c^T *with* the transpose notation are row vectors. We follow convention and use lower case letters to denote vectors and upper case letters to denote matrices.

A tuple of numeric values is often represented as a vector. A tuple, however, is neither a “row” nor a “column.” Thus, the representation as a vector carries the additional information that it is either a row or a column vector.

Basics: Matrix arithmetic

Two matrices (or vectors, since they are also matrices) can be added or subtracted provided that they have the same dimension. Just as with adding or subtracting tuples, the elements are added or subtracted. Thus if $A = [a_{i,j}]$ and $B = [b_{i,j}]$ and both have dimension $M \times N$, then

$$A + B = [a_{i,j} + b_{i,j}].$$

Under certain circumstances, matrices can also be multiplied. If A has dimension $M \times N$ and B has dimension $N \times P$, then the product AB is defined. The number of columns of A must equal the number of rows of B . Suppose the matrices are given by

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,N} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,N} \\ \cdots & \cdots & \cdots & \cdots \\ a_{M,1} & a_{M,2} & \cdots & a_{M,N} \end{bmatrix}, \quad B = \begin{bmatrix} b_{1,1} & b_{1,2} & \cdots & b_{1,P} \\ b_{2,1} & b_{2,2} & \cdots & b_{2,P} \\ \cdots & \cdots & \cdots & \cdots \\ b_{N,1} & b_{N,2} & \cdots & b_{N,P} \end{bmatrix}.$$

Then the i, j element of the product $C = AB$ is^a

$$c_{i,j} = \sum_{m=1}^N a_{i,m} b_{m,j}. \tag{5.9}$$

The product C has dimension $M \times P$. (Continued on page 224.)

^aIf this notation is unfamiliar, see box on page 77.

Basics: Matrix arithmetic (continued from page 223)

Matrix multiplication also works if one of the matrices is a vector. If b is a column vector of dimension N , then $c = Ab$ as defined by (5.9) is a column vector of dimension M . If on the other hand b^T is a row vector of dimension M , then $c^T = b^TA$ as defined by (5.9) is a row vector of dimension N .

Multiplying a matrix by a vector can be interpreted as applying a function to a tuple. The vector is the tuple and the matrix (together with the definition of matrix multiplication) defines the function. Thus, in introducing matrix multiplication into our systems, we are doing nothing new except introducing a more compact notation for defining a particular class of functions.

A matrix A is a **square matrix** if it has the same number of rows and columns. A square matrix may be multiplied by itself. Thus, A^n for some integer $n > 0$ is defined to be A multiplied by itself n times. A^0 is defined to be the **identity matrix**, also written I , which has ones along the diagonal and zeros everywhere else. If A has an inverse, then that inverse is denoted A^{-1} , and $AA^{-1} = A^{-1}A = I$.

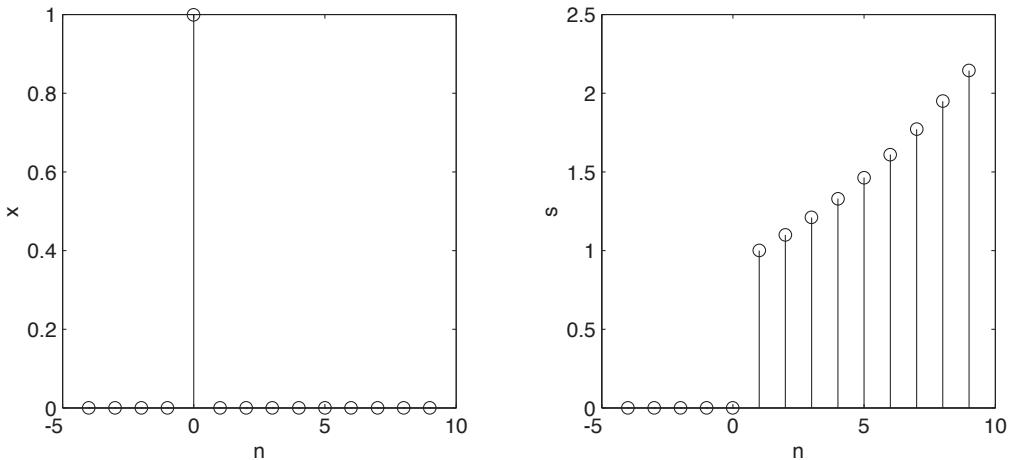


Figure 5.2: Plots of the impulse (left) and the impulse response of example 5.12 (right) for $r = 0.1$.

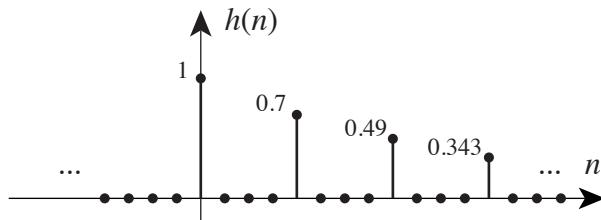


Figure 5.3: Impulse response of the echo example 5.16 for $\alpha = 0.7$ and $N = 4$.

Probing Further: Impulse Responses of MIMO Systems

The h function in (5.43) is not the impulse response of a MIMO system with representation $[A, B, C, D]$. However, with some care, it is possible to relate it to a set of impulse responses that characterize the system.

The system has M inputs and K outputs, and for each integer n , $h(n)$ in (5.43) is a $K \times M$ matrix. Each input symbol $x(n)$ is an M -tuple of reals. Let $x_m(n)$ represent the m -th element in this tuple, and let x_m represent the sequence of such elements. Similarly, let $y_k(n)$ represent the k -th element of the output tuple, and y_k the sequence of such outputs. Finally, let $h_{k,m}(n)$ represent the k, m -th element of the matrix $h(n)$, and let $h_{k,m}$ represent the sequence of such elements.

The SISO system comprising the k -th output and m -th input has impulse response $h_{k,m}$. Specifically, if $x_m = \delta$ and $x_p(n) = 0$ for all $p \neq m$ and for all $n \in \mathbb{Z}$, then $y_k = h_{k,m}$. Thus, h can be viewed as a matrix of impulse responses, one for each possible pairing of input and output signals.

Probing Further: Approximating continuous-time

Discrete LTI systems often arise as approximations of systems where **differential equations** describe the physics. A differential equation has the form

$$\forall t \in \mathbb{R}, \quad \dot{z}(t) = g(z(t), v(t)). \quad (5.47)$$

Here $t \in \mathbb{R}$ stands for continuous time, $z: \mathbb{R} \rightarrow \mathbb{R}^N$ is the state response, and $v: \mathbb{R} \rightarrow \mathbb{R}^M$ is the input signal. That is, at any time t , $z(t)$ is the state and $v(t)$ is the input. The notation \dot{z} stands for derivative of the state response z with respect to t , so $g: \mathbb{R}^N \times \mathbb{R}^M \rightarrow \mathbb{R}^N$ is a given function specifying the derivative of the state. Specifying the derivative of the state is similar to specifying a state update. In a continuous-time system, state updates occur continuously rather than discretely.

In general, z is an N -tuple, $z = (z_1, \dots, z_N)$, where $z_i: \mathbb{R}_+ \rightarrow \mathbb{R}$. The derivative of an N -tuple is the N -tuple of derivatives, $\dot{z} = (\dot{z}_1, \dots, \dot{z}_N)$. From calculus,

$$\dot{z}(t) = \frac{dz}{dt} = \lim_{\delta \rightarrow 0} \frac{z(t + \delta) - z(t)}{\delta},$$

and so, if $\delta > 0$ is a small number, we can approximate this derivative by

$$\dot{z}(t) \approx \frac{z(t + \delta) - z(t)}{\delta}.$$

Using this for the derivative in the left-hand side of (5.47) we get

$$z(t + \delta) - z(t) = \delta g(z(t), v(t)). \quad (5.48)$$

Suppose we look at this equation at sample times $t = 0, \delta, 2\delta, \dots$. Denote the value of the state response at the n -th sample time by $s(n) = z(n\delta)$, and the value of the input by $x(n) = v(n\delta)$. In terms of these variables, (5.48) becomes

$$s(n + 1) - s(n) = \delta g(s(n), x(n))$$

which we can write as a state update equation,

$$s(n + 1) = s(n) + \delta g(s(n), x(n)).$$

Exercises

Each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires conceptualization. Some of the problems require using Matlab.

1. **E** Use induction to obtain (5.13) as a consequence of (5.12).
2. **E** Use induction to show that if

$$A = \begin{bmatrix} a & 1 \\ 0 & a \end{bmatrix},$$

then for all $n \geq 0$,

$$A^n = \begin{bmatrix} a^n & na^{n-1} \\ 0 & a^n \end{bmatrix}.$$

3. **E** Let $f: \mathbb{R}^N \rightarrow \mathbb{R}^N$ be a linear function given by $\forall x \in \mathbb{R}^N, f(x) = Ax$ for some $N \times N$ matrix A . Give a similar definition for the composition $f \circ f$. Is it also linear?
4. **E** What would be the monthly payment in example 5.10 if the monthly interest is 0.015? Also, what would be the total payment over the 32 months?
5. **E** Construct a SISO state-space model for a system whose input and output are related by

$$\forall n \in \mathbb{Z}, \quad y(n) = x(n-1) + x(n-2).$$

You may assume the system is initially at rest. It is sufficient to give the A matrix, vectors b and c , and scalar d of (5.30) and (5.31).

6. **E** The A matrix in (5.30) for a SISO system is

$$A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}.$$

Calculate the zero-input state response if

- (a) the initial state is $[1, 0]^T$,
- (b) the initial state is $[0, 1]^T$,
- (c) the initial state is $[1, 1]^T$.

7. E Consider the one-dimensional state-space model, $\forall n \in \mathbb{Z}_+$,

$$\begin{aligned}s(n+1) &= s(n) + x(n) \\y(n) &= s(n)\end{aligned}$$

Suppose the initial state is $s(0) = a$ for some given constant a . Find another constant b such that if the first three inputs are $x(0) = x(1) = x(2) = b$, then $y(3) = 0$. Note: In general, problems of this type are concerned with **controllability**. The question is whether you can find an input (in this case constrained to be constant) such that some particular condition on the output is met. The input becomes a **control signal**.

8. E A SISO LTI system has the A matrix given by

$$A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$$

and the b vector by $[0, 1]^T$. Suppose that $s(0) = [0, 0]^T$. Find the input sequence $x(0), x(1)$ so that the state at step 2 is $s(2) = [1, 2]^T$.

9. E In example 5.13, the state was chosen to be $s(n) = [x(n-1), x(n-2)]^T$. How would the $[A, b, c, d]$ representation change if the state were chosen to be

- (a) $[x(n-2), x(n-1)]^T$?
(b) $[x(n-1) + x(n-2), x(n-1) - x(n-2)]^T$?

10. E Suppose the A matrix of a two-dimensional SISO system is

$$A = \sigma \begin{bmatrix} \cos(\pi/6) & \sin(\pi/6) \\ -\sin(\pi/6) & \cos(\pi/6) \end{bmatrix}.$$

Suppose the initial state is $s(0) = [1, 0]^T$, and the input is zero. Sketch the zero-input state response for $n = 0, 1, \dots, 12$ for the cases

- (a) $\sigma = 0$
(b) $\sigma = 0.9$
(c) $\sigma = 1.1$

11. E In this problem we further consider example 5.9. As in the example, suppose *initialState* = 100, and you deposit 1,000 dollars on day 0 and withdraw 30 dollars every subsequent day for the next 30 days.

- (a) Write a Matlab program to compute your bank balance $s(n)$, $0 \leq n \leq 31$, and plot the result.
- (b) Use formula (5.24) to calculate your bank balance at the beginning of day 31.
The following identity may prove useful:

$$\sum_{m=0}^N a^m = \frac{1-a^{N+1}}{1-a},$$

where $a \neq 1$.

12. E Use Matlab to calculate and plot the impulse response of the system

$$\begin{aligned}s(n+1) &= as(n) + bx(n) \\ y(n) &= cs(n)\end{aligned}$$

for the following cases:

- (a) $a = 1.1$
- (b) $a = 1.0$
- (c) $a = 0.9$
- (d) $a = -0.5$

where in all cases, $b = c = 1$ and $d = 0$.

13. E Use induction to derive the SISO response expressions (5.34) and (5.35).
14. E Consider the two-dimensional system given in example 5.17, which has

$$A = \begin{bmatrix} \cos(\omega) & -\sin(\omega) \\ \sin(\omega) & \cos(\omega) \end{bmatrix}.$$

Show that for all $n = 0, 1, 2, \dots$

$$A^n = \begin{bmatrix} \cos(n\omega) & -\sin(n\omega) \\ \sin(n\omega) & \cos(n\omega) \end{bmatrix},$$

Hint: use induction and the identities

$$\cos(\alpha + \beta) = \cos(\alpha)\cos(\beta) - \sin(\alpha)\sin(\beta)$$

$$\sin(\alpha + \beta) = \sin(\alpha)\cos(\beta) + \cos(\alpha)\sin(\beta)$$

15. **E** A **damped oscillator** is a variant of the oscillator in example 5.17, where the sinusoidal signal decays with time. The damped oscillator is identical, except that the A matrix is given by

$$A = \alpha \begin{bmatrix} \cos(\omega) & -\sin(\omega) \\ \sin(\omega) & \cos(\omega) \end{bmatrix},$$

where $0 < \alpha < 1$ is a constant damping factor.

- (a) Find the zero-input state response and the zero-input response for the initial state

$$\text{initialState} = [0, 1]^T.$$

- (b) Find the zero-state impulse response.

16. **T** Consider the audio echo system in example 5.6. A more interesting effect (sometimes called **reverberation**) can be obtained by simultaneously combining multiple echos. In this problem, consider the following difference equation, which combines two echos,

$$y(n) = x(n) + \alpha y(n-M) + \beta y(n-N),$$

where the (discrete-time) audio input is x , the output is y , and $0 \leq \alpha < 1$ and $0 \leq \beta < 1$ are constants that specify two distinct echo terms. Suppose for simplicity that $M = 4$ and $N = 5$. These numbers are not large enough to yield an audible echo, but the mathematical model is similar for larger numbers, so these are adequate for study. Note that the zero-state impulse response of this system is much more complicated than the simple echo system (try to find it!), which accounts for a considerably more realistic echo effect.

- (a) Give a state-space representation $[A, B, C, D]$ of this system.
(b) Modify the system so that the audio input has two channels (stereo), but the output is still one channel. Combine the two input channels by adding them with equal weight. Give $[A, B, C, D]$.

6

Hybrid Systems

Contents

6.1	Mixed models	233
6.2	Modal models	235
6.3	Timed automata	240
6.4	More interesting dynamics	250
	<i>Probing Further: Internet protocols</i>	251
6.5	Supervisory control	260
6.6	Formal model	266
6.7	Summary	268
	Exercises	269

This text models signals and systems as functions. To develop understanding, we study the structure of the domain and range of these functions, as well as the structure of the mapping from the domain to the range. Despite the uniformity of this approach, we have begun to evolve two distinct families of models. Chapters 3 and 4 structure this mapping using state machines. Chapter 5 generalizes these state machines so that the number of possible states is infinite, and specializes them so that the systems are linear and time-invariant (LTI). LTI systems prove to yield to powerful analytical techniques, which are only hinted at in Chapter 5. Chapters 7 through 14 will further develop these analytical techniques by structuring the system mapping using frequency-domain concepts.

The analytical methods available for LTI systems prove so compelling that we wish to apply them even to systems that are not LTI. In fact, no real-world system is truly LTI. At a minimum, its properties were certainly different during the initial stages of the big bang, so it cannot be time invariant. More practically, systems change over time; they are turned on and off, they deteriorate, etc. Moreover, systems that behave as linear systems typically do so only over some regime of operation. For example, if the magnitude of the inputs exceed some threshold, a real-world system will overload, and will no longer behave linearly. A similar effect might result when the state wanders beyond some modest range. This chapter shows how models that are only applicable some of the time can be used effectively.

In chapters 3 and 4, signals are sequences of events. Their domain is (typically) \mathbb{N}_0 , and their range is (typically) a finite and arbitrary set of symbols. The domain is not interpreted as time, but rather as indexes of a sequence. In chapters 5 and 7 through 14, the domain of signals is interpreted as time. For continuous-time signals, the domain is either \mathbb{R} or \mathbb{R}_+ , whereas for discrete-time signals it is either \mathbb{Z} or \mathbb{N}_0 . This interpretation of the domain as time is essential to the notion of frequency that is used throughout the forthcoming chapters.

Chapter 5 and this one provide a bridge between **state-machine models** and such **time-based models** by developing state machine models for time-based systems. In this chapter, we build another bridge between these two families of models by showing that they can often be usefully combined and used *simultaneously* in the *same* model, rather than as alternative views of a system. The resulting models are called **hybrid systems**. They are a powerful tool for understanding real-world systems.

To understand the value of hybrid systems, it is useful to reflect on the relative strengths and weaknesses of time-based models and state-machine models. Chapter 5 demonstrates that state-machine models are more general by showing how they can be used to describe time-based models. Since they are more general, why not just always use state-machine models? The methods of state-machine models, such as composition by forming a product of the state spaces and **simulation** do not yield the depth of understanding that we will get in the subsequent chapters from looking at frequency response. Why not always use frequency response? Frequency response is a rather specialized analytical tool. It applies only to LTI systems. Most real-world systems are not LTI, so such powerful analytical tools must be applied with careful caveats about the regime of operation over which they do apply.

Consider for example a home audio system. It takes data from a compact disc and converts it into auditory stimulus. Is it LTI? Well, obviously not, since its system function changes rather drastically when you turn it on and off. The acts of turning it on and off, however, seem to match well the state transitions of a state machine. Can we come up with a model where there is a state machine with two states, “on” and “off,” and associated with each state there is an LTI system that describes the behavior of the system in the corresponding mode of operation? Indeed we can. Such a model is called a hybrid system.

In order to get state machine models to coexist with time-based models, we need to interpret state transitions on the time line used for the time-based portion of the system, be it continuous time or discrete time. In the audio system, for example, we need to associate a time with the acts of turning it on or off. The models used in chapters 3 and 4 do not naturally do this, since the signals there are sequences of events. That is, they are functions whose domain is \mathbb{N}_0 , where there is no temporal association with an $n \in \mathbb{N}_0$.

Recall from Chapter 3 that the input and output alphabets of a state machine are required to include a stuttering element, typically denoted *absent*. Whenever the state machine reacts, if its input is the stuttering element, then it does not change state and its output will be the stuttering element. This is key to hybrid system models because it allows us to embed the state machine into a time-based model. At any time where there is no interesting input event, the machine stutters.

A hybrid system combines time-based signals with sequences of events. The time-based signals are of the form $x: T \rightarrow R$, where R is some range (such as \mathbb{R} or \mathbb{C}), and T is either \mathbb{R} , \mathbb{R}_+ , \mathbb{Z} , or \mathbb{N}_0 , depending on whether the time domain is discrete or continuous and whether the model includes a time origin. In chapters 3 and 4, the event signals had the form $u: \mathbb{N}_0 \rightarrow Symbols$, where the set *Symbols* has a stuttering element. For a hybrid system, however, these have to share a common time base with the time-based signals, so they have the form $u: T \rightarrow Symbols$. Thus, events occur in time. Typically, for most $t \in T$, $u(t) = absent$, the stuttering element. The non-stuttering element is used only at those discrete values of time where an event occurs.

6.1 Mixed models

A state machine model becomes a time-based model if it reacts at all times in the time base T . This means that state machines and time-based models can interact as peers, sending time-based signals to one another.

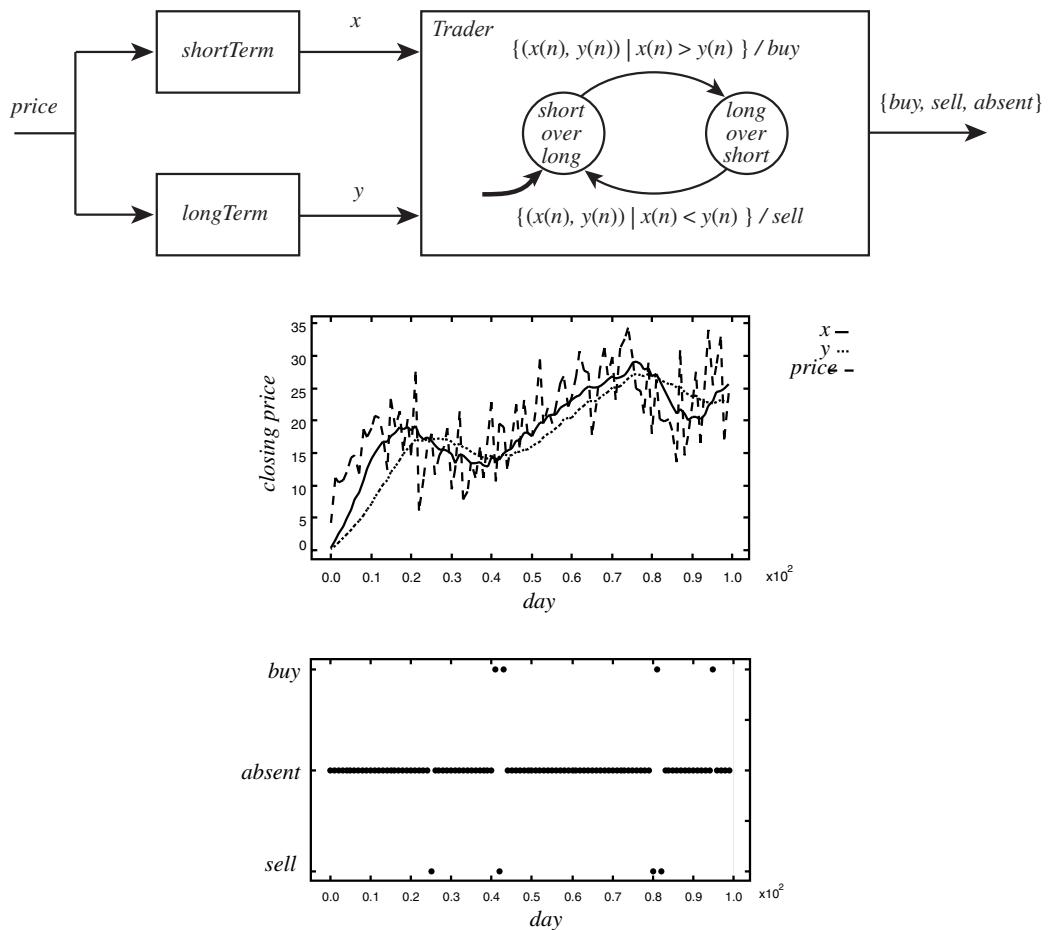


Figure 6.1: An implementation of the classical moving average cross-over method for trading stocks.

Example 6.1: Moving averages are popular on Wall Street for detecting trends in stock prices. But in using them, a key question arises: how long should the moving average be? A short-term moving average might detect short-term trends, while a long-term moving average might detect long term trends. A classical method combines the two and compares them to generate buy and sell signals. If the short-term trend is more sharply upward than the long term trend, a buy signal is generated. If the short term trend is more sharply downward than the long term trend, a sell signal is generated.

A system implementing this **moving average cross-over method** is shown in Figure 6.1. The input is the discrete-time signal $price: \mathbb{Z} \rightarrow \mathbb{R}$ representing the closing price of a stock each day. The LTI systems $shortTerm$ and $longTerm$ are both moving average systems, but $shortTerm$ averages fewer successive inputs than $longTerm$. The outputs of these systems are the discrete-time signals x and y . The finite state machine reacts on each sample from these signals. It begins in the state $short over long$. The transition out of this state has the guard

$$\{(x(n), y(n)) \mid x(n) > y(n)\}.$$

When this transition is taken, a *buy* signal is generated. The sell signal is generated similarly. The plots below show the buy and sell signals generated by a (synthetic) sequence of stock prices.

This example illustrates a simple form of technical stock trading. In this extreme form, it has the controversial feature that it ignores the fundamentals of the company whose stock is being traded. It is using the stock price alone as the indicator of worth. In fact, much more sophisticated signal processing methods are used by technical stock traders, and they often do take as inputs other quantifiers of company worth, such as reported revenues and profits.

6.2 Modal models

In the previous section, time-based systems are combined with state machines as peers. A richer interaction is possible with a hierarchical combination. The general structure of a

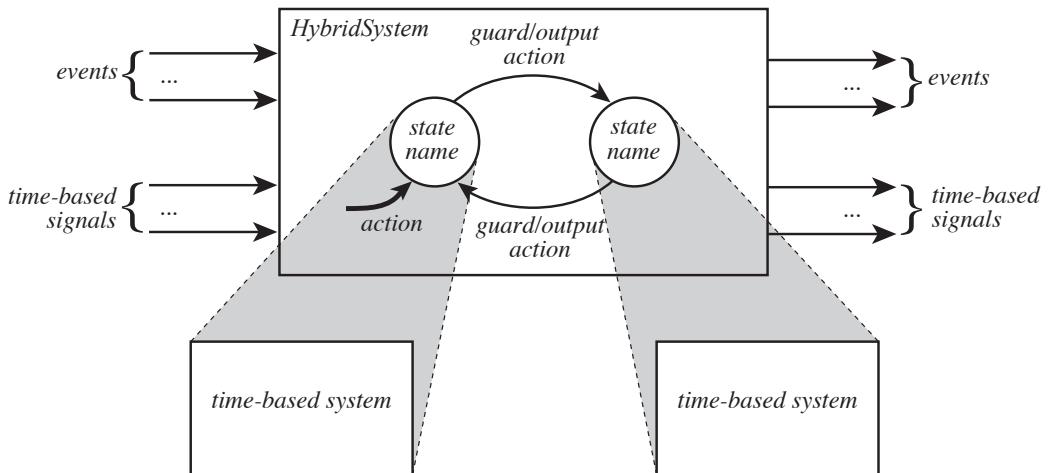


Figure 6.2: Notation for hybrid systems.

hierarchical hybrid system model is shown in figure 6.2. In that figure, there is a two-state finite state machine. There are some changes to the notation, however, from what was used in chapters 3 and 4.

First, notice that the inputs and outputs include both event signals and time-based signals. Second, notice that each state of the state machine is associated with a time-based system, called the **refinement** of the state. The refinement of a state gives the time-based behavior of *HybridSystem* while the machine is in that state. Thus, the states of the state machine define **modes** of operation of the system, where the behavior in a given mode is given by the refinement. A hybrid system is sometimes called a **modal model** for this reason. The refinement has access to all the inputs of *HybridSystem*, and produces the time-based output signals of *HybridSystem* while the machine is in its mode.

Note that the term “state” for such a hybrid system can become confusing. The state machine has states, but so do the refinement systems (unless they are memoryless). When there is any possibility of confusion we explicitly refer to the states of the machine as **modes**, and we refer to the states of the refinement as **refinement states**. The (complete) state of the hybrid system is a pair (m, s) where m is the mode and s is the state of the time-based refinement system associated with mode m .

Another difference from the notation used in chapters 3 and 4 is that state transitions in the machine have, in addition to the usual guard and output notations, an **action**. The action will typically set the initial refinement state of the time-based system in the destination mode.

The guards are, as usual, sets. However, we need for the guards to be rich enough that a transition can be triggered by a particular value of a refinement state or by a value of a time-based input. Thus, the elements of the guards are tuples containing values of input events, time-based signals, and the refinement states. In the state machines in chapters 3 and 4, the elements of the guards only contained values of input events. For hybrid systems, we add time-based signals and refinement states.

Example 6.2: Overload of an electronic system might be modeled by a state transition that is triggered by the magnitude of the current refinement state exceeding some threshold.

On the other hand, when the system is in some mode, the refinement state is only affected by the time-based inputs. It is not affected by the event inputs. This keeps the time-based models simple, so that they don't have to deal with stuttering inputs.

Correspondingly, the time-based outputs are generated by the refinement, and hence need not be mentioned after the slash on the transitions.

The state machine may react at any time in the time base T . The mode in which it is before this reaction is called the **current mode**. It will take a discrete state transition and switch to the **destination mode** if the input values and the refinement state at that time match a guard. If it does not take a discrete state transition, then the state machine stutters. In either case, the refinement of the current mode also reacts to the time-based inputs, changes its state and produces outputs.

Example 6.3: Many high-end audio systems offer “digital signal processing.” Such a system typically has an embedded computer (a digital signal processor or DSP, see box on page 402). This computer is used to process the audio signal in various ways, for example to add reverberation or to perform frequency selective filtering. A particularly simple function that might be performed is **loudness** compensation, something offered by all but the cheapest audio systems.

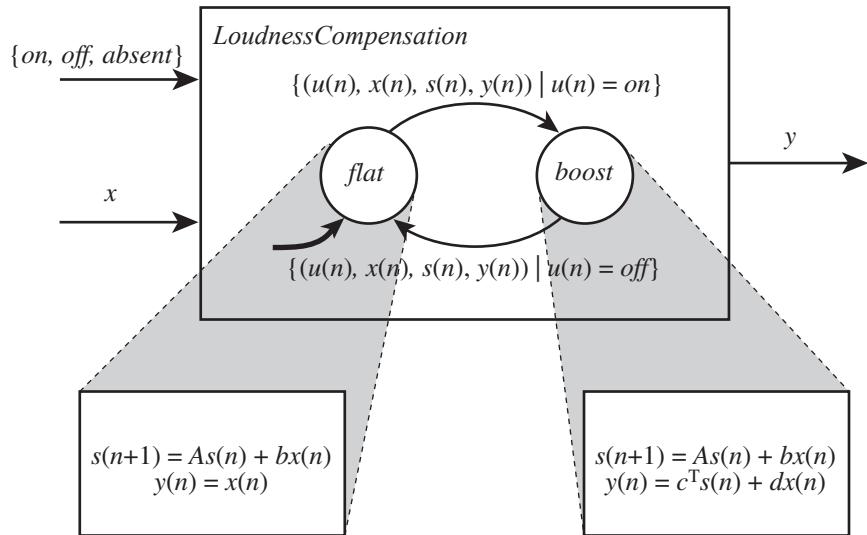


Figure 6.3: This system implements loudness compensation, described in example 6.3

At low volumes, the human ear is less sensitive to low frequencies (base notes) than to high frequencies. Loudness compensation boosts the low frequencies. This is done simply by implementing a filter, which is a [linear time-invariant system](#) that can be described by a state-space model, as in the previous chapter. Thus, there are two modes, one where the low frequencies are boosted (using the filter), and one where they are not.

A simple realization of loudness compensation offers a switch on a control panel to turn on and off the compensation. Figure 6.3 shows a hybrid system that reacts to input events from this switch to select from among two modes. The upper input is simply an event indicating the position of the control switch when it is thrown. The lower input x is a discrete-time signal, probably sampled at 44,100 samples/second, the CD rate. The *LoudnessCompensation* hybrid system has two modes. In the *flat* mode, the output y is simply set equal to the input x . That is, if $T_{flat} \subset \mathbb{Z}$ is the time indexes during which the machine is in the *flat* mode, then

$$\forall n \in T_{flat}, \quad y(n) = x(n).$$

This (obviously) does not boost low frequencies, since the output is equal to the input.

When the *on* event occurs, the machine transitions to the *boost* mode, where the filter is applied to the input x . This is done using the state update and output equations

$$\begin{aligned} \forall n \in T_{boost}, \quad s(n+1) &= As(n) + bx(n) \\ y(n) &= c^T s(n) + dx(n), \end{aligned}$$

where A, b, c, d are chosen to boost the low frequencies (how to do that is explained in Chapter 9).

Note that in the *flat* mode, even though the output equation does not depend on the state, the state update equation is still applied. This ensures that when switching between states, no glitches are heard in the audio signal. The state of the *boost* refinement is maintained even when the mode is *flat*.

This loudness compensator is not very sophisticated. A more sophisticated version would have a set of compensation filters and would select among them depending on the volume level. This is explored in Exercise 1.

We consider a sequence of special cases of hybrid systems. Although the next few examples are all continuous-time models, it is easy to construct similar discrete-time models.

6.3 Timed automata

Timed automata are the simplest continuous-time hybrid systems. They are modal models where the time-based refinements have very simple dynamics; all they do is measure the passage of time. Such refinements are called **clocks**. The resulting models are finite state machines (automata) with time. Note that although all the examples in this section use continuous time, discrete-time versions are very similar.

A clock is modeled by a first-order differential equation,

$$\forall t \in T_m, \quad \dot{s}(t) = a,$$

where $s: \mathbb{R} \rightarrow \mathbb{R}$ is a function, $s(t)$ is the value of the clock at time t , and $T_m \subset T$ is the subset of time during which the hybrid system is in mode m . The rate of the clock, a , is a constant while the system is in this mode.

Example 6.4: Suppose we want to produce a sequence of output events called *tick* with the time between two consecutive *ticks* alternating between 1 and 2 seconds. That is, we want to produce a *tick* at times $1, 3, 4, 6, 7, 9, \dots$.

A hybrid system *tickGenerator* that does this is illustrated in Figure 6.4. There are two modes labeled *mode 1* and *mode 2*. The refinement state in each mode is the value of a clock at time t , denoted by $s \in \mathbb{R}$. So at any time t the state of *tickGenerator* is the pair $(\text{mode}(t), s(t))$. The output is the event signal v and the time-based signal s . There is no input.

In both modes, s evolves according to the differential equation $\dot{s}(t) = 1$, where $\dot{s}(t)$ is the derivative of s with respect to time evaluated at some time t . Thus, s simply measures the passage of time, with its value rising 1 second for every second of elapsed time.

The behavior of the system is shown in Figure 6.5. At time 0, as indicated by the bold arrow in Figure 6.4, the system initially enters *mode 1*. The bold arrow has an action, “ $s(0) := 0$,” which sets $s(0)$ to 0. The notation “ $:=$ ” is used instead of “ $=$ ” to emphasize that this is an **assignment**, not an assertion (see Section A.1.1).

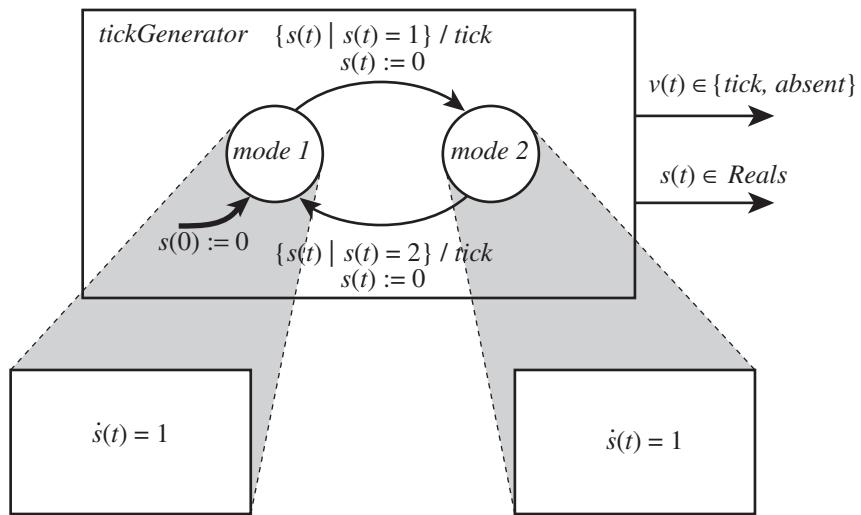


Figure 6.4: This hybrid system generates *tick* at time intervals alternating between 1 and 2 seconds. It is a timed automaton.

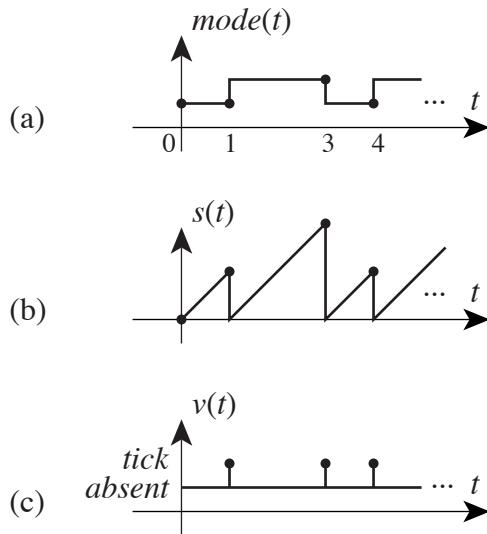


Figure 6.5: (a) The modes of the hybrid system of Figure 6.4, (b) the refinement state s , and (c) the discrete event output v .

In this example, there is no input, so a guard is a subset of the possible values (\mathbb{R}) of the refinement states. The guard on the transition from *mode 1* to *mode 2* is

$$\{s(t) \mid s(t) = 1\},$$

which is satisfied one time unit after beginning. For all $t \in [0, 1]$, $s(t) = t$. At time $t = 1$, this guard is satisfied, the transition is taken, and the output event $v(1) = \text{tick}$ is produced. For all $t \in [0, 1)$, $v(t)$ has value *absent*.

This transition also has an action, “ $s(t) := 0$,” which resets s to zero. This gives the initial condition for the refinement system of the destination mode. In our definition, at time $t = 1$, $s(t) = 1$, even though the action seems to contradict this. This is emphasized in Figure 6.5 by showing with a bold dot the value of s at each discontinuity. The action $s(t) := 0$ is merely providing the initial conditions for the refinement of the destination mode. But the destination mode is not active until $t > 1$, so the action is setting $s(1+)$ to 0, where $1+$ denotes a time infinitesimally larger than 1.

For $t \in (1, 3]$, the system remains in *mode 2*, evolving according to the differential equation

$$\begin{aligned}\dot{s}(t) &= 1, \\ s(1) &= 0.\end{aligned}$$

So for $1 < t \leq 3$,

$$s(t) = s(1) + \int_1^t 1 dt = t - 1.$$

At time $t = 3$, the guard on the arc from *mode 2* to *mode 1* is satisfied, so the transition is taken. The output event *tick* is again produced, and s is reset to 0 again.

Notice in Figure 6.5 that the output v is *absent* for all but a few discrete values of $t \in \mathbb{R}$. This signal is called a **discrete event** signal for this reason. Of course, this signal can also be reinterpreted as a sequence of *tick* events with an arbitrary number of stuttering events in between. That signal could therefore be supplied as input to an ordinary state machine, enabling compositions of ordinary state machines with hybrid systems.

Also notice in Figure 6.5 that the hybrid system evolves in alternating phases: there is a **time-passage phase** in which the system stays in the same mode and its refinement state changes with the passage of time; this is followed by an instantaneous **discrete-event phase** in which a mode transition occurs, an output event is produced, and the refinement state in the destination mode is initialized. In the figure, the time-passage phases are $(0, 1], (1, 3], (3, 4], \dots$ and the discrete-event phases occur at $1, 3, 4, \dots$.

Transitions between modes have actions associated with them. Sometimes, it is useful to have transitions from one mode back to itself, just so that the action can be realized. This is illustrated in the next example.

Example 6.5: Figure 6.6 shows a hybrid system representation of the 60-minute parking meter considered in Chapter 3. In the version in Figure 3.6, the states of a state machine are used to measure the passage of time by counting ticks provided by the environment. In the hybrid version of figure 6.6, the passage of time is explicitly modeled by first-order differential equations.

There are two modes, *expired* and *safe*, and the refinement state at time t is $s(t) \in \mathbb{R}$. At time $t = 0$, the initial mode is *expired*, and $s(0) = 0$. In the *expired* mode, s

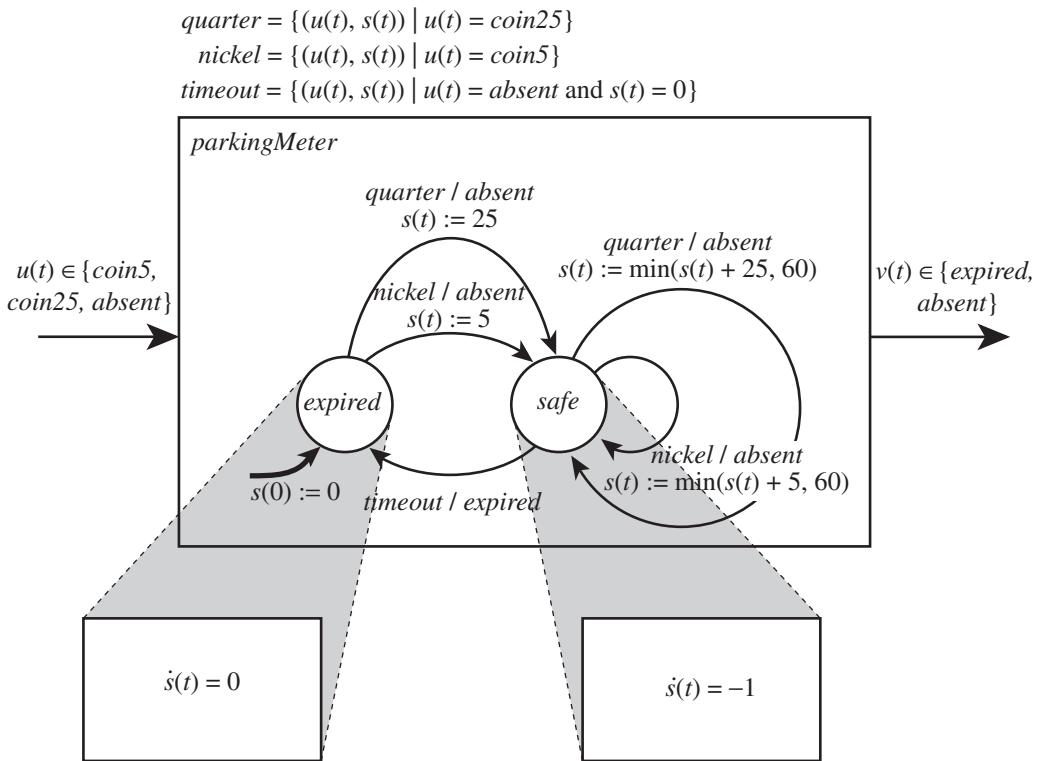


Figure 6.6: A hybrid system representation of a 60-minute parking meter.

remains at 0. The input events *coin5* and *coin25* cause one of two transitions from *expired* to *safe* to be taken. These transitions have guards that are named *nickel* and *quarter* and are defined by

$$\textit{nickel} = \{(u(t), s(t)) \mid u(t) = \textit{coin5}\}$$

$$\textit{quarter} = \{(u(t), s(t)) \mid u(t) = \textit{coin25}\}.$$

Using names for these guards in the figure makes it more readable. It would be cluttered if the guards were directly noted on the transitions.

The transitions from *expired* to *safe* produce *absent*. The actions on the transitions change the value of s to 5 and 25, depending on whether *coin5* or *coin25* is received.

In the *safe* mode, the refinement state decreases according to the differential equation of the clock,

$$\forall t \in T_{\textit{safe}}, \quad \dot{s}(t) = -1.$$

There are three possible outgoing transitions from this mode. If the input event *coin5* or *coin25* occurs, then one of two self-loop transitions is taken, no output is produced, and the associated action increments s by setting as $s(t) := \min(s(t) + 5, 60)$ or $s(t) := \min(s(t) + 25, 60)$. But if the guard *timeout* is satisfied, where

$$\textit{timeout} = \{(u(t), s(t)) \mid u(t) = \textit{absent} \text{ and } s(t) = 0\}$$

then there is a transition to *expired* and the output event *expired* is produced. Note that this guard requires that $u(t) = \textit{absent}$, so that if the parking meter expires at the very moment that a coin arrives, then the coin is properly registered.

In this system, the refinement state evolves differently in the two modes; in *expired*, s remains at 0 (since $\dot{s}(t) = 0$), but in *safe*, s obeys the differential equation $\dot{s}(t) = -1$.

In the previous example, the transitions from *safe* back to *safe* were used for their actions, which react to input events by setting the values of refinement states. This gives a clean way to model discontinuities in continuous-time signals, because the state trajectory is a continuous-time signal. A more extreme example is given next, where there is only one mode.

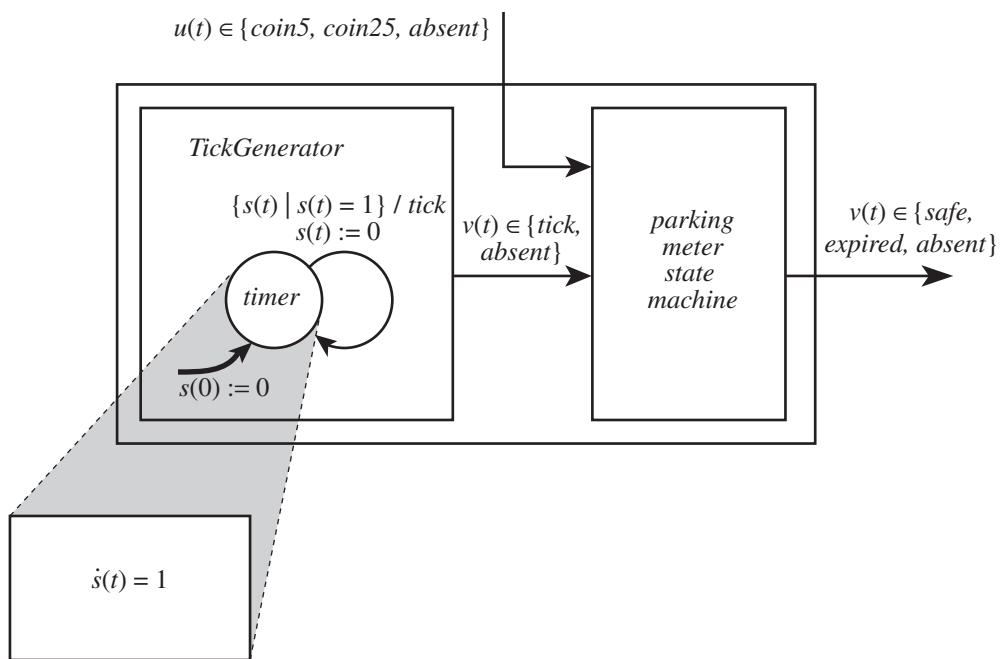


Figure 6.7: The 60-minute parking meter as a cascade composition of *tickGenerator* and an ordinary finite state machine.

Example 6.6: We could also implement the parking meter as a cascade composition using a timed automaton, *TickGenerator*, with only one mode, *timer*, and which produces a *tick* event every minute. This event serves as an input to the parking meter finite state machine of Figure 3.6. The cascade composition is shown in Figure 6.7. The parking meter machine also accepts an additional (product-form) input event from $\{coin5, coin25\}$, and produces the output event *safe* or *expired*. The difference between Figure 3.6 and 6.7 is that in the former *tick* was an input event from the environment, whereas in the latter we explicitly construct a component, namely *TickGenerator*, which produces a *tick* every minute.

Timed automata are commonly used in modeling **communication protocols**, the logic used to achieve communication over a network. The following example models the transport layer of a sender of data on the internet.

Example 6.7: Consider how an application such as an e-mail program sends a file over a communication network like the internet. There are two host computers called the *Sender* and *Receiver*. The file that *Sender* wants to send to *Receiver* is first divided into a sequence of finite bit strings called **packets**. For the purposes of this example, we do not care what is contained by the packets, so we consider *packet* to be an event. We are interested in the fact that it needs to be transmitted, not in its contents.

The problem we address in this example is that the network is unreliable. Packets that are launched into it may never emerge. If the network is congested, packets get dropped. We will design a protocol whereby the sender of a packet waits a certain amount of time for an acknowledgement. If it does not receive the acknowledgement in that time, then it retransmits the packet. This is an ideal application for timed automata.

The upper diagram in Figure 6.8 shows the structure of the communication system. Everything begins when the sender produces a *packet* event. The *SenderProtocol* system reacts by producing a *transmit* event, which instructs its **network interface card** or **NIC** to launch the packet into the internet. The NIC is the physical device (such as the ethernet card in your desktop computer) that converts the packet

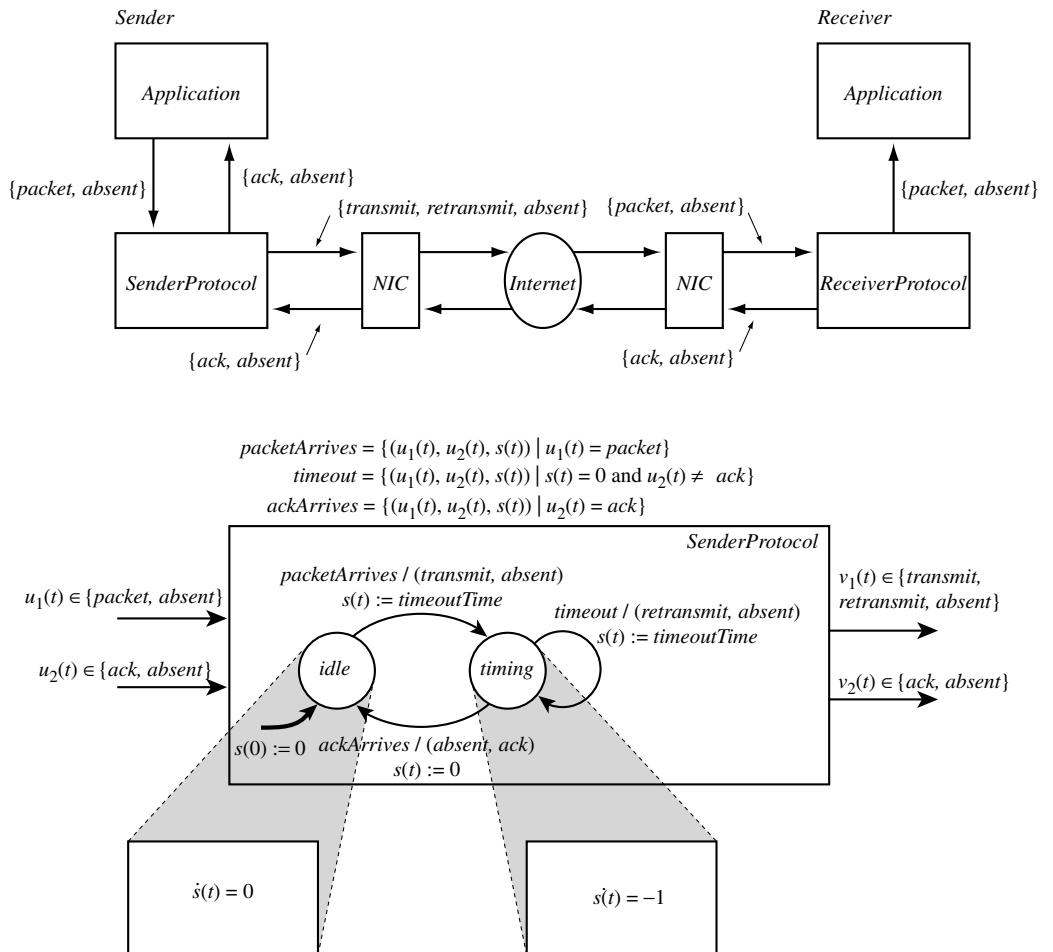


Figure 6.8: The top diagram describes the structure of a communication system. The lower diagram is the timed automaton that implements the sender protocol.

into the appropriate electrical signal that is transmitted through the network. The internet transfers this signal to the NIC of the receiver. That NIC converts the signal back into the packet and forwards it to the *ReceiverProtocol* component. The *ReceiverProtocol* in turn forwards the packet to the e-mail application in the *Receiver* and simultaneously sends an acknowledgement packet, called *ack*, to its NIC.

The receiver's NIC sends the *ack* packet back through the network to the *Sender*. The sender's NIC receives this packet and forwards an *ack* to the *SenderProtocol*. The *SenderProtocol* notifies the application that the packet was indeed delivered. The application can now send the next *packet*, and the cycle is repeated until the entire file is delivered.

In reality, the network may drop the packet so that it is not delivered to the receiver, who therefore will not send the corresponding *ack*. The *SenderProtocol* system is designed to take care of this contingency. It is a timed automaton with two modes, *idle* and *timing*, and one refinement state s corresponding to a clock. Initially it is in the *idle* mode and $s(0) = 0$. In the idle mode, $\dot{s}(t) = 0$, so the refinement state remains at zero. When *SenderProtocol* receives a *packet* it makes a transition to the *timing* mode, sends the output event *transmit* to its NIC, and resets s to a timeout value *timeoutTime*.

In the *timing* mode, there are two possible transitions. In the normal case, the input event *ack* is received before the guard $\{s(t) == 0\}$ is satisfied. The transition to mode *idle* is taken, the output event *ack* is sent to the application, and the clock value $s(t)$ is reset to 0. The system waits for another *packet* from the application. In the second case, the guard $\{s(t) == 0\}$ is satisfied (before event *ack*), and the self-loop transition is taken. In this case, the output event *retransmit* is sent to the NIC, and $s(t)$ is reset to *timeoutTime*.

Notice a feature of this design that may not be expected. If a packet arrives while the machine is in mode *timing*, the packet is ignored. What happens if a packet happens to arrive simultaneously with an *ack* while the machine is mode *timing*?

Exercise 10 asks you to construct the corresponding receiver protocol, which is simpler.

In summary, the *SenderProtocol* machine repeatedly retransmits a packet every *timeoutTime* seconds until it receives an *ack*. This reveals a flaw in the protocol. If the network is for some reason unable ever to successfully transmit a packet to the receiver, the machine will continue retransmission for ever. A better protocol

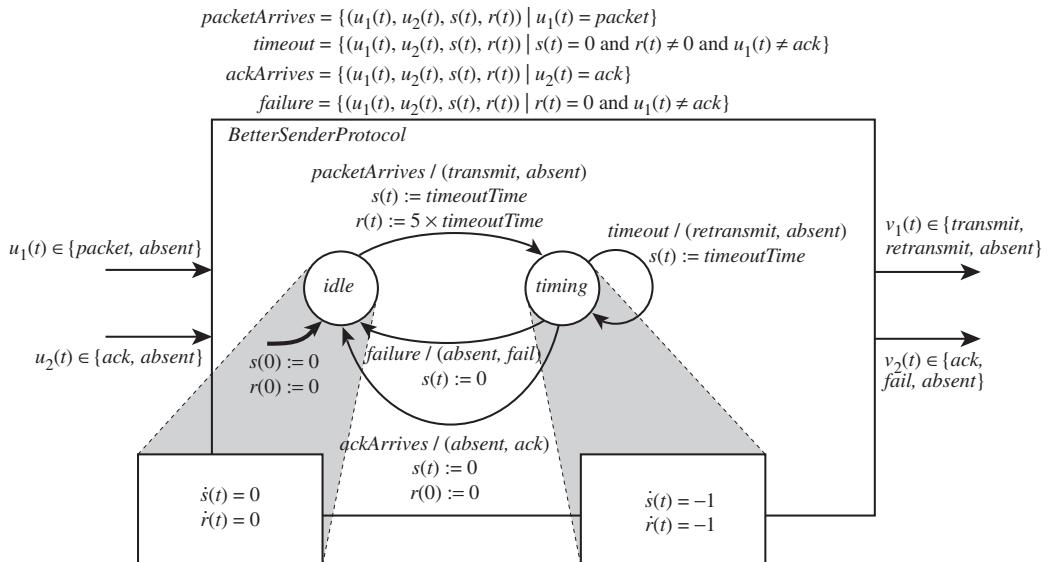


Figure 6.9: An improved sender protocol with two clocks, one of which detects a failed connection.

would retransmit a packet a certain number of times, say five times, and if it is unsuccessful, it would return to *idle* and send a message *connectionFailed* to the application. The hybrid system of Figure 6.9 incorporates this feature by adding another clock whose value is $r(t)$.

6.4 More interesting dynamics

In timed automata, all that happens in the time-based refinement systems is that time passes. Hybrid systems, however, are much more interesting when the behavior of the refinements is more complex.

Example 6.8: Consider the physical system depicted in Figure 6.11. Two sticky round masses are attached to springs. The springs are compressed or extended and

Probing Further: Internet protocols

Communication between two computers, *Sender* and *Receiver*, each connected to the internet, is coordinated by a set of **protocols**. Each protocol can be modeled by a pair of hybrid systems, one in the *Sender* and the other in the *Receiver*. These protocols are arranged in a **protocol stack**, as shown in figure 6.10. Each layer in the stack performs a certain function, and interacts with the corresponding layer in the other computer. The physical layer converts a bit stream into an electrical signal and vice versa and transfers the signal over one link of the network.

The network itself consists of many physical links connected by routers. The routers act as computers, but are missing the higher levels of the protocol stack. The physical layer transports bits over wires, optical fibers, or radio links. The **medium access layer** manages contention for the physical communication resource, preventing collisions among multiple users of the link. The **network layer** routes packets appropriately through the network. The **transport layer** ensures that the end-to-end transfer of packets is reliable, even if the network layer is unreliable. The **application layer** converts whatever information is to be sent (such as an image or e-mail) into packets and then reassembles the packets into the appropriate information.

This layered approach provides an *abstraction* mechanism. Each layer conceptually interacts with the corresponding layer at a remote machine, as suggested by the dotted lines in figure 6.10. Each layer provides a “service” to the layer above it. For example, the medium access layer offers as a service the transfer of a packet over a single link. The network layer uses this service to transfer a packet over a sequence of links between the end hosts. This abstraction mechanism permits the design of a single layer, say the transport layer, assuming the service of the network layer, without regard to the layers below the network layer. The hybrid system in example 6.7, for instance, models only the transport layer.

The transport layer in an end-to-end protocol, so it is implemented only at the end points in the connection, as shown in Figure 6.10. The routers in the network only need to implement the lower layers.

Each protocol layer is modeled as a pair of hybrid systems. Typically, these are timed automata, since coordination between end hosts is achieved via several clocks as in example 6.7. When a guard associated with a clock is satisfied, this signals some contingency in the communication, just as the timeout of the clock in Figure 6.8 signals that a packet may be lost.

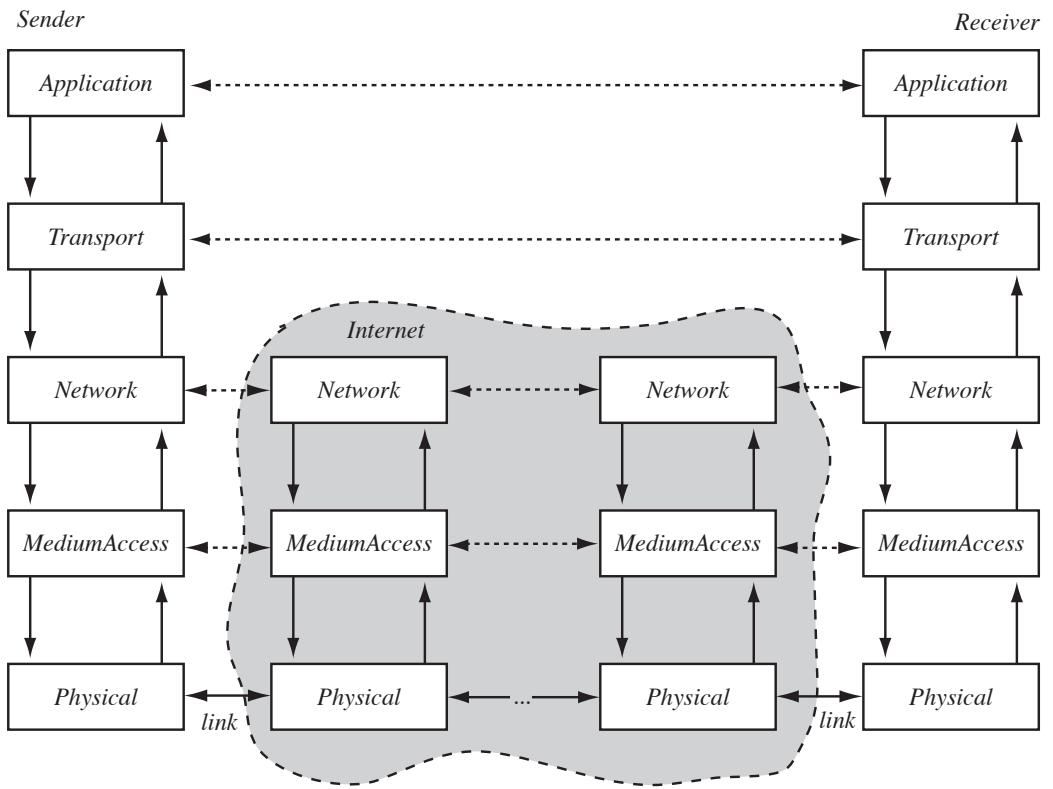


Figure 6.10: Network protocols are organized in a stack. Each protocol interacts with the corresponding layer in a remote computer. The dotted lines indicate conceptual interactions, whereas the solid lines indicate physical interactions.

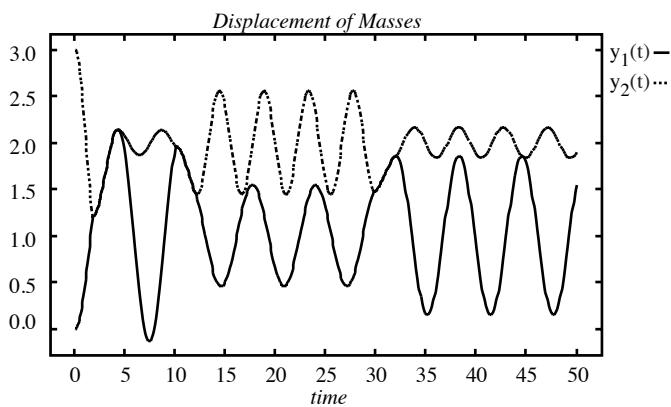
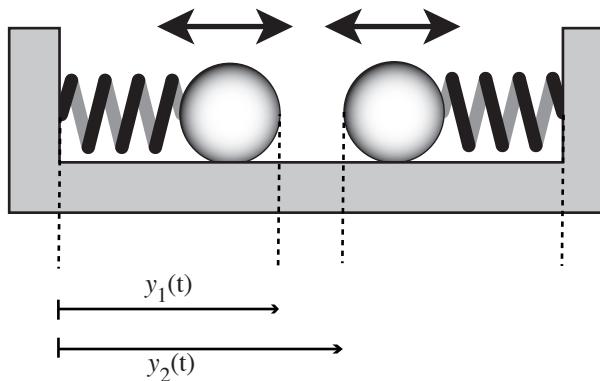


Figure 6.11: Sticky masses system considered in example 6.8.

$$\begin{aligned}
 stick &= \{(y_1(t), \dot{y}_1(t), y_2(t), \dot{y}_2(t)) \mid y_1(t) == y_2(t)\} \\
 unstick &= \{(y(t), \dot{y}(t)) \mid (k_1 - k_2)y(t) + k_2 p_2 - k_1 p_1 > stickiness\}
 \end{aligned}$$

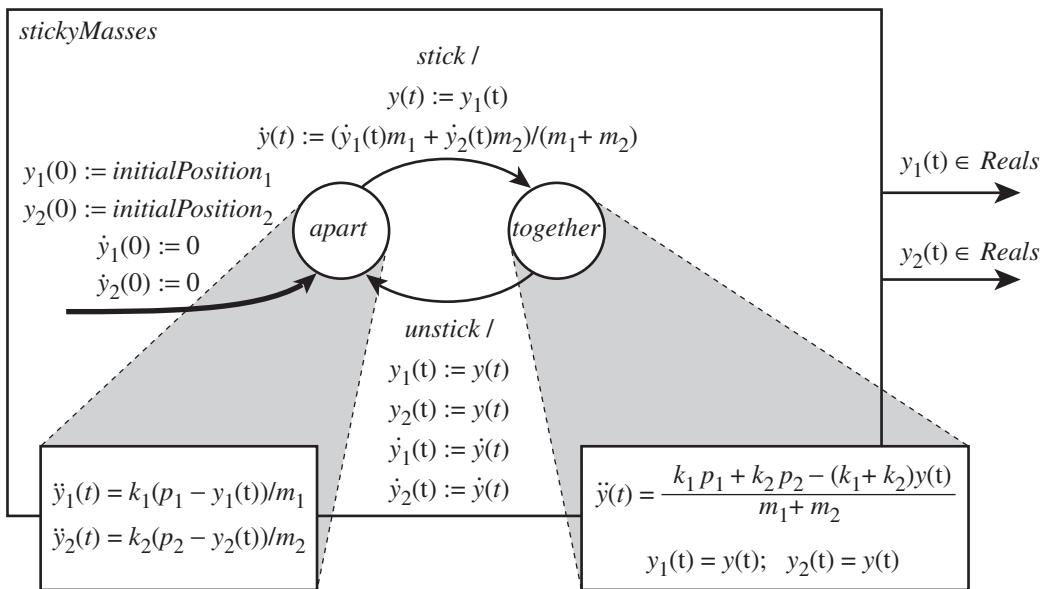


Figure 6.12: Hybrid system model for the sticky masses system considered in example 6.8.

then released. The masses oscillate on a frictionless table. If they collide, they stick together and oscillate together. After some time, the stickiness decays, and masses pull apart again.

A plot of the displacement of the two masses as a function of time is shown in the figure. Both springs begin compressed, so the masses begin moving towards one another. They almost immediately collide, and then oscillate together for a brief period until they pull apart. In this plot, they collide two more times, and almost collide a third time.

The physics of this problem is quite simple if we assume idealized springs. Let $y_1(t)$ denote the right edge of the left mass at time t , and $y_2(t)$ denote the left edge of the right mass at time t , as shown in Figure 6.11. Let p_1 and p_2 denote the neutral positions of the two masses, i.e. when the springs are neither extended nor compressed, so the force is zero. For an ideal spring, the force at time t on the mass is proportional to $p_1 - y_1(t)$ (for the left mass) and $p_2 - y_2(t)$ (for the right mass). The force is positive to the right and negative to the left.

Let the spring constants be k_1 and k_2 , respectively. Then the force on the left spring is $k_1(p_1 - y_1(t))$, and the force on the right spring is $k_2(p_2 - y_2(t))$. Let the masses be m_1 and m_2 respectively. Now we can use Newton's law, which relates force, mass, and acceleration,

$$f = ma.$$

The acceleration is the second derivative of the position with respect to time, which we write $\ddot{y}_1(t)$ and $\ddot{y}_2(t)$ respectively. Thus, as long as the masses are separate, their dynamics are given by

$$\ddot{y}_1(t) = k_1(p_1 - y_1(t))/m_1 \quad (6.1)$$

$$\ddot{y}_2(t) = k_2(p_2 - y_2(t))/m_2. \quad (6.2)$$

When the masses collide, however, the situation changes. With the masses stuck together, they behave as a single object with mass $m_1 + m_2$. This single object is pulled in opposite directions by two springs. While the masses are stuck together, $y_1(t) = y_2(t)$. Let

$$y(t) = y_1(t) = y_2(t).$$

The dynamics are then given by

$$\ddot{y}(t) = \frac{k_1 p_1 + k_2 p_2 - (k_1 + k_2)y(t)}{m_1 + m_2}. \quad (6.3)$$

It is easy to see now how to construct a hybrid systems model for this physical system. The model is shown in Figure 6.12. It has two modes, *apart* and *together*. The refinement of the *apart* mode is given by (6.1) and (6.2), while the refinement of the *together* mode is given by (6.3).

We still have work to do, however, to label the transitions. The initial transition is shown in Figure 6.12 entering the *apart* mode. Thus, we are assuming the masses begin apart. Moreover, this transition is labeled with an action that sets the initial refinement state. Intuitively, the initial state of the masses is their positions and their initial velocities. In fact, we can define the refinement state to be

$$s(t) = \begin{bmatrix} y_1(t) \\ \dot{y}_1(t) \\ y_2(t) \\ \dot{y}_2(t) \end{bmatrix}.$$

It is then a simple matter to rewrite (6.1) and (6.2) in the form

$$\dot{s}(t) = g(s(t)) \quad (6.4)$$

for a suitably chosen function g (see Exercise 12).

In Figure 6.12, the initial state has the masses at some specified displacement, and the velocities at zero.

The transition from *apart* to *together* has the guard

$$\text{stick} = \{(y_1(t), \dot{y}_1(t), y_2(t), \dot{y}_2(t)) \mid y_1(t) == y_2(t)\}.$$

Thus, when the refinement state of *apart* satisfies this guard, the transition will be taken. No event output is produced, as indicated by the blank after the slash. However, an action is taken to set the initial refinement state of *together*. The refinement state of *together* could be the same $s(t)$ as above, with the additional constraint that $y_1(t) = y_2(t)$ and $\dot{y}_1(t) = \dot{y}_2(t)$, because the masses are stuck together. Or more simply, we could define the state $z(t)$ of *together* to be the position $y(t)$ and velocity $\dot{y}(t)$, where $y(t) = y_1(t) = y_2(t)$,

$$z(t) = \begin{bmatrix} y(t) \\ \dot{y}(t) \end{bmatrix}.$$

The transition from *apart* to *together* sets $y(t)$ equal to $y_1(t)$ (it could equally well have chosen $y_2(t)$, since these are equal). It sets the velocity to conserve momentum. The momentum of the left mass is $\dot{y}_1(t)m_1$, the momentum of the right mass

is $y_2(t)m_2$, and the momentum of the combined masses is $\dot{y}(t)(m_1 + m_2)$. To make these equal, it sets

$$\dot{y}(t) = \frac{y_1(t)m_1 + y_2(t)m_2}{m_1 + m_2}.$$

The transition from *together* to *apart* has the more complicated guard

$$unstick = \{(y(t), \dot{y}(t)) \mid (k_1 - k_2)y(t) + k_2 p_2 - k_1 p_1 > stickiness\}.$$

This guard is satisfied when the right-pulling force on the right mass exceeds the right-pulling force on the left mass by more than the stickiness. The right-pulling force on the right mass is simply

$$f_2(t) = k_2(p_2 - y(t))$$

and the right-pulling force on the left mass is

$$f_1(t) = k_1(p_1 - y(t)).$$

Thus,

$$f_2(t) - f_1(t) = (k_1 - k_2)y(t) + k_2 p_2 - k_1 p_1.$$

When this exceeds the stickiness, then the masses pull apart.

An interesting elaboration on this example, considered in problem 13, modifies the *together* mode so that the stickiness is initialized to a starting value, but then decays according to the differential equation

$$\dot{s}(t) = -as(t)$$

where $s(t)$ is the stickiness at time t , and a is some positive constant. In fact, it is the dynamics of such an elaboration that is plotted in Figure 6.11.

As in example 6.7, it is sometimes useful to have hybrid system models with only one state. The actions on one or more state transitions define the discrete event behavior that combines with the time-based behavior.

Example 6.9: Consider a bouncing ball. At time $t = 0$, the ball is dropped from a height $y(0) = \text{initialHeight}$ meters. It falls freely. At some later time t_1 it hits the ground with a velocity $\dot{y}(t_1) < 0$ m/sec. A *bump* event is produced when the ball hits the ground. The collision is inelastic, and the ball bounces back up with velocity $-a\dot{y}(t_1)$, where a is constant in $(0, 1)$. The ball will then rise to a certain height and fall back to the ground repeatedly.

The behavior of the bouncing ball can be described by the hybrid system of Figure 6.13. There is only one mode, called *free*. When it is not in contact with the ground, we know that the ball follows the second-order differential equation,

$$\ddot{y}(t) = -g, \quad (6.5)$$

where $g = 10$ m/sec² is the acceleration imposed by gravity. We can define the refinement state of the *free* mode to be

$$s(t) = \begin{bmatrix} y(t) \\ \dot{y}(t) \end{bmatrix}$$

with the initial conditions $y(0) = \text{initialHeight}$ and $\dot{y}(0) = 0$. It is then a simple matter to rewrite (6.5) as a first-order differential equation,

$$\dot{s}(t) = f(s(t)) \quad (6.6)$$

for a suitably chosen function f (see Exercise 12).

At the time t_1 when the ball first hits the ground, the guard

$$\text{hit} = \{(y(t), \dot{y}(t)) \mid y(t) = 0\}$$

is satisfied, and the self-loop transition is taken. The output *bump* is produced, and the action $\dot{y}(t) := -a\dot{y}(t)$ assigns $\dot{y}(t_1+) = -a\dot{y}(t_1)$. Here, $\dot{y}(t_1+)$ is the velocity after the bump, and $\dot{y}(t_1)$ is the velocity before the bump. Then (6.5) is followed again until the guard becomes true again.

By integrating (6.5) we get, for all $t \in (0, t_1)$,

$$\begin{aligned} \dot{y}(t) &= -gt, \\ y(t) &= y(0) + \int_0^t \dot{y}(\tau) d\tau = \text{initialHeight} - \frac{1}{2}gt^2. \end{aligned}$$

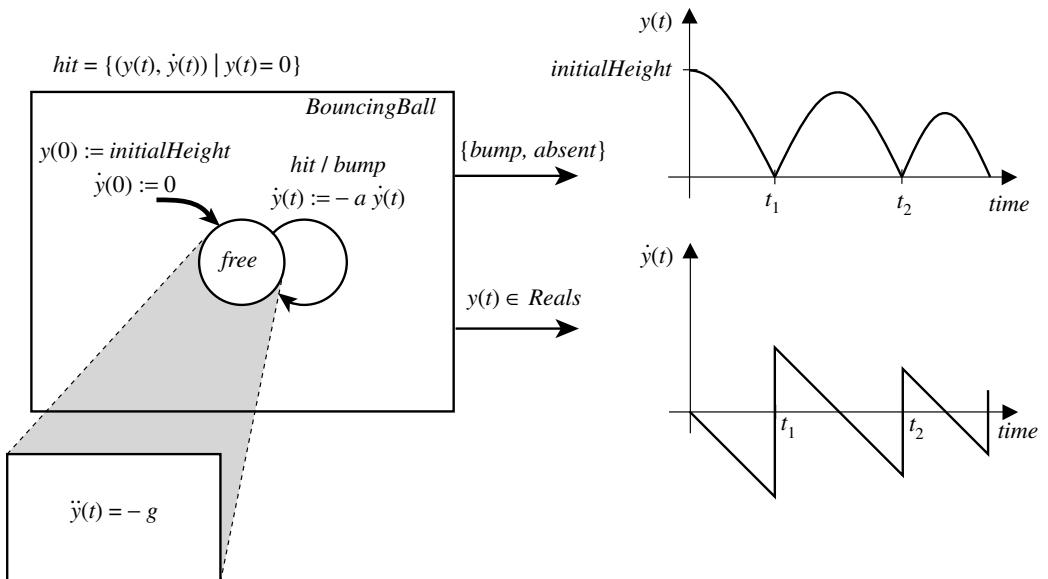


Figure 6.13: The motion of a bouncing ball may be described as a hybrid system with only one mode. The system outputs a *bump* each time the ball hits the ground, and also outputs the position of the ball. The position and velocity are plotted versus time at the right.

So $t_1 > 0$ is determined by $y(t_1) = 0$. It is the solution to the equation

$$initialHeight - \frac{1}{2}gt^2 = 0.$$

Thus,

$$t_1 = \sqrt{2 \frac{initialHeight}{g}}.$$

Figure 6.13 plots the refinement state versus time.

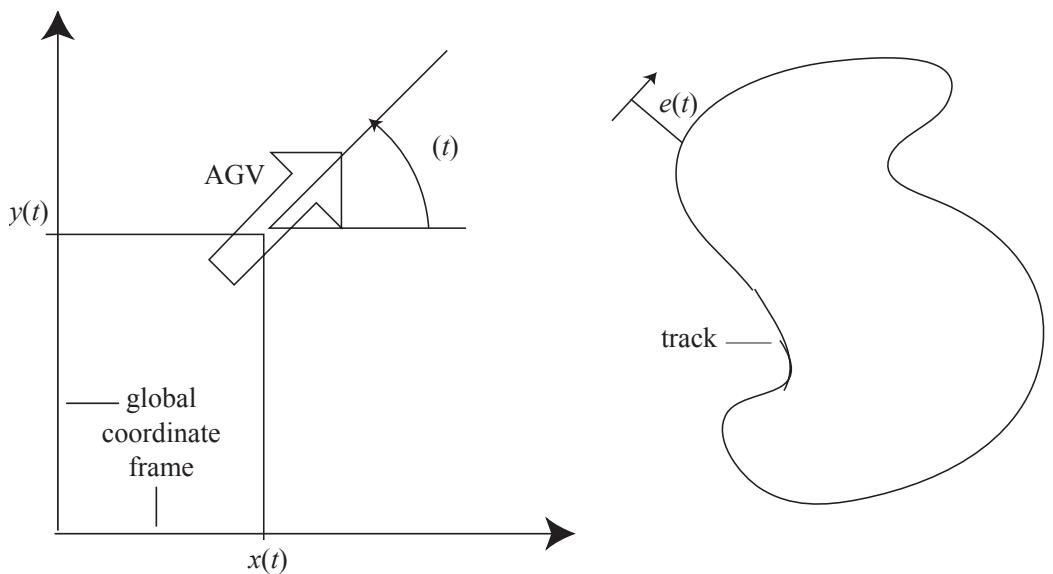


Figure 6.14: Illustration of the automated guided vehicle of example 6.10. The vehicle is shown as a large arrow on the left and as a small arrow on the right. On the right, the vehicle is following a curved painted track, and has deviated from the track by a distance $e(t)$. The coordinates of the vehicle at time t with respect to the global coordinate frame are $(x(t), y(t), \phi(t))$.

6.5 Supervisory control

We introduce supervisory control through a detailed example. A control system involves four components. There is a system called the **plant**—the physical process that is to be controlled; the environment in which the plant operates; the sensors that measure some variables of the plant and the environment; and the controller that determines the mode transition structure and selects the time-based inputs to the plant. The controller has two levels: the supervisory control that determines the mode transition structure, and the ‘low-level’ control that selects the time-based inputs which control the behavior of the refinements. A complete design includes both levels of control as in the following example.

$$goStraight = \{(u(t), x(t), y(t), \phi(t)) \mid u(t) \neq stop, |e(t)| < \varepsilon_1\}$$

$$goRight = \{(u(t), x(t), y(t), \phi(t)) \mid u(t) \neq stop, \varepsilon_2 < e(t)\}$$

$$goLeft = \{(u(t), x(t), y(t), \phi(t)) \mid u(t) \neq stop, -\varepsilon_2 > -e(t)\}$$

$$goStop = \{(u(t), x(t), y(t), \phi(t)) \mid u(t) = stop\}$$

$$goStart = \{(u(t), x(t), y(t), \phi(t)) \mid u(t) = start\}$$

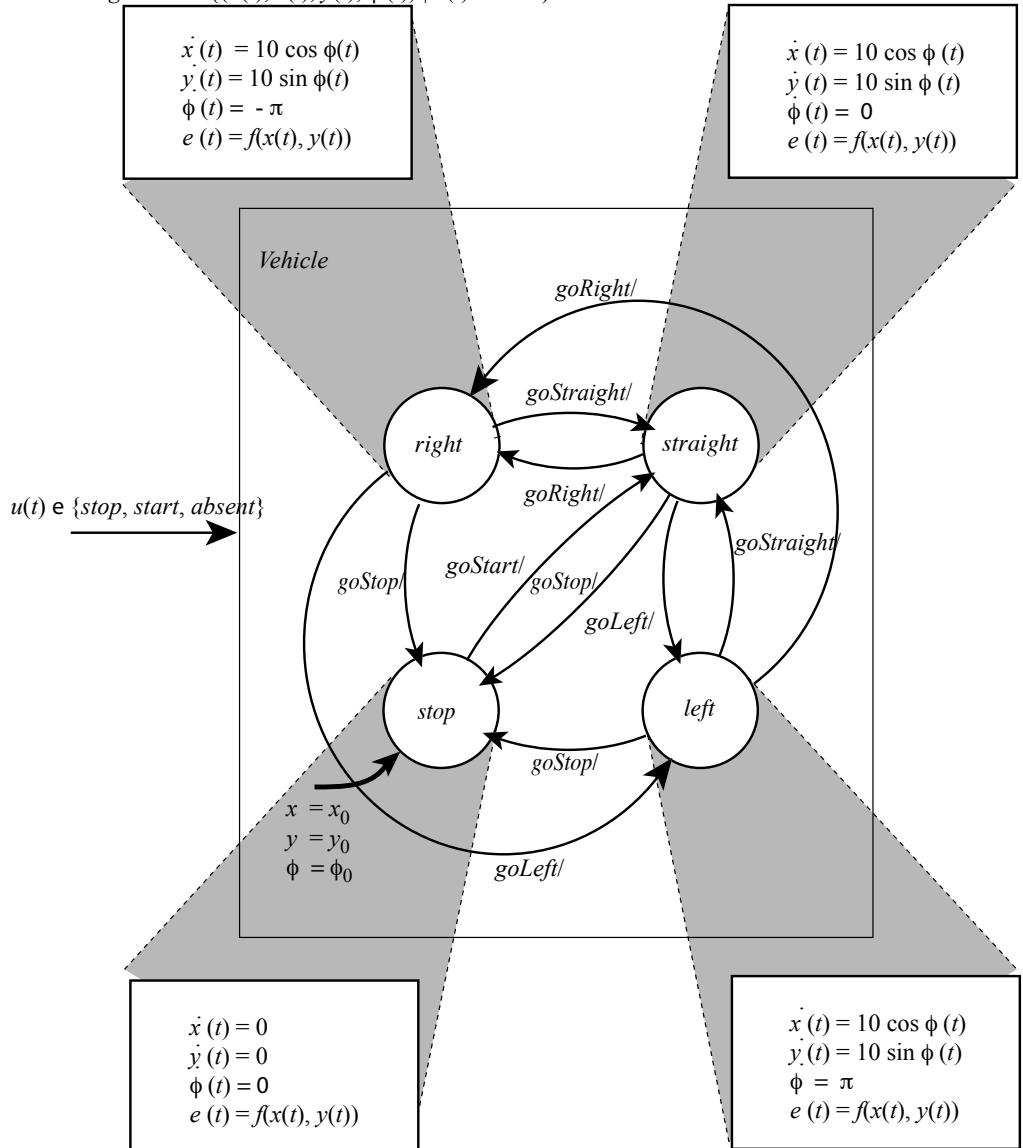


Figure 6.15: The automatic guided vehicle of example 6.10 has four modes: *stop*, *straight*, *left*, *right*.

Example 6.10: The plant is an **automated guided vehicle** or AGV that moves along a closed track painted on a warehouse or factory floor. We will design a controller so that the vehicle closely follows the track.

The vehicle has two degrees of freedom. At any time t , it can move forward along its body axis at speed $u(t)$ with the restriction that $0 \leq u(t) \leq 10$ mph. It can also rotate about its center of gravity with an angular speed $\omega(t)$ restricted to $-\pi \leq \omega(t) \leq \pi$ radians/second. We ignore the inertia of the vehicle.

Let $(x(t), y(t)) \in \mathbb{R}^2$ be the position and $\phi(t) \in [-\pi, \pi]$ the angle (in radians) of the vehicle at time t relative to some fixed coordinate frame, as shown on the left in Figure 6.14. In terms of this coordinate frame, the motion of the vehicle is given by a system of three differential equations,

$$\begin{aligned}\dot{x}(t) &= u(t) \cos \phi(t), \\ \dot{y}(t) &= u(t) \sin \phi(t), \\ \dot{\phi}(t) &= \omega(t).\end{aligned}\tag{6.7}$$

The track and the vehicle are shown on the right of Figure 6.14. Equations (6.7) describe the plant. The environment is the closed painted track. It could be described by an equation, but instead we will use a sensor to detect it.

The two-level controller design is based on a simple idea. The vehicle always moves at its maximum speed of 10 mph. If the vehicle strays too far to the left of the track, the controller steers it towards the right; if it strays too far to the right of the track, the controller steers it towards the left. If the vehicle is close to the track, the controller maintains the vehicle in a straight direction. Thus the controller guides the vehicle in four modes, *left*, *right*, *straight*, and *stop*. In *stop* mode an operator may bring the vehicle to a halt.

The following differential equations govern the AGV's motion in the refinement of the four modes. They describe the low-level controller, i.e. the selection of the time-based inputs in each mode.

straight

$$\begin{aligned}\dot{x}(t) &= 10 \cos \phi(t) \\ \dot{y}(t) &= 10 \sin \phi(t) \\ \dot{\phi}(t) &= 0\end{aligned}$$

left

$$\begin{aligned}\dot{x}(t) &= 10 \cos \phi(t) \\ \dot{y}(t) &= 10 \sin \phi(t) \\ \dot{\phi}(t) &= \pi\end{aligned}$$

right

$$\begin{aligned}\dot{x}(t) &= 10 \cos \phi(t) \\ \dot{y}(t) &= 10 \sin \phi(t) \\ \dot{\phi}(t) &= -\pi\end{aligned}$$

stop

$$\begin{aligned}\dot{x}(t) &= 0 \\ \dot{y}(t) &= 0 \\ \dot{\phi}(t) &= 0\end{aligned}$$

In the *stop* mode, the vehicle is stopped, $x(t), y(t), \phi(t)$ are constant. In the *left* mode, $\phi(t)$ increases at the rate of π radians/second, so from Figure 6.14 we see that the vehicle moves to the left. In the *right* mode, it moves to the right. In the *straight* mode, $\phi(t)$ is constant, and the vehicle moves straight ahead with a constant heading. The refinements of the four modes are shown in the boxes of Figure 6.15.

We design the supervisory control governing transitions between modes in such a way that the vehicle closely follows the track, using a sensor that determines how far the vehicle is to the left or right of the track. We can build such a sensor using photodiodes. Let's suppose the track is painted with a light-reflecting color, whereas the floor is relatively dark. Underneath the AGV we place an array of photodiodes as shown in figure 6.16. The array is perpendicular to the AGV body axis. As the AGV passes over the track, the diode directly above the track generates more current than the other diodes. By comparing the magnitudes of the currents through the different diodes, the sensor gives the displacement $e(t)$ of the center of the array (hence, the center of the AGV) from the track. We adopt the convention that $e(t) < 0$ means that the AGV is to the right of the track and $e(t) > 0$ means it is to the left.

We model the sensor output as a function f of the AGV's position,

$$\forall t, \quad e(t) = f(x(t), y(t)).$$

The function f of course depends on the environment—the track. We now specify the supervisory controller precisely. We select two thresholds, $0 < \varepsilon_1 < \varepsilon_2$, as shown in Figure 6.16. If the magnitude of the displacement is small, $|e(t)| < \varepsilon_1$, we consider that the AGV is close enough to the track, and the AGV can move straight ahead, in *straight* mode. If $0 < \varepsilon_2 < e(t)$ ($e(t)$ is large and positive), the AGV has strayed too far to the left and must be steered to the right, by switching to *right* mode. If $0 > -\varepsilon_2 > e(t)$ ($e(t)$ is large and negative), the AGV has strayed too far to the right and must be steered to the left, by switching to *left* mode. This control logic is captured in the mode transitions of Figure 6.15. The input events are $\{stop, start, absent\}$. By selecting events *stop* and *start* an operator can stop or start the AGV. There is no time-based input. There is no external output. The initial mode is *stop*, and the initial values of its refinement are (x_0, y_0, ϕ_0) .

We analyze how the AGV will move. Figure 6.17 sketches one possible trajectory. Initially the vehicle is within distance ε_1 of the track, so it moves straight. At some later time, the vehicle goes too far to the left, the guard

$$goRight = \{(u(t), x(t), y(t), \phi(t)) \mid u(t) \neq stop, \varepsilon_2 < e(t)\}$$

is satisfied, and there is a mode switch to *right*. After some time, the vehicle is close enough to the track, the guard

$$goStraight = \{(u(t), x(t), y(t), \phi(t)) \mid u(t) \neq stop, |e(t)| < \varepsilon_1\}$$

is satisfied, and there is a mode switch to *straight*. Some time later, the vehicle is too far to the right, the guard

$$goLeft = \{(u(t), x(t), \phi(t)) \mid u(t) \neq stop \mid -\varepsilon_2 > e(t)\}$$

is satisfied, there is a mode switch to *left*, and so on.

The example illustrates the four components of a control system. The plant is described by the differential equations (6.7) that govern the evolution of the refinement state at time t , $(x(t), y(t), \phi(t))$, in terms of the time-based input, $(u(t), \omega(t))$. The second component is the environment—the closed track. The third component is the sensor, whose output at time t , $e(t) = f(x(t), y(t))$, gives the position of the AGV relative to the track. The fourth component is the two-level controller. The supervisory controller comprises the four modes and the guards that determine when to switch between modes. The low-level

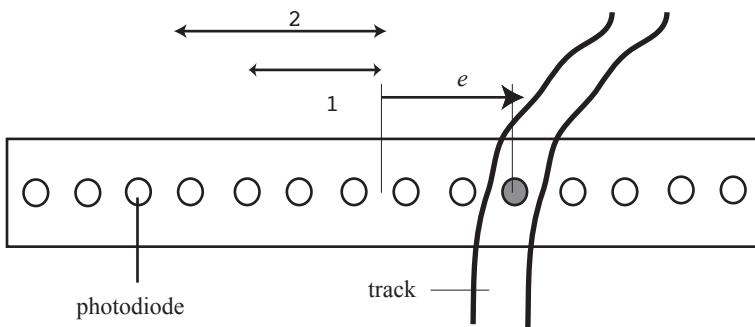


Figure 6.16: An array of photodiodes under the AGV is used to estimate the displacement e of the AGV relative to the track. The photodiode directly above the track generates more current.

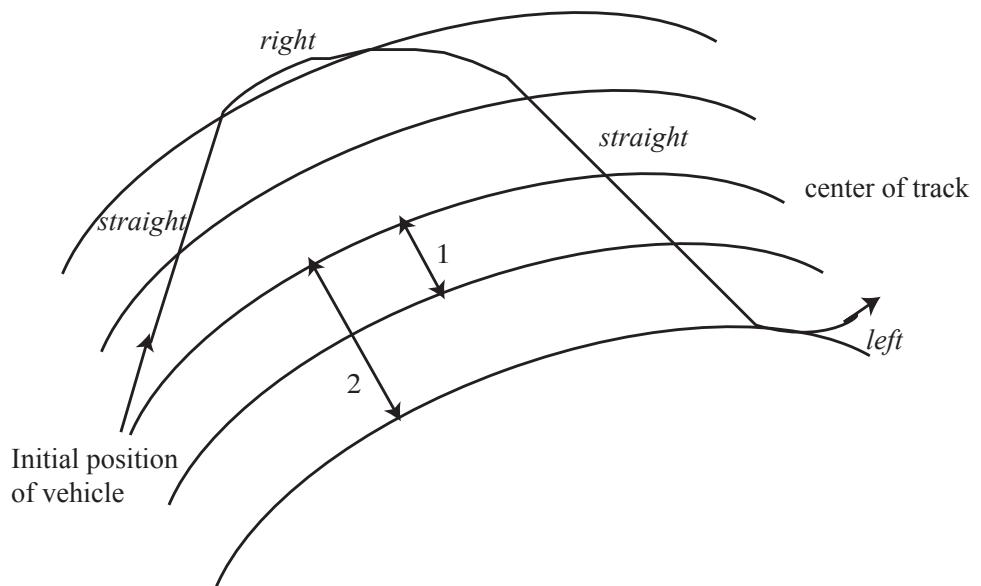


Figure 6.17: A trajectory of the AGV, annotated with modes.

controller specifies how the time-based inputs to the plant, u and ω , are selected in each mode.

6.6 Formal model

We develop a formal model of a hybrid system similar to the ‘sets and functions’ model of Section 3.1. A hybrid system *HybridSystem* is a 5-tuple,

$$\text{HybridSystem} = (\text{States}, \text{Inputs}, \text{Outputs}, \text{TransitionStructure}, \text{initialState}),$$

where, *States*, *Inputs*, *Outputs* are sets, and *initialState* $\in \text{States}$ is the initial state. *TransitionStructure* consists of several items that determine how the hybrid system evolves in time $t \in T$. T may be \mathbb{R}_+ or \mathbb{N}_0 . Here we assume $T = \mathbb{R}_+$.

States = *Modes* \times *RefinementStates* is the state space. *Modes* is the finite set of modes. *RefinementStates* is the state space of the refinements. If the current state at time t is $(m(t), s(t))$ we say that the system is in mode $m(t)$ and its refinement is in state $s(t)$.

Inputs = *InputEvents* \times *TimeBasedInputs* is the set of input symbols. The finite alphabet of discrete input symbols is *InputEvents*, which includes a stuttering symbol. *TimeBasedInputs* is the set of input values to which the refinement reacts. An input signal consists of a pair of functions (u, x) where $u: \mathbb{R}_+ \rightarrow \text{InputEvents}$ and $x: \mathbb{R}_+ \rightarrow \text{TimeBasedInputs}$. For all except a discrete set of times t , $u(t)$ is the stuttering symbol, *absent*.

Outputs = *OutputEvents* \times *TimeBasedOutputs* is the set of output symbols, where *OutputEvents* is the finite alphabet of discrete output symbols, including a stuttering output, *absent*, and *TimeBasedOutputs* is the set of continuous output values. An output signal consists of a pair of functions (v, y) where $v: \mathbb{R}_+ \rightarrow \text{OutputEvents}$ and $y: \mathbb{R}_+ \rightarrow \text{TimeBasedOutputs}$. For all except a discrete set of times, $v(t) = \text{absent}$.

The transition structure determines how a mode transition occurs and how the refinement state changes over time. Suppose the inputs signal is (u, x) . Suppose at time t the mode is m and the refinement state is s . For each destination mode d there is a guard

$$\begin{aligned} G_{m,d} &= U_{m,d} \times X_{m,d} \times S_{m,d} \\ &\subset \text{InputEvents} \times \text{TimeBasedInputs} \times \text{RefinementStates}. \end{aligned}$$

There is also an output event, say $v_{m,d}$, and an action $A_{m,d}: \text{RefinementStates} \rightarrow \text{RefinementStates}$ that assigns a (possibly new) value to each refinement state, (possibly) depending on the

current value of the refinement state. If there is a match $(u(t), x(t), s(t)) \in G_{m,d}$, then there is a discrete transition at t ; the mode after the transition is d , the output event $v(t) = v_{m,d}$ is produced, and the refinement state in mode d at time $t+$ immediately after the transition is set to $s(t+) = A_{m,d}(s(t))$.

If no guard is satisfied at time t , then the refinement state $s(t)$ and the time-based output $y(t)$ are determined by the time-based input signal x according to the equations governing the refinement dynamics. Here we will need to be concrete. In all of the examples above, we have taken

$$\text{RefinementStates} = \mathbb{R}^N,$$

$$\text{TimeBasedInputs} = \mathbb{R}^M, \text{ and}$$

$$\text{TimeBasedOutputs} = \mathbb{R}^K.$$

In this concrete setting, the refinement dynamics are given as

$$\forall t \in T_m, \quad \dot{s}(t) = f_m(s(t), x(t)), \quad (6.8)$$

$$y(t) = g_m(s(t), x(t)), \quad (6.9)$$

where $T_m \subset T$ is the set of times t when the system is in mode m , and the functions

$$f_m : \mathbb{R}^N \times \mathbb{R}^M : \rightarrow \mathbb{R}^N,$$

$$g_m : \mathbb{R}^N \times \mathbb{R}^M : \rightarrow \mathbb{R}^K$$

characterize the behavior of the refinement system in mode m . The function

$$s : \mathbb{R}_+ \rightarrow \text{RefinementStates}$$

is the trajectory of the refinement states.

We can now see how the hybrid system evolves over time. At time $t = 0$, the system starts in the initial state, say $(m(0), s(0))$. It evolves in alternating phases of time passage, $(t_0 = 0, t_1], (t_1, t_2], \dots$, and discrete transitions at t_1, t_2, \dots . During the first interval $(t_0, t_1]$, no guard is satisfied and the system remains in mode $m(0)$; the refinement state $s(t)$ and time-based output $y(t)$ are determined by (6.8), (6.9); and the discrete event output $v(t) = \text{absent}$.

At time t_1 , the guard $G_{m(0), m(1)}$ for some destination mode $m(1)$ is matched by $(u(t_1), x(t_1), s(t_1))$. There is a mode transition to $m(1)$, the output event $v(t_1)$ is produced, and the continuous state is set to $s(t_1+) = A_{m(0)m(1)}(s(t_1))$. The discrete transition phase is now over, and the system begins the time passage phase in the new mode $m(1)$ and the continuous state $s(t_1+)$.

6.7 Summary

Hybrid systems bridge time-based models and state-machine models. The combination of the two families of models provides a rich framework for describing real-world systems. There are two key ideas. First, discrete events are embedded in a time base. Second, a hierarchical description is particularly useful, where the system undergoes discrete transitions between different modes of operation. Associated with each mode of operation is a time-based system called the refinement of the mode. Mode transitions are taken when guards that specify the combination of inputs and refinement states are satisfied. The action associated with a transition, in turn, sets the refinement state in the destination mode.

The behavior of a hybrid system is understood using the tools of state machine analysis for mode transitions the tools of time-based analysis for the refinement systems. The design of hybrid systems similarly proceeds on two levels: state machines are designed to achieve the appropriate logic of mode transitions, and refinement systems are designed to secure the desired time-based behavior in each mode.

Exercises

In some of the following exercises you are asked to design state machines that carry out a given task. The design is simple and elegant if the state space is properly chosen. Although the state space is not unique, there often is a natural choice. As usual, each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **C** Consider the loudness compensation of example 6.3. Suppose that instead of a switch on the front panel, the system automatically selects from among four compensation filters with state-space models $[A, b, c_1, d_1]$, $[A, b, c_2, d_2]$, $[A, b, c_3, d_3]$, and $[A, b, c_4, d_4]$. The A matrix and b vector are the same for all four. Which filter is used depends on a discrete-time v input, where at index n , $v(n)$ represents the current volume level. When the volume is high, above some threshold, filter 4 should be used. When it is low, filter 1 should be used. Design a hybrid system that does this.
2. **E** Construct a timed automaton similar to that of Figure 6.4 which produces *tick* at times $1, 2, 3, 5, 6, 7, 8, 10, 11, \dots$. That is, ticks are produced with intervals between them of 1 second (three times) and 2 seconds (once).
3. **E** The objective of this problem is to understand a timed automaton, and then to modify it as specified.
 - (a) For the timed automaton shown in Figure 6.18, describe the output y . Avoid imprecise or sloppy notation.
 - (b) Assume there is a new input $u: \mathbb{R} \rightarrow \text{Inputs}$ with alphabet

$$\text{Inputs} = \{\text{reset}, \text{absent}\},$$

and that when the input has value *reset*, the hybrid system starts over, behaving as if it were starting at time 0 again. Modify the hybrid system from part (a) so that it behaves like the system in (a).

4. **E** You have an analog source that produces a pure tone. You can switch the source on or off by the input event *on* or *off*. Construct a system that upon receiving

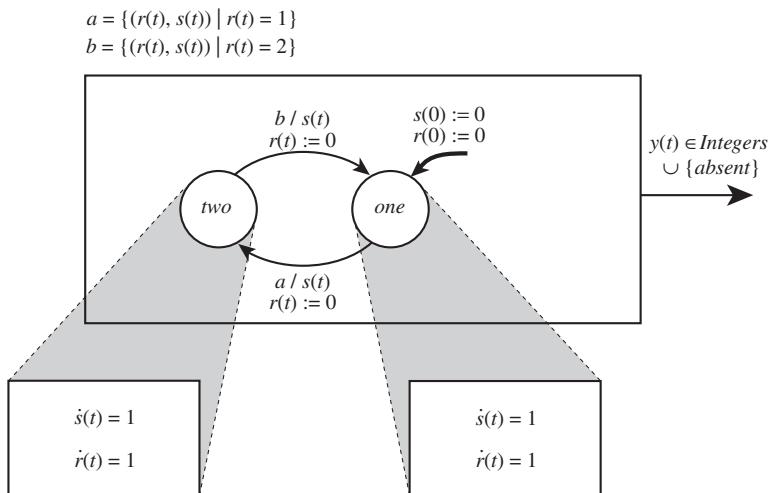


Figure 6.18: Timed automaton considered in Exercise 3.

an input event *ring* produces an 80 ms-long sound consisting of three 20 ms-long bursts of the pure tone separated by two 10 ms intervals of silence. What does your system do if it receives two *ring* events that are 50 ms apart?

5. C Automobiles today have the features listed below. Implement each feature as a timed automaton.
- The dome light is turned on as soon as any door is opened. It stays on for 30 seconds after all doors are shut. What sensors are needed?
 - Once the engine is started, a beeper is sounded and a red light warning is indicated if there are passengers that have not buckled their seat belt. The beeper stops sounding after 30 seconds, or as soon as the seat belts are buckled, whichever is sooner. The warning light is on all the time the seat belt is unbuckled. **Hint:** Assume the sensors provide a *warn* event when the ignition is turned on and there is a seat with passenger not buckled in, or if the ignition is already on and a passenger sits in a seat without buckling the seatbelt. Assume further that the sensors provide a *noWarn* event when a passenger departs from a seat, or when the buckle is buckled, or when the ignition is turned off.

6. **E** A programmable thermostat allows you to select 4 times, $0 \leq T_1 \leq \dots \leq T_4 < 24$ (for a 24-hour cycle) and the corresponding temperatures a_1, \dots, a_4 . Construct a timed automaton that sends the event a_i to the heating systems controller. The controller maintains the temperature close to the value a_i until it receives the next event. How many timers and modes do you need?
7. **E** Construct a parking meter similar to that in figure 6.6 that allows a maximum of 30 minutes (rather than 60 minutes) and accepts *coin5* and *coin25* as inputs. Then draw the state trajectories (both the mode and the clock state) and the output signal when *coin5* occurs at time 0, *coin25* occurs at time 3, and then there is no input event for the next 35 minutes.
8. **T** Consider the timed automaton of Figure 6.6. Suppose we view the box as a discrete-event system with $\{\text{coin5}, \text{coin25}, \text{absent}\}$ as the input alphabet and $\{\text{expired}, \text{absent}\}$ as the output alphabet. Does the box behave as a finite state machine?
9. **C** Figure 6.19 depicts the intersection of two one-way streets, called Main and Secondary. A light on each street controls its traffic. Each light goes through a cycle consisting of a red (R), green (G), and yellow (Y) phases. It is a safety requirement that when one light is in its green or yellow phase, the other is in its red phase. The yellow phase is always 20 seconds long.

The traffic lights operate as follows, in one of two modes. In the normal mode, there is a 5 minute-long cycle with the main light having 4 minutes of green and 20 seconds of yellow—the secondary light is red for these 4 minutes and 20 seconds—and 40 seconds of red—during which the secondary light is green for 20 seconds followed by 20 seconds of yellow.

The second, or interrupt mode works as follows. Its purpose is to quickly give a right of way to the secondary road. A sensor in the secondary road detects if a vehicle has crossed it. When this happens, the main light aborts its green phase and immediately switches to its 20 second yellow phase. If the vehicle is detected while the main light is yellow or red, the system continues in its normal mode.

Design a hybrid system that controls the lights. Let this hybrid system have discrete outputs that are pairs *GG*, *GY*, *GR*, etc. where the first letter denotes the color of the main light second letter denotes the color of the secondary light.

10. **T** Design a *ReceiverProtocol* hybrid system that works together with the *SenderProtocol* of example 6.7.

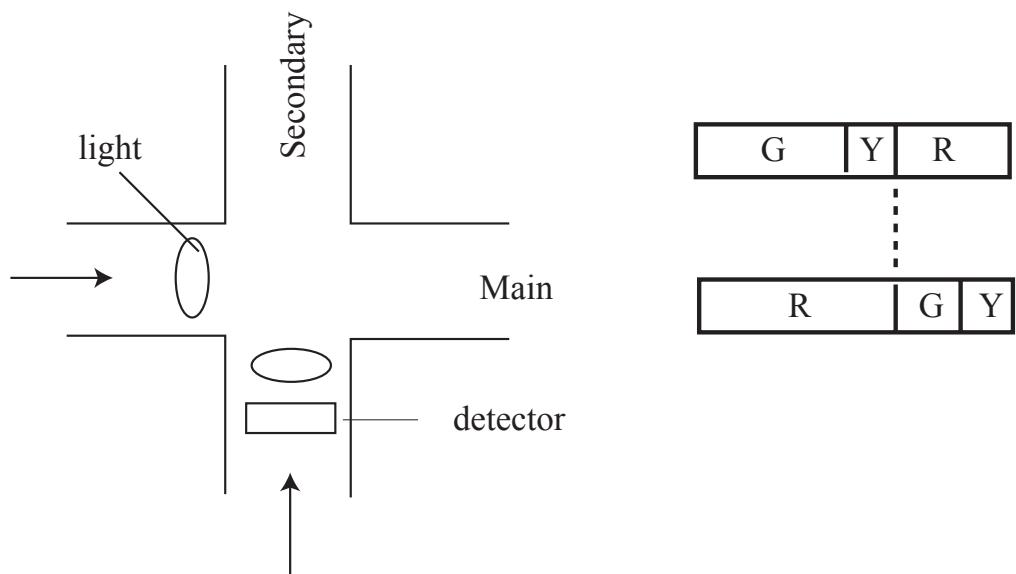


Figure 6.19: Traffic lights control the intersection of a main street and a secondary street. A detector senses when a vehicle crosses it. The red phase of one light must coincide with the green and yellow phases of the other light.

11. **E** For the bouncing ball of example 6.9 let t_n be the time when the ball hits the ground for the n -th time, and let $v(n) = \dot{y}(t_n)$ be the velocity at that time.
- Find a relation between $v(n+1)$ and $v(n)$ and then calculate $v(n)$ in terms of $v(1)$.
 - Obtain t_n in terms of $v(n)$.
 - Calculate the maximum height reached by the ball after successive bumps.
12. **E** Translate refinement systems that are described as second-order differential equations into first-order differential equations. Specifically:
- For the sticky masses system in example 6.8, find the function g such that (6.1) and (6.2) are represented as (6.4). Is this function linear?
 - For the bouncing ball system in example 6.9, find the function f such that (6.5) is represented as (6.6). Is this function linear?
13. **T** Elaborate the hybrid system model of Figure 6.12 so that in the *together* mode, the stickiness decays according to the differential equation

$$\dot{s}(t) = -as(t)$$

where $s(t)$ is the stickiness at time t , and a is some positive constant. On the transition into this mode, the stickiness should be initialized to some starting stickiness b .

14. **T** Show that the trajectory of the AGV of Figure 6.15 while it is in *left* or *right* mode is a circle. What is the radius of this circle, and how long does it take to complete a circle?
15. **E** Express the hybrid system of Figure 6.15 in terms of the formal model of Section 6.6. That is, identify the sets *Inputs*, *Outputs*, and the *TransitionStructure*.

Frequency Domain

Contents

7.1	Frequency decomposition	277
	<i>Basics: Frequencies in Hertz and radians</i>	278
	<i>Basics: Ranges of frequencies</i>	279
	<i>Probing Further: Circle of fifths</i>	281
7.2	Phase	283
7.3	Spatial frequency	284
7.4	Periodic and finite signals	285
7.5	Fourier series	289
	<i>Probing Further: Uniform convergence</i>	295
	<i>Probing Further: Mean square convergence</i>	296
7.5.1	Uniqueness of the Fourier series	297
	<i>Probing Further: Dirichlet conditions</i>	297
7.5.2	Periodic, finite, and aperiodic signals	298
7.5.3	Fourier series approximations to images	300
7.6	Discrete-time signals	300
7.6.1	Periodicity	300
	<i>Basics: Discrete-time frequencies</i>	301
7.6.2	The discrete-time Fourier series	302
7.7	Summary	303
	Exercises	304

We are interested in manipulating signals. We may wish to synthesize signals, as modems need to do in order to transmit a voice-like signal through the telephone channel. We may instead wish to analyze signals, as modems need to do in order to extract digital information from a received voice-like signal. In general, the field of **communications** is all about synthesizing signals with characteristics that match a channel, and then analyzing signals that have often been corrupted by the channel in order to extract the original information.

We may also wish to synthesize natural signals such as images or speech. The field of **computer graphics** puts much of its energy into synthesizing natural-looking images. **Image processing** includes **image understanding**, which involves analyzing images to determine their content. The field of **signal processing** includes analysis and synthesis of speech and music signals.

We may wish to control a physical process. The physical process is sensed (using temperature, pressure, position and speed sensors). The sensed signals are processed in order to estimate the internal state of the physical process. The physical process is controlled on the basis of the state estimate. Control system design includes the design of **state estimators** and **controllers**.

In order to analyze or synthesize signals, we need models of those signals. Since a signal is a function, a model of the signal is a description or a definition of the function. We use two approaches. The first is a **declarative** (what is) approach. The second is an **imperative** (how to) approach. These two approaches are complementary. Depending on the situation, one approach is better than the other.

Signals are functions. This chapter in particular deals with signals where the domain is time (discrete or continuous). It introduces the concept of frequency-domain representation of these signals. The idea is that arbitrary signals can be described as sums of sinusoidal signals. This concept is first motivated by referring to psychoacoustics, how humans hear sounds. Sinusoidal signals have particular psychoacoustic significance. But the real justification for the frequency domain approach is much broader. It turns out to be particularly easy to understand the effect that **LTI systems (linear time invariant systems)**, discussed in Chapter 5, have on sinusoidal signals. A powerful set of analysis and design techniques then follow for arbitrary signals and the LTI systems that operate on them.

Although we know that few (if any) real-world systems are truly LTI, we can easily construe models where the approximation is valid over some regime of operation. The previ-

ous chapter showed how modal models can be constructed to build realistic models over a broader range of operating conditions. Frequency domain methods are amenable to such hybrid system treatment.

7.1 Frequency decomposition

For some signals, particularly natural signals like voice, music, and images, finding a concise and precise definition of the signal can be difficult. In such cases, we try to model signals as compositions of simpler signals that we can more easily model.

Psychoacoustics is the study of how humans hear sounds. Pure tones and their frequency turn out to be a very convenient way to describe sounds. Musical notes can be reasonably accurately modeled as combinations of relatively few pure tones (although subtle properties of musical sounds, such as the timbre of a sound, are harder to model accurately).

When studying sounds, it is reasonable on psychoacoustic grounds to decompose the sounds into sums of sinusoids. It turns out that the motivation for doing this extends well beyond psychoacoustics. Pure tones have very convenient mathematical properties that make it useful to model other types of signals as sums of sinusoids, even when there is no psychoacoustic basis for doing so. For example, there is no psychoacoustic reason for modeling radio signals as sums of sinusoids.

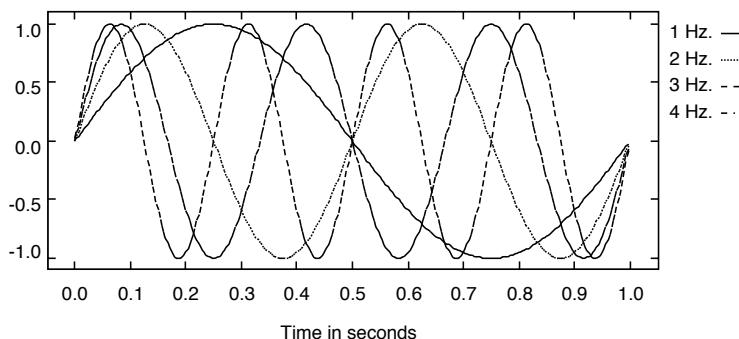


Figure 7.1: Plot of four sinusoidal signals.

Consider the range of frequencies covering one **octave**, ranging from 440Hz to 880 Hz. “Octave” is the musical term for a factor of two in frequency. The frequencies 440 Hz and 880 Hz both correspond to the musical note A, but one octave apart. The next higher A in the musical scale would have the frequency 1760 Hz, twice 880 Hz. In the western musical scale, there are 12 notes in every octave. These notes are evenly distributed

Basics: Frequencies in Hertz and radians

A standard measure of frequency is **Hertz**, meaning cycles per second. Figure 7.1 shows a plot of one second of four sine waves of different frequencies. For example, the frequencies in Hertz of the musical note A on the piano keyboard are

$$f_1 = 55, f_2 = 110, f_3 = 220, f_4 = 440, \\ f_5 = 880, f_6 = 1760, f_7 = 3520, f_8 = 7040.$$

A sinusoidal waveform x with frequency $f_4 = 440$ can be defined by

$$\forall t \in \mathbb{R}, \quad x(t) = \sin(440 \times 2\pi t).$$

The factor 2π in this expression is a nuisance. An argument to a sine function has units of **radians**, so 2π has units of radians/cycle. Explicitly showing all the units (in square brackets), we have

$$440[\text{cycles/second}] \times 2\pi[\text{radians/cycle}]t[\text{seconds}] = (440 \times 2\pi t)[\text{radians}].$$

To avoid having to keep track of the factor 2π everywhere, it is common to use the alternative units for frequency, **radians per second**. The symbol ω is commonly used to denote frequencies in radians per second, while f is used for frequencies in Hertz. The relationship between Hertz and radians per second is simple,

$$\omega = 2\pi f,$$

as is easily confirmed by checking the units. Thus, in radians per second, the frequencies of the musical note A on the piano keyboard are

$$\omega_1 = 2\pi \times 55, \omega_2 = 2\pi \times 110, \omega_3 = 2\pi \times 220, \omega_4 = 2\pi \times 440, \\ \omega_5 = 2\pi \times 880, \omega_6 = 2\pi \times 1760, \omega_7 = 2\pi \times 3520, \omega_8 = 2\pi \times 7040.$$

(geometrically), so the next note above A, which is B flat, has frequency $440 \times \sqrt[12]{2}$, where $\sqrt[12]{2} \approx 1.0595$. The next note above B flat, which is B, has frequency $440 \times \sqrt[12]{2} \times \sqrt[12]{2}$.

In table 7.1, the frequencies of the complete musical scale between middle A and A-880 are shown. Each frequency is $\beta = \sqrt[12]{2}$ times the frequency below it.

Frequencies that are harmonically related tend to sound good together. Figure 7.2 shows the graph of a signal that is a major triad, a combination of the notes A, C \sharp (C sharp), and E. By “combination” we mean “sum.” The A is a sinusoidal signal at 440 Hz. It is added to a C \sharp , which is a sinusoidal signal at 554 Hz. This sum is then added to an E, which is a sinusoidal signal at 659 Hz. Each of the components is also shown, so you can verify graphically that at each point in time, the value of the solid signal is equal to the sum of values of the dashed signals at that time.

The stimulus presented to the ear is the solid waveform. What you hear, however, assuming a small amount of musical training, is the three sinusoidal components, which the human ear interprets as musical notes. The human ear decomposes the stimulus into its sinusoidal components.

Basics: Ranges of frequencies

An extremely wide range of frequencies occur in natural and man-made signals. The following abbreviations are common:

- Hz - hertz, cycles per second.
- kHz - kilohertz, thousands of cycles per second.
- MHz - megahertz, millions of cycles per second.
- GHz - gigahertz, billions of cycles per second.
- THz - terahertz, trillions of cycles per second.

Audible sounds signals are in the range of 20 Hz to 20 kHz. Sounds above this frequency are called ultrasonic. Electromagnetic waves range from less than one hertz (used speculatively in seismology for earthquake prediction) through visible light near 10^{15} Hz to cosmic ray radiation up to 10^{25} Hz.

A	880
A \flat	831
G	784
F \sharp	740
F	698
E	659
D \sharp	622
D	587
C \sharp	554
C	523
B	494
B \flat	466
A	440

Table 7.1: Frequencies of notes over one octave of the western musical scale, in Hertz.

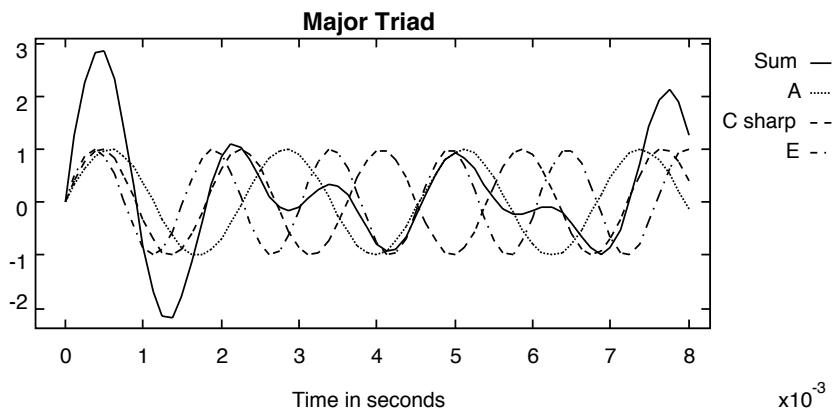


Figure 7.2: Graph of a major triad, showing its three sinusoidal components and their sum.

Probing Further: Circle of fifths

The western musical scale is based on our perception of frequency and the harmonic relationships between frequencies. The following frequencies all correspond to the note A:

$$110, 220, 440, 880, 1760, \text{ and } 3520.$$

What about $440 \times 3 = 1320$? Notice that $1320/2 = 660$, which is almost exactly the E in table 7.1. Thus, 440×3 is (roughly) the note E, one octave above the E above A-440. E and A are closely harmonically related, and to most people, they sound good together. It is because

$$440 \times 3 \approx 659 \times 2$$

The notes A, C \sharp , and E form a major triad. Where does the C \sharp come from? Its frequency is 554 (see table 7.1). Notice that

$$440 \times 5 \approx 554 \times 4.$$

Among all the harmonic relationships in the scale, A, C \sharp , and E have one of the simplest. This is the reason for their pleasing sound together.

For more arcane reasons, the interval between A and E, which is a frequency rise of approximately 3/2, is called a **fifth**. The note 3/2 (a fifth) above E has frequency 988, which is one octave above B-494. Another 3/2 above that is approximately F sharp (740 Hz). Continuing in this fashion, multiplying frequencies by 3/2, and then possibly dividing by two, you can approximately trace the twelve notes of the scale. On the 13-th, you return to A, approximately. This progression is called the **circle of fifths**. The notion of **key** and **scale** in music are based on this circle of fifths, as is the fact that there are 12 notes in the scale.

Table 7.1 is calculated by multiplying each frequency by $\sqrt[12]{2}$ to get the next higher frequency, not by using the circle of fifths. Indeed, the $\sqrt[12]{2}$ method applied twelve times yields a note that is *exactly* one octave higher than the starting point, while the circle of fifths only yields an approximation. The $\sqrt[12]{2}$ method yields the **well-tempered scale**. This scale was popularized by the composer J. S. Bach. It sounds much better than a scale based on the circle of fifths when the range of notes spans more than one octave.

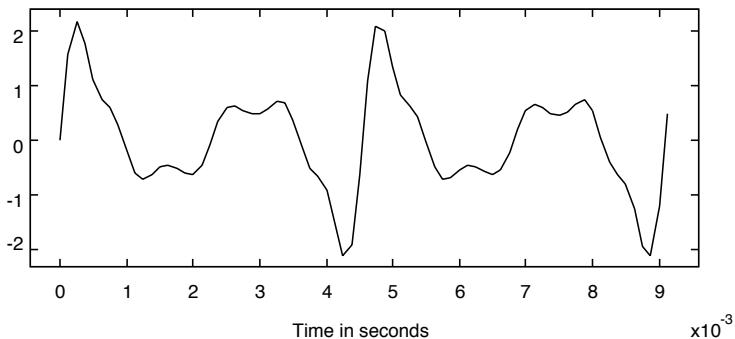


Figure 7.3: A sound waveform for an A-220 with more interesting timbre.

Example 7.1: The major triad signal can be written as a sum of sinusoids

$$s(t) = \sin(440 \times 2\pi t) + \sin(554 \times 2\pi t) + \sin(659 \times 2\pi t),$$

for all $t \in \mathbb{R}$. The human ear hears as distinct tones the frequencies of these sinusoidal components. Musical sounds such as chords can be characterized as sums of pure tones.

Purely sinusoidal signals, however, do not sound very good. Although they are recognizable as notes, they do not sound like any familiar musical instrument. Truly musical sounds are much more complex than a pure sinusoid. The characteristic sound of an instrument is its **timbre**, and as we shall see, some aspects of timbre can also be characterized as sums of sinusoids.

Timbre is due in part to the fact that musical instruments do not produce purely sinusoidal sounds. Instead, to a first approximation, they produce sounds that consist of a fundamental sinusoidal component and harmonics. The fundamental is at the frequency of the note being played, and the harmonics are at multiples of that frequency. Figure 7.3 shows a waveform for a sound that is heard as an A-220 but has a much more interesting timbre than a sinusoidal signal with frequency 220 Hz. In fact, this waveform is generated by adding together sinusoidal signals with frequencies 220 Hz, 440 Hz, 660 Hz, 880 Hz,

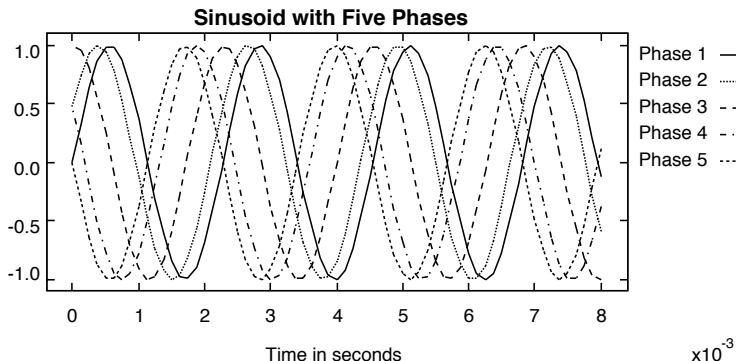


Figure 7.4: Five sinusoidal signals with different phases.

1100 Hz, 1320 Hz, and higher multiples, with varying weights. The 220 Hz component is called the **fundamental**, while the others are called **harmonics**. The **first harmonic** is the component at 440 Hz. The **second harmonic** is the component at 660 Hz. Etc. The relative weights of the harmonics is a major part of what makes one musical instrument sound different from another.

7.2 Phase

A sinusoidal sound has not just a frequency, but also a **phase**. The phase may be thought of as the relative starting point of the waveform. Figure 7.4 shows five sinusoidal signals with the same frequency but five different phases. These signals all represent the sound A-440, and all sound identical. For a simple sinusoidal signal, obviously, phase has no bearing on what the human ear hears.

Somewhat more surprising is that when two or more sinusoids are added together, the relative phase has a significant impact on the shape of the waveform, but no impact on the perceived sound. The human ear is relatively insensitive to the phase of sinusoidal components of a signal, even though the phase of those components can strongly affect the shape. If these waveforms represent something other than sound, like stock prices for example, the effect of phase could be quite significant. For a sinusoidal signal, the phase



Figure 7.5: Images that are sinusoidal horizontally, vertically, and both.

affects whether a particular point in time corresponds to a peak or a valley, for example. For stock prices, it makes a difference whether you sell at a high or a low.

There are certain circumstances in which the human ear is sensitive to phase. In particular, when two sinusoids of the same frequency combine, the relative phase has a big impact, since it affects the amplitude of the sum. For example, if the two sinusoids differ in phase by 180 degrees (π radians), then when they add, they exactly cancel, yielding a zero signal. The human brain can use the relative phase of a sound in the two ears to help spatially locate the origin of a sound. Also, audio systems with two speakers, which simulate spatially distributed sounds (“stereo”), can be significantly affected by the relative phase of the signal produced by the two speakers.

Phase is measured in either radians or degrees. An A-440 can be given by

$$g(t) = \sin(440 \times 2\pi t + \phi),$$

for all $t \in \mathbb{R}$, where $\phi \in \mathbb{R}$ is the phase. Regardless of the value of ϕ , this signal is still an A-440. If $\phi = \pi/2$ then

$$g(t) = \cos(440 \times 2\pi t).$$

7.3 Spatial frequency

Psychoacoustics provides a compelling motivation for decomposing audio signals as sums of sinusoids. In principle, images can also be similarly decomposed. However, the motivations in this case are more mathematical than perceptual.

Figure 7.5 shows three images that are sinusoidal. Specifically, the **intensity** of the image (the amount of white light that is reflected by the page) varies spatially according to a sinusoidal function. In the leftmost image, it varies horizontally only. There is no vertical variation in intensity. In the middle image, it varies vertically only. In the rightmost image, it varies in both dimensions.

The sinusoidal image has **spatial frequency** rather than temporal frequency. Its units are cycles per unit distance. The images in figure 7.5 have frequencies of roughly 2.5 cycles/inch. Recall that a grayscale picture is represented by a function

$$\text{Image} : \text{VerticalSpace} \times \text{HorizontalSpace} \rightarrow \text{Intensity}.$$

So an image that varies sinusoidally along the horizontal direction (with a spatial period of H inches) and is constant along the vertical direction is represented by

$$\forall x \in \text{VerticalSpace} \quad \forall y \in \text{HorizontalSpace} \quad \text{Image}(x, y) = \sin(2\pi y/H).$$

Similarly, an image that varies sinusoidally along the vertical direction (with a spatial period of V inches) and is constant along the horizontal direction is represented by

$$\forall x \in \text{VerticalSpace} \quad \forall y \in \text{HorizontalSpace} \quad \text{Image}(x, y) = \sin(2\pi x/V).$$

An image that varies sinusoidally along both directions is represented by

$$\forall x \in \text{VerticalSpace} \quad \forall y \in \text{HorizontalSpace} \quad \text{Image}(x, y) = \sin(2\pi x/V) \times \sin(2\pi y/H).$$

These sinusoidal images have much less meaning than audio sinusoids, which we perceive as musical tones. Nonetheless, we will see that images can be described as sums of sinusoids, and that such description is sometimes useful.

7.4 Periodic and finite signals

When the domain is continuous or discrete time, we can define a **periodic signal**. Assuming the domain is \mathbb{R} , a periodic signal x with period $p \in \mathbb{R}$ is one where for all $t \in \mathbb{R}$

$$x(t) = x(t + p). \tag{7.1}$$

A signal with period p also has period $2p$, since

$$x(t) = x(t + p) = x(t + 2p).$$

In fact, it has period Kp , for any positive integer K . Usually, we define the period to be the *smallest* $p > 0$ such that

$$\boxed{\forall t \in \mathbb{R}, \quad x(t) = x(t + p).}$$

Example 7.2: The sinusoidal signal x where for all $t \in \mathbb{R}$

$$x(t) = \sin(\omega_0 t)$$

is a periodic signal with period $2\pi/\omega_0$ since for all $t \in \mathbb{R}$

$$\sin(\omega_0(t + 2\pi/\omega_0)) = \sin(\omega_0 t).$$

A periodic signal is defined over an infinite interval. If the domain is instead a subset $[a, b] \subset \mathbb{R}$, for some finite a and b , then we call this a **finite signal**.

Example 7.3: The signal y where for all $t \in [0, 2\pi/\omega_0]$,

$$y(t) = \sin(\omega_0 t)$$

is a finite signal with duration $2\pi/\omega_0$. This interval spans exactly one cycle of the sine wave.

A finite signal with duration p can be used to define a periodic signal with period p . All that is needed is to periodically repeat the finite signal. Formally, given a finite signal $y: [a, b] \rightarrow \mathbb{R}$, we can define a signal $y': \mathbb{R} \rightarrow \mathbb{R}$ by

$$\forall t \in \mathbb{R}, \quad y'(t) = \begin{cases} y(t) & \text{if } t \in [a, b] \\ 0 & \text{otherwise} \end{cases} \quad (7.2)$$

In other words, $y'(t)$ is simply $y(t)$ inside its domain, and zero elsewhere. Then the periodic signal can be given by¹

$$x(t) = \sum_{m=-\infty}^{\infty} y'(t - mp) \quad (7.3)$$

where $p = b - a$. This is called a **shift-and-add summation**, illustrated in Figure 7.6. The periodic signal is a sum of versions of $y'(t)$ that have been shifted in time by multiples of p . Do not let the infinite sum intimidate: all but one of the terms of the summation are zero for any fixed t ! Thus, a periodic signal can be defined in terms of a finite signal, which represents one period. Conversely, a finite signal can be defined in terms of a periodic signal (by taking one period).

We can check that x given by (7.3) is indeed periodic with period p ,

$$\begin{aligned} x(t+p) &= \sum_{m=-\infty}^{\infty} y'(t+p - mp) = \sum_{m=-\infty}^{\infty} y'(t - (m-1)p) \\ &= \sum_{k=-\infty}^{\infty} y'(t - kp) = x(t), \end{aligned}$$

by using a change of variables, $k = m - 1$.

It is also important to note that the periodic signal x agrees with y in the finite domain $[a, b]$ of y , since

$$\begin{aligned} \forall t \in [a, b] \quad x(t) &= \sum_{m=-\infty}^{\infty} y'(t - mp) \\ &= y'(t) + \sum_{m \neq 0} y'(t - mp) \\ &= y(t), \end{aligned}$$

because, by (7.2), for $t \in [a, b]$, $y'(t) = y(t)$ and $y'(t - mp) = 0$ if $m \neq 0$.

We will see that any periodic signal, and hence any finite signal, can be described as a sum of sinusoidal signals. This result, known as the Fourier series, is one of the fundamental tools in the study of signals and systems.

¹If this notation is unfamiliar, see box on page 77.

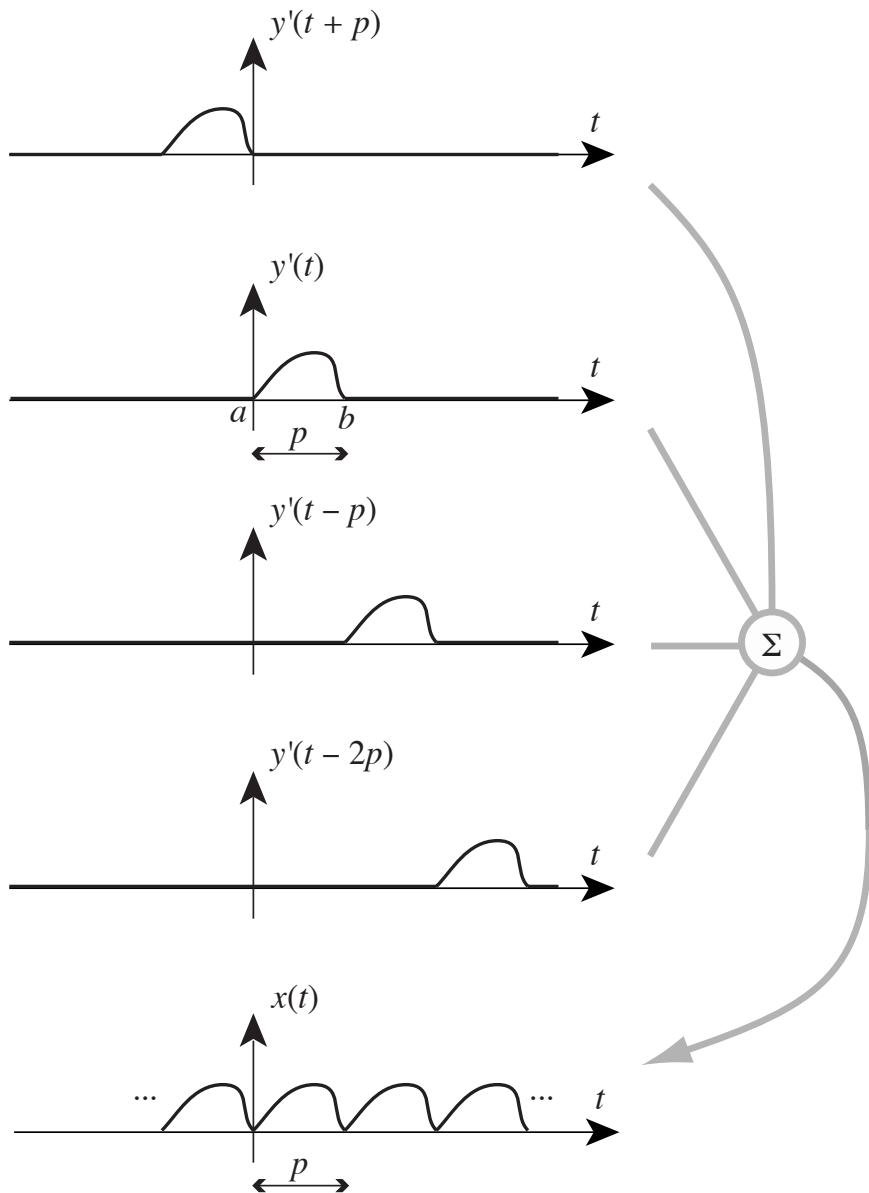


Figure 7.6: By repeating the finite signal y we can obtain a periodic signal x .

7.5 Fourier series

A remarkable result, due to Joseph Fourier, 1768-1830, is that a periodic signal $x: \mathbb{R} \rightarrow \mathbb{R}$ with period $p \in \mathbb{R}$ can (usually) be described as a constant term plus a sum of sinusoids,

$$x(t) = A_0 + \sum_{k=1}^{\infty} A_k \cos(k\omega_0 t + \phi_k) \quad (7.4)$$

This representation of x is called its **Fourier series**. The Fourier series is widely used for signal analysis. Each term in the summation is a cosine with amplitude A_k and phase ϕ_k . The particular values of A_k and ϕ_k depend on x , of course. The frequency ω_0 , which has units of radians per second (assuming the domain of x is in seconds), is called the **fundamental frequency**, and is related to the period p by

$$\omega_0 = 2\pi/p.$$

In other words, a signal with fundamental frequency ω_0 has period $p = 2\pi/\omega_0$. The constant term A_0 is sometimes called the **DC** term, where “DC” stands for **direct current**, a reference back to the early applications of this theory in electrical circuit analysis. The terms where $k \geq 2$ are called **harmonics**.

Equation (7.4) is often called the **Fourier series expansion** for x because it expands x in terms of its sinusoidal components.

If we had a facility for generating individual sinusoids, we could use the Fourier series representation (7.4) to synthesize any periodic signal. However, using the Fourier series expansion for synthesis of periodic signals is problematic because of the infinite summation. But for most practical signals, the coefficients A_k become very small (or even zero) for large k , so a finite summation can be used as an approximation. A **finite Fourier series approximation** with $K + 1$ terms has the form

$$\tilde{x}(t) = A_0 + \sum_{k=1}^K A_k \cos(k\omega_0 t + \phi_k). \quad (7.5)$$

The infinite summation of (7.4) is, in fact, the limit of (7.5) as K goes to infinity. We need to be concerned, therefore, with whether this limit exists. The Fourier series expansion is valid only if it exists. There are some technical mathematical conditions on x that, if satisfied, ensure that the limit exists (see boxes on pages 295 and 296). Fortunately, these conditions are met almost always by practical, real-world time-domain signals.

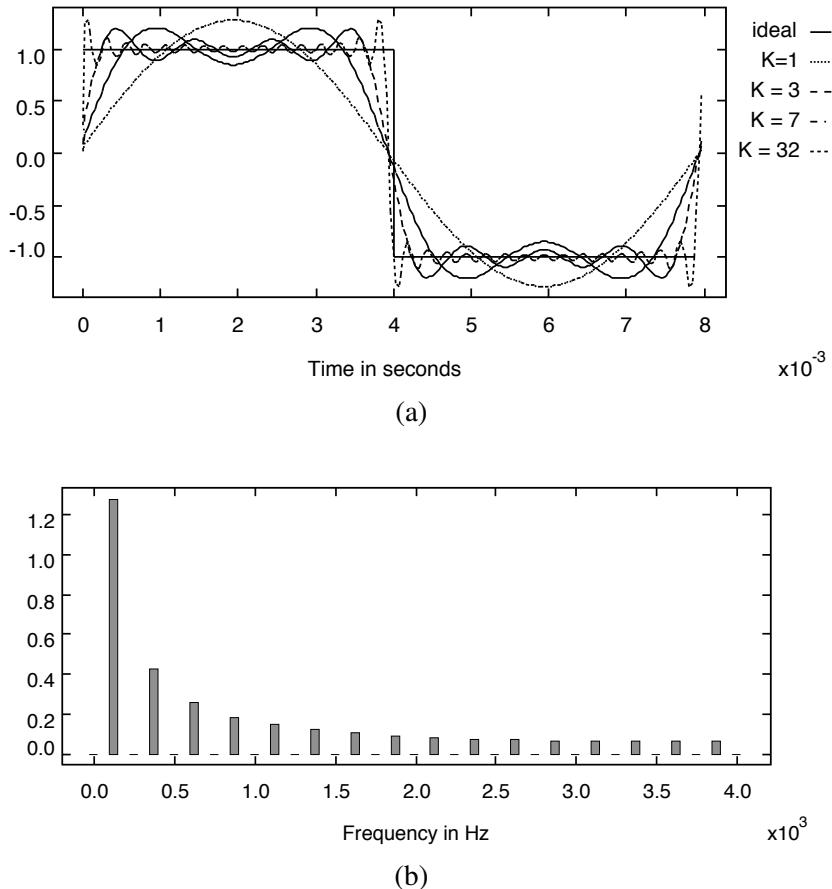


Figure 7.7: (a) One cycle of a square wave and some finite Fourier series approximations. (b) The amplitudes of the Fourier series terms for the square wave.

Example 7.4: Figure 7.7 shows a square wave with period 8 msec and some finite Fourier series approximations to the square wave. Only one period of the square wave is shown. The method for constructing these approximations will be covered in detail in Chapter 10. Here, we will just observe the general structure of the approximations.

Notice in Figure 7.7(a) that the $K = 1$ approximation consists only of the DC term (which is zero in this case) and a sinusoid with an amplitude slightly larger than that of the square wave. Its amplitude is depicted in Figure 7.7(b) as the height of the largest bar. The horizontal position of the bar corresponds to the frequency of the sinusoid, 125 Hz, which is $1/(8 \text{ msec})$, the fundamental frequency. The $K = 3$ waveform is the sum of the $K = 1$ waveform and one additional sinusoid with frequency 375 Hz and amplitude equal to the height of the second largest bar in Figure 7.7(b).

A plot like that in Figure 7.7(b) is called a **frequency domain** representation of the square wave, because it depicts the square wave by the amplitude and frequency of its sinusoidal components. Actually, a complete frequency domain representation also needs to give the phase of each sinusoidal component.

Notice in Figure 7.7(b) that all even terms of the Fourier series approximation have zero amplitude. Thus, for example, there is no component at 250 Hz. This is a consequence of the symmetry of the square wave, although it is beyond the scope of work now to explain exactly why.

Also notice that as the number of terms in the summation increases, the approximation more closely resembles a square wave, but the amount of its overshoot does not appear to decrease. This is known as **Gibb's phenomenon**. In fact, the maximum difference between the finite Fourier series approximation and the square wave does not converge to zero as the number of terms in the summation increases. In this sense, the square wave cannot be exactly described with a Fourier series (see box on page 295). Intuitively, the problem is due to the abrupt discontinuity in the square wave when it transitions between its high value and its low value. In another sense, however, the square wave *is* accurately described by a Fourier series. Although the maximum difference between the approximation and the square wave does not go to zero, the *mean square error* does go to zero (see box on page 296). For practical purposes, mean square error is an adequate

criterion for convergence, so we can work with the Fourier series expansion of the square wave.

Example 7.5: Figure 7.8 shows some finite Fourier series approximations for a triangle wave. This waveform has no discontinuities, and therefore the maximum error in the finite Fourier series approximation converges to zero (see box on page 295). Notice that its Fourier series components decrease in amplitude much more rapidly than those of the square wave. Moreover, the time-domain approximations appear to be more accurate with fewer terms in the finite summation.

Many practical, real-world signals, such as audio signals, do not have discontinuities, and thus do not exhibit the sort of convergence problems exhibited by the square wave (Gibbs phenomenon). Other signals, however, such as images, are full of discontinuities. A (spatial) discontinuity in an image is simply an edge. Most images have edges. Nonetheless, a Fourier series representation for such a signal is almost always still valid, in a mean square error sense (see box on page 296). This is sufficient for almost all engineering purposes.

Example 7.6: Consider an audio signal given by

$$s(t) = \sin(440 \times 2\pi t) + \sin(550 \times 2\pi t) + \sin(660 \times 2\pi t).$$

This is a major triad in a non-well-tempered scale. The first tone is A-440. The third is approximately E, with a frequency $3/2$ that of A-440. The middle term is approximately C \sharp , with a frequency $5/4$ that of A-440. It is these simple frequency relationships that result in a pleasant sound. We choose the non-well-tempered scale because it makes it much easier to construct a Fourier series expansion for this waveform. We leave the more difficult problem of finding the Fourier series coefficients for a well-tempered major triad to Exercise 5.

To construct the Fourier series expansion, we can follow these steps:

1. Find p , the period. The period is the smallest number $p > 0$ such that $s(t) = s(t - p)$ for all t in the domain. To do this, note that

$$\sin(2\pi f t) = \sin(2\pi f(t - p))$$

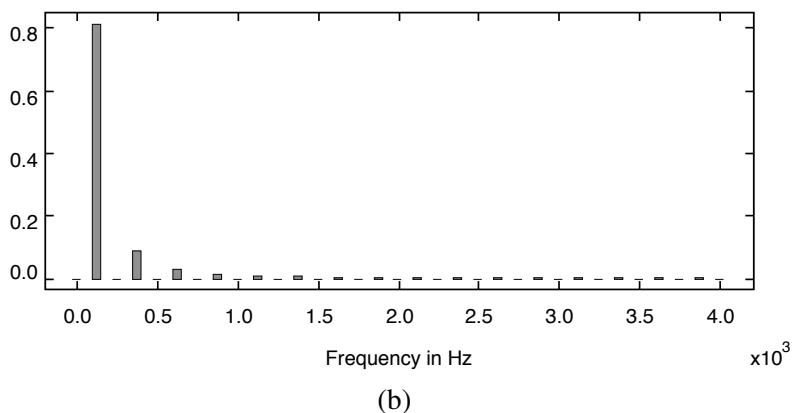
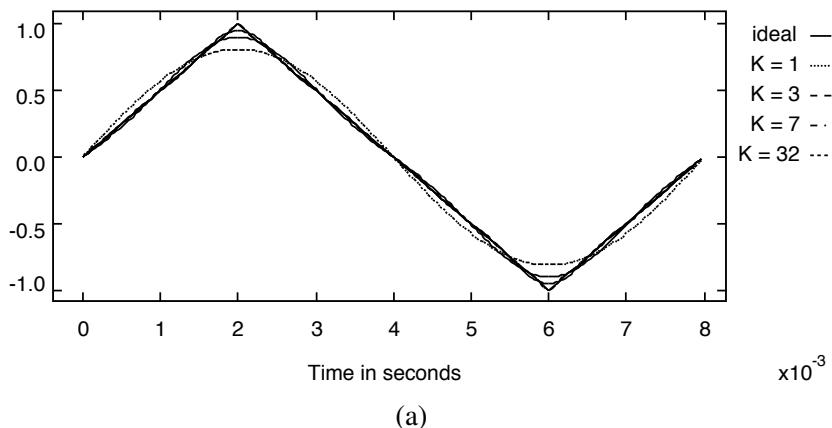


Figure 7.8: (a) One cycle of a triangle wave and some finite Fourier series approximations. (b) The amplitudes of the Fourier series terms for the triangle wave.

if fp is an integer. Thus, we want to find the smallest p such that $440p$, $550p$, and $660p$ are all integers. Equivalently, we want to find the largest fundamental frequency $f_0 = 1/p$ such that $440/f_0$, $550/f_0$, and $660/f_0$ are all integers. Such an f_0 is called the **greatest common divisor** of 440, 550, and 660. This can be computed using the `gcd` function in Matlab. In this case, however, we can do it in our heads, observing that $f_0 = 110$.

2. Find A_0 , the constant term. By inspection, there is no constant component in $s(t)$, only sinusoidal components, so $A_0 = 0$.
3. Find A_1 , the fundamental term. By inspection, there is no component at 110 Hz, so $A_1 = 0$. Since $A_1 = 0$, ϕ_1 is immaterial.
4. Find A_2 , the first harmonic. By inspection, there is no component at 220 Hz, so $A_2 = 0$.
5. Find A_3 . By inspection, there is no component at 330 Hz, so $A_3 = 0$.
6. Find A_4 . There is a component at 440 Hz, $\sin(440 \times 2\pi t)$. We need to find A_4 and ϕ_4 such that

$$A_4 \cos(440 \times 2\pi t + \phi_4) = \sin(440 \times 2\pi t).$$

By inspection, $\phi_4 = -\pi/2$ and $A_4 = 1$.

7. Similarly determine that $A_5 = A_6 = 1$, $\phi_5 = \phi_6 = -\pi/2$, and that all other terms are zero.

Putting this all together, the Fourier series expansion can be written

$$s(t) = \sum_{k=4}^6 \cos(k\omega_0 t - \pi/2)$$

where $\omega_0 = 2\pi f_0 = 220\pi$.

The method used in the above example for determining the Fourier series coefficients is tedious and error prone, and will only work for simple signals. We will see much better techniques in chapters 8 and 10.

Probing Further: Uniform convergence

The Fourier series representation of a periodic signal x is a limit of a sequence of functions x_N for $N = 1, 2, \dots$ where

$$\forall t \in \mathbb{R}, \quad x_N(t) = A_0 + \sum_{k=1}^N A_k \cos(k\omega_0 t + \phi_k).$$

Specifically, for the Fourier series representation to be valid, we would like that for all $t \in \mathbb{R}$,

$$x(t) = \lim_{N \rightarrow \infty} x_N(t).$$

A strong criterion for validity of the Fourier series is **uniform convergence** of this limit, in which for each real number $\epsilon > 0$, there exists a positive integer M such that for all $t \in \mathbb{R}$ and for all $N > M$,

$$|x(t) - x_N(t)| < \epsilon$$

A sufficient condition for uniform convergence is that the signal x be continuous and that its first derivative be piecewise continuous.

A square wave, for example, is not continuous, and hence does not satisfy this sufficient condition. Indeed, the Fourier series does not converge uniformly, as you can see in figure 7.7 by observing that the peak difference between $x(t)$ and $x_K(t)$ does not decrease to zero. A triangle wave, however, is continuous, and has a piecewise continuous first derivative. Thus, it does satisfy the sufficient condition. Its Fourier series approximation will therefore converge uniformly, as suggested in Figure 7.8. A weaker, but still useful, criterion for validity of the Fourier series is considered on page 296. That criterion is met by the square wave.

See for example R. G. Bartle, *The Elements of Real Analysis*, Second Edition, John Wiley & Sons, 1976, p. 117 (for uniform convergence) and p. 337 (for this sufficient condition).

Probing Further: Mean square convergence

The Fourier series representation of a periodic signal x with period p is a limit of a sequence of functions x_N for $N = 1, 2, \dots$ where

$$\forall t \in \mathbb{R}, \quad x_N(t) = A_0 + \sum_{k=1}^N A_k \cos(k\omega_0 t + \phi_k).$$

Specifically, for the Fourier series representation to be valid, we would like that for all $t \in \mathbb{R}$,

$$x(t) = \lim_{N \rightarrow \infty} x_N(t).$$

For some practical signals, such as the square wave of figure 7.7, this statement is not quite true for all $t \in \mathbb{R}$. For practical purposes, however, we don't really need for this to be true. A weaker condition for validity of the Fourier series is that the total **energy** in the error over one period be zero. Specifically, we say that $x_N(t)$ **converges in mean square** to $x(t)$ if

$$\lim_{N \rightarrow \infty} \int_0^p |x(t) - x_N(t)|^2 dt = 0.$$

The integral here is the energy in the error $x(t) - x_N(t)$ over one period. It turns out that if x itself has finite energy over one period, then $x_N(t)$ converges in mean square to $x(t)$. That is, all we need is that

$$\int_0^p |x(t)|^2 dt < \infty.$$

Virtually all signals with any engineering importance satisfy this criterion. Note that convergence in mean square does not guarantee that at any particular $t \in \mathbb{R}$, $x(t) = \lim_{N \rightarrow \infty} x_N(t)$. For a condition that (almost) ensures this for all practical signals, see box on page 297.

See for example R. V. Churchill, *Fourier Series and Boundary Value Problems*, Third Edition, McGraw-Hill Book Company, New York, 1978.

7.5.1 Uniqueness of the Fourier series

Suppose $x: \mathbb{R} \rightarrow \mathbb{R}$ is a periodic function with period p . Then the Fourier series expansion is unique. In other words if it is both true that

$$x(t) = A_0 + \sum_{k=1}^{\infty} A_k \cos(k\omega_0 t + \phi_k)$$

Probing Further: Dirichlet conditions

The Fourier series representation of a periodic signal x with period p is a limit of a sequence of finite Fourier series approximations x_N for $N = 1, 2, \dots$. We have seen in the box on page 295 a strong condition that ensures that $\forall t \in \mathbb{R}$,

$$x(t) = \lim_{N \rightarrow \infty} x_N(t). \quad (7.6)$$

We have seen in the box on page 296 a weaker condition that does not guarantee this, but instead guarantees that the energy in the error over one period is zero. It turns that for almost all signals of interest, we can assert that (7.6) holds for *almost all* $t \in \mathbb{R}$. In particular, if the **Dirichlet conditions** are satisfied, then (7.6) holds for all t except where x is discontinuous. The Dirichlet conditions are three:

- Over one period, x is **absolutely integrable**, meaning that

$$\int_0^p |x(t)| dt < \infty.$$

- Over one period, x is of **bounded variation**, meaning that there are no more than a finite number of maxima or minima. That is, if the signal is oscillating between high and low values, it can only oscillate a finite number of times in each period.
- Over one period, x is continuous at all but a finite number of points.

These conditions are satisfied by the square wave, and indeed by any signal of practical engineering importance.

and

$$x(t) = B_0 + \sum_{k=1}^{\infty} B_k \cos(k\omega_0 t + \theta_k),$$

where $\omega_0 = 2\pi/p$, then it must also be true that

$$\forall k \geq 0, \quad A_k = B_k \text{ and } \phi_k \bmod 2\pi = \theta_k \bmod 2\pi.$$

(The modulo operation is necessary because of the non-uniqueness of phase.) Thus, when we talk about *the* frequency content of a signal, we are talking about something that is unique and well defined. For a suggestion about how to prove this uniqueness, see problem 11.

7.5.2 Periodic, finite, and aperiodic signals

We have seen in Section 7.4 that periodic signals and finite signals have much in common. One can be defined in terms of the other. Thus, a Fourier series can be used to describe a finite signal as well as a periodic one. The “period” is simply the extent of the finite signal. Thus, if the domain of the signal is $[a, b] \subset \mathbb{R}$, then $p = b - a$. The fundamental frequency, therefore, is just $\omega_0 = 2\pi/(b - a)$.

An aperiodic signal, like an audio signal, can be partitioned into finite segments, and a Fourier series can be constructed from each segment.

Example 7.7: Consider the train whistle shown in Figure 7.9(a). Figure 7.9(b) shows a segment of 16 msec. Notice that within this segment, the sound clearly has a somewhat periodic structure. It is not hard to envision how it could be described as sums of sinusoids. The magnitudes of the A_k Fourier series coefficients for this 16 msec segment are shown in Figure 7.9(c). These are calculated on a computer using techniques we will discuss later, rather than being calculated by hand as in the previous example. Notice that there are three dominant frequency components that give the train whistle its tonality and timbre.

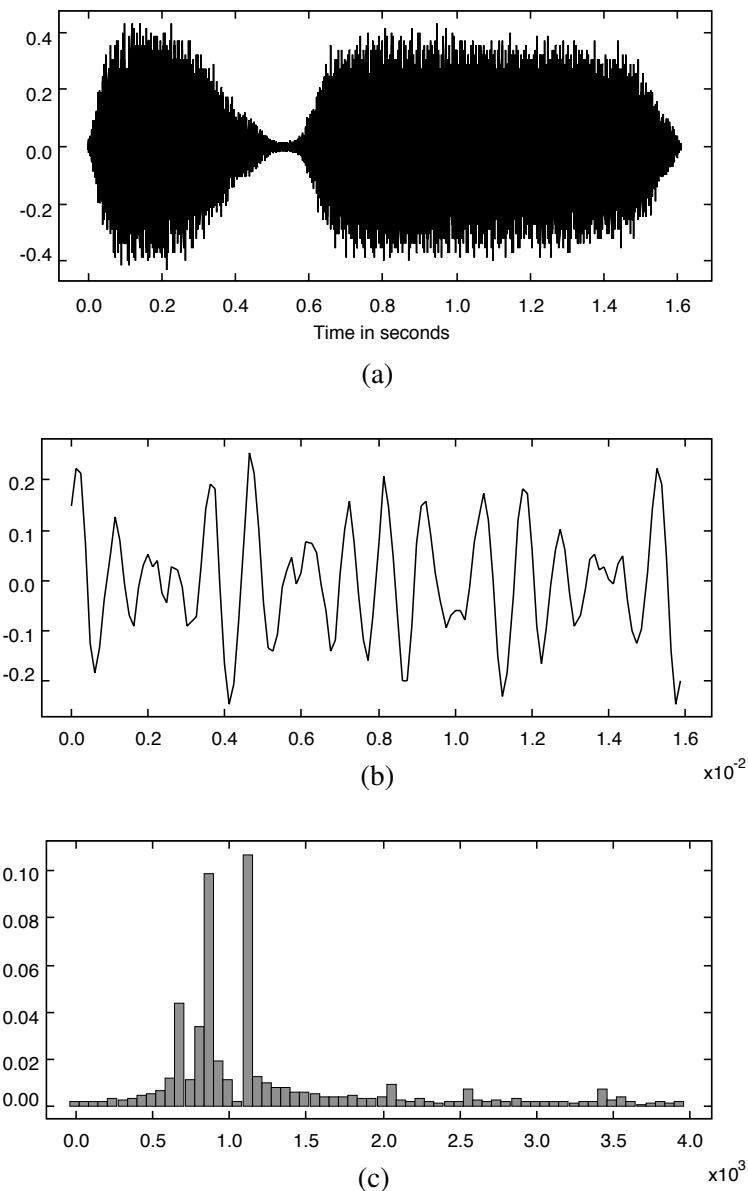


Figure 7.9: (a) A 1.6 second train whistle. (b) A 16 msec segment of the train whistle. (c) The Fourier series coefficients for the 16 msec segment.

7.5.3 Fourier series approximations to images

Images are invariably finite signals. Given any image, it is possible to construct a periodic image by just tiling a plane with the image. Thus, there is again a close relationship between a periodic image and a finite one.

We have seen sinusoidal images (Figure 7.5), so it follows that it ought to be possible to construct a Fourier series representation of an image. The only hard part is that images have a two-dimensional domain, and thus are finite in two distinct dimensions. The sinusoidal images in Figure 7.5 have a vertical frequency, a horizontal frequency, or both.

Suppose that the domain of an image is $[a, b] \times [c, d] \subset \mathbb{R} \times \mathbb{R}$. Let $p_H = b - a$, and $p_V = d - c$ represent the horizontal and vertical “periods” for the equivalent periodic image. For constructing a Fourier series representation, we can define the horizontal and vertical fundamental frequencies as follows:

$$\omega_H = 2\pi/p_H$$

$$\omega_V = 2\pi/p_V$$

The Fourier series representation of *Image*: $[a, b] \times [c, d] \rightarrow \text{Intensity}$ is

$$\text{Image}(x, y) = \sum_{k=0}^{\infty} \sum_{m=0}^{\infty} A_{k,m} \cos(k\omega_H x + \phi_k) \cos(m\omega_V y + \phi_m)$$

For convenience, we have included the constant term $A_{0,0}$ in the summation, so we assume that $\phi_0 = \phi_0 = 0$. (Recall that $\cos(0) = 1$).

7.6 Discrete-time signals

Consider signals of the form $x: \mathbb{Z} \rightarrow \mathbb{R}$, which if the domain is interpreted as time are **discrete-time signals**. Discrete-time signals can be decomposed into sinusoidal components much like continuous-time signals. There are some minor subtleties, however.

7.6.1 Periodicity

A discrete-time signal is **periodic** if there is a non-zero integer $p > 0$ such that

$$\boxed{\forall n \in \mathbb{Z}, \quad x(n+p) = x(n).}$$

Note that, somewhat counterintuitively, not all sinusoidal discrete-time signals are periodic. Consider

$$x(n) = \cos(2\pi fn). \quad (7.7)$$

For this to be periodic, we must be able to find a non-zero integer p such that for all integers n ,

$$x(n+p) = \cos(2\pi fn + 2\pi fp) = \cos(2\pi fn) = x(n).$$

This can be true only if $(2\pi fp)$ is an integer multiple of 2π . That is, if there is some integer m such that

$$2\pi fp = 2\pi m.$$

Dividing both sides by $2\pi p$, we see that this signal is periodic only if we can find nonzero integers p and m such that

$$f = m/p.$$

Basics: Discrete-time frequencies

When the domain of a signal is \mathbb{Z} , then the units of frequency are cycles/sample. Consider for example the discrete-time signal given by

$$\forall n \in \mathbb{Z}, \quad x(n) = \cos(2\pi fn).$$

Suppose this represents an audio signal that is sampled at 8000 samples/second. Then to convert f to Hertz, just watch the units:

$$f[\text{cycles/sample}] \times 8000[\text{samples/second}] = 8000f[\text{cycles/second}].$$

The frequency could have been equally well given in units of radians/sample, as in

$$x(n) = \cos(\omega n).$$

for all $n \in \mathbb{Z}$. To convert ω to Hertz,

$$\begin{aligned} \omega[\text{radians/sample}] \times 8000[\text{samples/second}] \times (1/2\pi)[\text{cycles/radian}] \\ = (8000\omega/2\pi)[\text{cycles/second}]. \end{aligned}$$

In other words, f must be rational. Only if f is rational is this signal periodic.

Example 7.8: Consider a discrete-time sinusoid x given by

$$\forall n \in \mathbb{Z}, \quad x(n) = \cos(4\pi n/5).$$

Putting this into the form of (7.7),

$$x(n) = \cos(2\pi(2/5)n),$$

we see that it has frequency $f = 2/5$ cycles/sample. If this were a continuous-time sinusoid, we could invert this to get the period. However, the inverse is not an integer, so it cannot possibly be the period. Noting that the inverse is $5/2$ samples/cycle, we need to find the smallest multiple of this that is an integer. Multiply by 2, we get 5 samples/(2 cycles). So the period is $p = 5$ samples.

In general, for a discrete sinusoid with frequency f cycles/sample, the period is $p = K/f$, where $K > 0$ is the smallest integer such that K/f is an integer.

7.6.2 The discrete-time Fourier series

Assume we are given a periodic discrete-time signal x with period p . Just as with continuous-time signals, this signal can be described as a sum of sinusoids, called the **discrete-time Fourier series (DFS)** expansion,

$$x(n) = A_0 + \sum_{k=1}^K A_k \cos(k\omega_0 n + \phi_k) \quad (7.8)$$

where

$$K = \begin{cases} (p-1)/2 & \text{if } p \text{ is odd} \\ p/2 & \text{if } p \text{ is even} \end{cases}$$

Unlike the continuous-time case, the sum is finite. Intuitively, this is because discrete-time signals cannot represent frequencies above a certain value. We will examine this phenomenon in more detail in Chapter 11, but for now, it proves extremely convenient.

Mathematically, the above relation is much simpler than the continuous-time Fourier series. All computations are finite. There is a finite number of signal values in one period of the waveform. There is a finite number of terms in the Fourier series representation for each signal value. Unlike the continuous-time case, it is easy for computers to manage this representation. Given a finite set of values, A_0, \dots, A_K , a computer can calculate $x(n)$. Moreover, the representation is exact for any periodic signal. No approximation is needed, and there is no question of convergence. In the continuous-time case, the Fourier series representation is accurate only for certain signals. For the discrete-time case, it is always accurate.

The DFS can be calculated efficiently on a computer using an algorithm called the **fast Fourier transform (FFT)**. All of the Fourier series examples that are plotted in this text were calculated using the FFT algorithm.

7.7 Summary

A time-based signal can be described as a sum of sinusoids. This sum is called a Fourier series. The magnitudes and phases of the sinusoids, taken together as a function of frequency, are called the frequency-domain representation of the signal. For audio signals, this frequency-domain representation has a direct psychoacoustic significance. But we will see in the next chapter that this representation has a significance for all signals when LTI systems are used to process the signals. We will see that the effect that an LTI system has on a signal is particularly easy to understand in the frequency domain.

Exercises

Note: each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **E** In (7.1) we defined periodic for continuous-time signals.
 - (a) Define **finite** and **periodic** for discrete-time signals, where the domain is \mathbb{Z} .
 - (b) Define **finite** and **periodic** for images.
2. **E** Which of the following signals is periodic with a period greater than zero, and what is that period? All functions are of the form $x: \mathbb{R} \rightarrow \mathbb{C}$. The domain is time, measured in seconds, and so the period is in seconds.
 - (a) $\forall t \in \mathbb{R}, \quad x(t) = 10 \sin(2\pi t) + (10 + 2i) \cos(2\pi t)$
 - (b) $\forall t \in \mathbb{R}, \quad x(t) = \sin(2\pi t) + \sin(\sqrt{2}\pi t)$
 - (c) $\forall t \in \mathbb{R}, \quad x(t) = \sin(2\sqrt{2}\pi t) + \sin(\sqrt{2}\pi t)$
3. **E** Consider the discrete-time signal x where
$$\forall n \in \mathbb{Z}, \quad x(n) = 1 + \cos(4\pi n/9).$$
 - (a) Find the period p , where $p > 0$.
 - (b) Give the fundamental frequency corresponding to the period in (1). Give the units.
 - (c) Give the coefficients A_0, A_1, A_2, \dots and ϕ_1, ϕ_2, \dots of the Fourier series expansion for this signal.
4. **E** Consider a continuous-time signal $x: \mathbb{R} \rightarrow \mathbb{R}$ defined by
$$\forall t \in \mathbb{R}, \quad x(t) = \cos(\omega_1 t) + \cos(\omega_2 t),$$
where $\omega_1 = 2\pi$ and $\omega_2 = 3\pi$ radians/second.
 - (a) Find the smallest period $p \in \mathbb{R}_+$, where $p > 0$.
 - (b) Give the fundamental frequency corresponding to the period in (a). Give the units.

- (c) Give the coefficients A_0, A_1, A_2, \dots and ϕ_1, ϕ_2, \dots of the Fourier series expansion for x .
5. **T** Determine the fundamental frequency and the Fourier series coefficients for the well-tempered major triad,

$$s(t) = \sin(440 \times 2\pi t) + \sin(554 \times 2\pi t) + \sin(659 \times 2\pi t).$$

6. **E** Define $x: \mathbb{R} \rightarrow \mathbb{R}$

$$\begin{aligned} \forall t \in \mathbb{R}, \quad x(t) = & 5\cos(\omega_0 t + \pi/2) \\ & + 5\cos(\omega_0 t - \pi/6) \\ & + 5\cos(\omega_0 t - 2\pi/3). \end{aligned}$$

Find A and ϕ so that

$$\forall t \in \mathbb{R}, \quad x(t) = A \cos(\omega_0 t + \phi).$$

Hint: Appendix B might be useful.

7. **T** In this problem, we examine a practical application of the mathematical result in problem 6. In particular, we consider multipath interference, a common problem with wireless systems where multiple paths from a transmitter to a receiver can result in destructive interference of a signal.

When a transmitter sends a radio signal to a receiver, the received signal consists of the direct path plus several reflected paths. In Figure 7.10, the transmitter is on a tower at the left of the figure, the receiver is the telephone in the foreground, and there are three paths: the direct path is l_0 meters long, the path reflected from the hill is l_1 meters long, and the path reflected from the building is l_2 meters long.

Suppose the transmitted signal is a f Hz sinusoid $x: \mathbb{R} \rightarrow \mathbb{R}$,

$$\forall t \in \mathbb{R}, \quad x(t) = A \cos(2\pi f t)$$

So the received signal is y such that $\forall t \in \mathbb{R}$,

$$\begin{aligned} y(t) = & \alpha_0 A \cos\left(2\pi f\left(t - \frac{l_0}{c}\right)\right) \\ & + \alpha_1 A \cos\left(2\pi f\left(t - \frac{l_1}{c}\right)\right) \\ & + \alpha_2 A \cos\left(2\pi f\left(t - \frac{l_2}{c}\right)\right). \end{aligned} \tag{7.9}$$

Here, $0 \leq \alpha_i \leq 1$ are numbers that represent the attenuation (or reduction in signal amplitude) of the signal, and $c = 3 \times 10^8$ m/s is the speed of light in a vacuum.² Answer the following questions.

- Explain why the description of y given in (7.9) is a reasonable model of the received signal.
- What would be the description if instead of the 3 paths as shown in Figure 7.10, there were 10 paths (one direct and 9 reflected).
- The signals received over the different paths cause different phase shifts, ϕ_i , so the signal y (with three paths) can also be written as

$$\forall t \in \mathbb{R}, \quad y(t) = \sum_{k=0}^2 \alpha_k A \cos(2\pi ft - \phi_k)$$

What are the ϕ_k ? Give an expression in terms of f , l_k , and c .

- Let $\Phi = \max\{\phi_1 - \phi_0, \phi_2 - \phi_0\}$ be the largest difference in the phase of the received signals and let $L = \max\{l_1 - l_0, l_2 - l_0\}$ be the maximum path length difference. What is the relationship between Φ, L, f ?
 - Suppose for simplicity that there is only one reflected path of distance l_1 , i.e. take $\alpha_2 = 0$ in the expressions above. Then $\Phi = \phi_1 - \phi_0$. When $\Phi = \pi$, the reflected signal is said to *destroy* the direct signal. Explain why the term “destroy” is appropriate. (This phenomenon is called destructive interference.)
 - In the context of mobile radio shown in the figure, typically $L \leq 500$ m. For what values of f is $\Phi \leq \pi/10$? (Note that if $\Phi \leq \pi/10$ the signals will not interact destructively by much.)
 - For the two-path case, derive an expression that relates the frequencies f that interfere destructively to the path length difference $L = l_1 - l_0$.
8. T The function $x: \mathbb{R} \rightarrow \mathbb{R}$ is given by its graph shown in Figure 7.11. Note that $\forall t \notin [0, 1]$, $x(t) = 0$, and $x(0.4) = 1$. Define y by

$$\forall t \in \mathbb{R}, \quad y(t) = \sum_{k=-\infty}^{\infty} x(t - kp)$$

where p is the period.

²In reality, the reflections are more complicated than the model here.

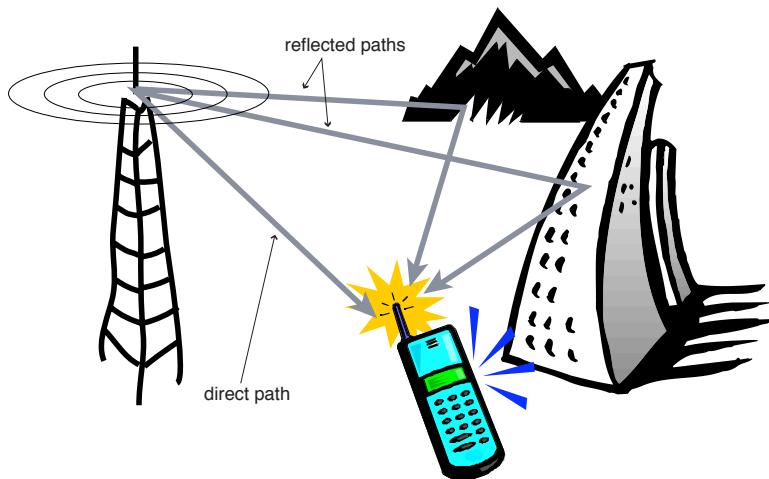


Figure 7.10: A direct and two reflected paths from transmitter to receiver.

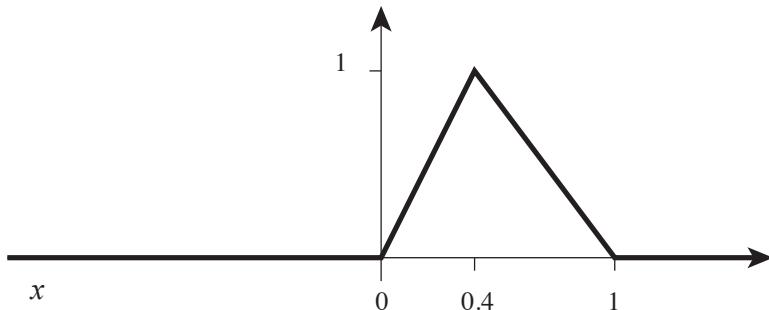


Figure 7.11: The graph of x .

- (a) Prove that y is periodic with period p , i.e.

$$\forall t \in \mathbb{R}, y(t) = y(t + p).$$

- (b) Plot y for $p = 1$.
 (c) Plot y for $p = 2$.
 (d) Plot y for $p = 0.8$.
 (e) Plot y for $p = 0.5$.
 (f) Suppose the function z is obtained by advancing x by 0.4, i.e.

$$\forall t \in \mathbb{R}, z(t) = x(t + 0.4).$$

Define w by

$$\forall t \in \mathbb{R}, w(t) = \sum_{k=-\infty}^{\infty} z(t - kp)$$

What is the relation between w and y . Use this relation to plot w for $p = 1$.

9. **T** Suppose $x: \mathbb{R} \rightarrow \mathbb{R}$ is a periodic signal with period p , i.e.

$$\forall t \in \mathbb{R}, x(t) = x(t + p).$$

Let $f: \mathbb{R} \rightarrow \mathbb{R}$ be any function, and define the signal $y: \mathbb{R} \rightarrow \mathbb{R}$ by $y = f \circ x$, i.e.

$$\forall t \in \mathbb{R}, y(t) = f(x(t)).$$

- (a) Prove that y is periodic with period p .
 (b) Suppose $\forall t \in \mathbb{R}, x(t) = \sin(2\pi t)$. Suppose f is the sign function, $\forall a \in \mathbb{R}$,

$$f(a) = \begin{cases} 1 & \text{if } a \geq 0 \\ -1 & \text{if } a < 0 \end{cases}$$

Plot x and y .

- (c) Suppose $\forall t \in \mathbb{R}, x(t) = \sin(2\pi t)$. Suppose f is the square function, $\forall x \in \mathbb{R}, f(x) = x^2$. Plot y .

10. **C** Suppose the periodic square wave shown on the left in Figure 7.12 has the Fourier series representation

$$A_0 + \sum_{k=1}^{\infty} A_k \cos(2\pi kt/p + \phi_k)$$

Use this to obtain a Fourier series representation of the two-dimensional pattern of rectangles on the right.

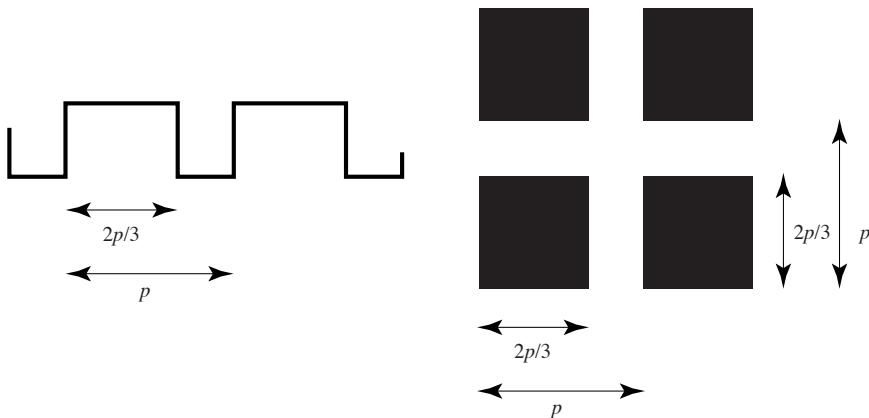


Figure 7.12: A periodic square wave (left) and a periodic pattern (right).

11. **T** Suppose $A_k \in \mathbb{C}$, $\omega_k \in \mathbb{R}$, and $k = 1, 2$, such that

$$\forall t \in \mathbb{R}, \quad A_1 e^{i\omega_1 t} = A_2 e^{i\omega_2 t}. \quad (7.10)$$

Show that $A_1 = A_2$ and $\omega_1 = \omega_2$. **Hint:** Evaluate both sides of (7.10) at $t = 0$, and evaluate their derivatives at $t = 0$.

Discussion: This result shows that in order for two complex exponential signals to be equal, their frequencies, phases, and amplitudes must be equal. More interestingly, this result can be used to show that if a signal can be described as a sum of complex exponential signals, then that description is unique. There is no other sum of complex exponentials (one involving different frequencies, phases, or amplitudes) that will also describe the signal. In particular, the Fourier series representation of a periodic signal is unique, as stated above in theorem 7.5.1.

8

Frequency Response

Contents

8.1	LTI systems	313
8.1.1	Time invariance	313
8.1.2	Linearity	318
8.1.3	Linearity and time-invariance	321
8.2	Finding and using the frequency response	325
8.2.1	Linear difference and differential equations	328
<i>Basics: Sinusoids in terms of complex exponentials</i>	330	
<i>Tips and Tricks: Phasors</i>	331	
8.2.2	The Fourier series with complex exponentials	338
8.2.3	Examples	339
8.3	Determining the Fourier series coefficients	339
8.3.1	Negative frequencies	340
8.4	Frequency response and the Fourier series	340
8.5	Frequency response of composite systems	342
8.5.1	Cascade connection	342
8.5.2	Feedback connection	344
8.6	Summary	346
<i>Probing Further: Relating DFS coefficients</i>	347	
<i>Probing Further: Formula for Fourier series coefficients</i>	349	
<i>Probing Further: Exchanging integrals and summations</i>	350	
<i>Probing Further: Feedback systems are LTI</i>	352	
Exercises	355	

A class of systems that yield to sophisticated analysis techniques is the class of [linear time-invariant systems \(LTI system\)](#), discussed in Chapter 5. LTI systems have a key property: given a sinusoidal input, the output is a sinusoidal signal with the same frequency, but possibly different amplitude and phase. Given an input that is a sum of sinusoids, the output will be a sum of the same sinusoids, each with its amplitude and phase (possibly) modified.

We can justify describing audio signals as sums of sinusoids on purely psychoacoustic grounds. However, because of this property of LTI systems, it is often convenient to describe any signal as a sum of sinusoids, regardless of whether there is a psychoacoustic justification. The real value in this mathematical device is that by using the theory of LTI systems, we can design systems that operate more-or-less independently on the sinusoidal components of a signal. For example, abrupt changes in the signal value require higher frequency components. Thus, we can enhance or suppress these abrupt changes by enhancing or suppressing the higher frequency components. Such an operation is called **filtering** because it filters frequency components. We design systems by crafting their **frequency response**, their response to sinusoidal inputs. An audio equalizer, for example, is a filter that enhances or suppresses certain frequency components. Images can also be filtered. Enhancing the high frequency components will sharpen the image, whereas suppressing the high frequency components will blur the image.

State-space models described in previous chapters are precise and concise, but in a sense, not as powerful as a frequency response. For an LTI system, given a frequency response, you can assert a great deal about the relationship between an input signal and an output signal. Fewer assertions are practical in general with state-space models.

LTI systems, in fact, can also be described with state-space models, using **difference equations** and **differential equations**, as explored in Chapter 5. But state-space models can also describe systems that are not LTI. Thus, state-space models are more general. It should come as no surprise that the price we pay for this increased generality is fewer analysis and design techniques. In this chapter, we explore the (very powerful) analysis and design techniques that apply to the special case of LTI systems.

8.1 LTI systems

LTI systems have received a great deal of intellectual attention for two reasons. First, they are relatively easy to understand. Their behavior is predictable, and can be fully characterized in fairly simple terms, based on the frequency domain representation of signals that we introduced in the previous chapter. Second, many physical systems can be reasonably approximated by them. Few physical systems perfectly fit the model, but many fit very well within a certain regime of operation. Hybrid system models can be used when we wish to model more than one such regime of operation.

8.1.1 Time invariance

Consider the set of signals whose domain is interpreted as time. Such signals are functions of time, sometimes called **time-domain signals**. The domain might be \mathbb{R} , for **continuous-time signals**, or \mathbb{Z} , for **discrete-time signals**. Physical audio signals, for example, are continuous-time signals, while a digital audio file is a discrete-time signal. Systems with continuous-time input and output signals are called **continuous-time systems**. Systems with discrete-time input and output signals are called **discrete-time systems**.

A simple continuous-time system is the **delay** system D_τ , where if the input is x , then the output $y = D_\tau(x)$ is given by

$$\forall t \in \mathbb{R}, \quad y(t) = x(t - \tau). \quad (8.1)$$

Positive values of τ result in positive delays (despite the subtraction in $x(t - \tau)$). Any delay results in a shifting left or right of the graph of a signal, as shown in Figure 8.1.

Example 8.1: Consider a continuous-time signal x given by

$$\forall t \in \mathbb{R}, \quad x(t) = \cos(2\pi t).$$

Let $y = D_{0.5}(x)$. Then

$$\forall t \in \mathbb{R}, \quad y(t) = \cos(2\pi(t - 0.5)) = \cos(2\pi t - \pi).$$

The delay by 0.5 seconds is equivalent to a phase shift of $-\pi$ radians. For a sinusoidal signal, and only for a sinusoidal signal, time delay and phase changes are

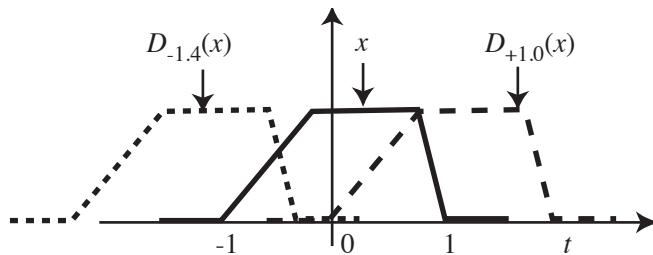


Figure 8.1: Illustration of the delay system D_τ . $D_{-1.4}(x)$ is the signal x to the left by 1.4, and $D_{+1.0}(x)$ is x moved to the right by 1.0.

equivalent, except for the fact that phase is measured in radians (or degrees) rather than in seconds. In addition, a phase change of q is equivalent to a phase change of $q + K2\pi$ for any integer K . Phase applies to sinusoidal signals, whereas delay applies to any signal that is a function of time.

Intuitively, a **time-invariant system** is one whose response to inputs does not change with time. More precisely, a continuous-time system S is said to be time invariant if

$$\forall \tau \in \mathbb{R}, \quad S \circ D_\tau = D_\tau \circ S. \quad (8.2)$$

Figure 8.2 illustrates this equivalence, where the left hand side, $S \circ D_\tau$, is shown on top, and the right hand side, $D_\tau \circ S$, is shown on the bottom. Time invariance implies that the upper and lower systems in figure 8.2 have identical behavior.

Equivalently, S is time-invariant if for all x and τ ,

$$S(D_\tau(x)) = D_\tau(S(x)).$$

Since both sides above are functions, this equation means that

$$\forall t \in \mathbb{R}, \quad S(D_\tau(x))(t) = D_\tau(S(x))(t).$$

Thus a less compact version of (8.2) is¹

$$\forall \tau, t, x, \quad S(D_\tau(x))(t) = D_\tau(S(x))(t).$$

¹We use the shorthand “ $\forall x$ ” instead of “ $\forall x \in [\mathbb{R} \rightarrow \mathbb{R}]$ ” when the set is understood. Similarly, we can write “ $\forall \tau, t, x$ ” instead of “ $\forall \tau \in \mathbb{R}, \forall t \in \mathbb{R}, \forall x \in [\mathbb{R} \rightarrow \mathbb{R}]$ ”.

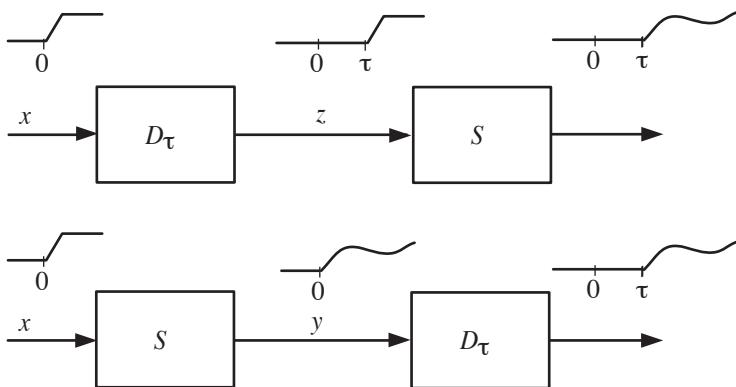


Figure 8.2: Time invariance implies that the top and bottom systems produce the same output signal for the same input signal.

This is interpreted as follows:

A system S is time invariant if, for any input x that produces output y , a delayed input $D_\tau(x)$ produces output $D_\tau(y)$.

Similarly, the discrete-time M -sample **delay** is written D_M . The signal $y = D_M(x)$ is given by

$$\forall n \in \mathbb{Z}, \quad y(n) = x(n - M). \quad (8.3)$$

A discrete-time system S is time invariant if

$$\forall M, x, \quad S(D_M(x)) = D_M(S(x)). \quad (8.4)$$

Example 8.2: Consider a discrete-time system S ,

$$S: [\mathbb{Z} \rightarrow \mathbb{R}] \rightarrow [\mathbb{Z} \rightarrow \mathbb{R}].$$

Suppose that any input x produces output y where

$$\forall n \in \mathbb{Z}, \quad y(n) = x(n) + 0.9x(n - 1). \quad (8.5)$$

This system is time-invariant. To show this, consider a delayed input $\hat{x} = D_M(x)$, for some integer M . That is,

$$\forall n, \quad \hat{x}(n) = x(n - M). \quad (8.6)$$

Suppose that this input produces output $\hat{y} = S(\hat{x})$. Then by the relation (8.5) between an input and an output,

$$\forall n, \quad \hat{y}(n) = \hat{x}(n) + 0.9\hat{x}(n-1).$$

Substituting (8.6), we see that

$$\forall n, \quad \hat{y}(n) = x(n-M) + 0.9x(n-M-1) = y(n-M).$$

Since $\hat{y} = D_M(y)$, the system is time-invariant.

Example 8.3: Consider the system *DelayAndSquare*, or *DS* for short,

$$DS : [\mathbb{R} \rightarrow \mathbb{R}] \rightarrow [\mathbb{R} \rightarrow \mathbb{R}].$$

Suppose that any input x produces output y where

$$\forall t \in \mathbb{R}, \quad y(t) = (x(t-1))^2. \quad (8.7)$$

This system is time-invariant. To show this, consider a delayed input $\hat{x} = D_\tau(x)$, for some real number τ . That is,

$$\forall t, \quad \hat{x}(t) = x(t-\tau). \quad (8.8)$$

Suppose that this input produces output $\hat{y} = S(\hat{x})$. Then by the relation (8.7) between an input and an output,

$$\forall t, \quad \hat{y}(t) = (\hat{x}(t-1))^2.$$

Substituting (8.8), we see that

$$\forall t, \quad \hat{y}(t) = (x(t-1-\tau))^2 = y(t-\tau).$$

Since $\hat{y} = D_\tau(y)$, the system is time-invariant.

Example 8.4: Consider a system *ReverseTime* or RT ,

$$RT : [\mathbb{R} \rightarrow \mathbb{R}] \rightarrow [\mathbb{R} \rightarrow \mathbb{R}],$$

where any input x produces output y related by

$$\forall t \in \mathbb{R}, \quad y(t) = x(-t). \quad (8.9)$$

This system is *not* time-invariant. To show this, consider a delayed input $\hat{x} = D_\tau(x)$, for some real number τ . That is,

$$\forall t, \quad \hat{x}(t) = x(t - \tau). \quad (8.10)$$

Suppose that this input produces output $\hat{y} = S(\hat{x})$. Then by the relation (8.9) between an input and an output,

$$\forall t, \quad \hat{y}(t) = \hat{x}(-t).$$

Substituting (8.10), we see that

$$\forall t, \quad \hat{y}(t) = x(-t - \tau) \neq y(t - \tau) = x(-t + \tau).$$

Since $\hat{y} \neq D_\tau(y)$, the system is *not* time-invariant.

To be completely convinced that these two signals are different in general, consider a particular signal x such that $\forall t, x(t) = t$, and take $\tau = 1$. Then $\hat{y}(0) = -1$, but $(D_\tau(y))(0) = 1$.

Time invariance is a mathematical fiction. No electronic system is time invariant in the strict sense. For one thing, such a system is turned on at some point in time. Clearly, its behavior before it is turned on is not the same as its behavior after it is turned on. Nevertheless, it proves to be a very convenient mathematical fiction, and it is a reasonable approximation for many systems if their behavior is constant over a relatively long period of time (relative to whatever phenomenon we are studying). For example, your audio amplifier is not a time-invariant system. Its behavior changes drastically when you turn it on or off, and changes less drastically when you raise or lower the volume. However, for

the duration of a compact disc, if you leave the volume fixed, the system can be reasonably approximated as being time-invariant.

Some systems have a similar property even though they operate on signals whose domain is not time. For example, the domain of an image is a region of a plane. The output of an image processing system may not depend significantly on where in the plane the input image is placed. Shifting the input image will only shift the output image by the same amount. This property which generalizes time invariance and holds for some image processing systems, is called **shift invariance** (see problem 5).

8.1.2 Linearity

Consider the set of signals whose range is \mathbb{R} or \mathbb{C} . Such signals are real-valued functions or complex-valued functions. Since real-valued functions are a subset of complex-valued functions, we only need to talk about complex-valued functions. It does not matter (for now) whether they are continuous-time signals or discrete-time signals. The domain could be \mathbb{R} or \mathbb{Z} .

Suppose x is a complex-valued function and a is a complex constant. Then we can define a new complex-valued function ax such that for all t in the domain of x ,

$$(ax)(t) = a(x(t)).$$

In other words, the new function, which we call ax , is simply scaled by the constant a .

Similarly, given two complex-valued functions x_1 and x_2 with the same domain and range, we can define a new function $(x_1 + x_2)$ such that for all t in the domain,

$$(x_1 + x_2)(t) = x_1(t) + x_2(t).$$

Consider the set of all systems that map complex-valued functions to complex-valued functions. Such systems are called **complex systems**. Again, it does not matter (for now) whether they are discrete-time systems or continuous-time systems. Suppose that S is a complex system. S is said to be **linear** if for all $a \in \mathbb{C}$ and for all complex signals x ,

$$\boxed{S(ax) = aS(x)} \tag{8.11}$$

and for all complex signals x_1 and x_2 in the domain of S ,

$$\boxed{S(x_1 + x_2) = S(x_1) + S(x_2)} \tag{8.12}$$

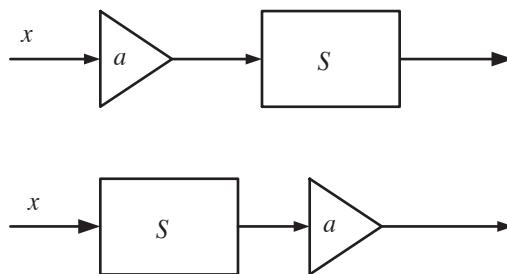


Figure 8.3: If S is linear, then these two systems are equivalent. The triangle represents a system that scales a signal by some complex constant a .

The first of these—called the **homogeneity** property—says that if you scale the input, the output is scaled. The second one—called the **additivity** property—says that if the input is described as the sum of two component signals, then the output can be described as the sum of two signals that would result from the components alone. Recall that linear functions were introduced in Section 5.2. A **linear system** is one whose function relating the output to the input is linear.

In pictures, the first property says that the two systems in Figure 8.3 are equivalent if S is linear. Here, the triangle represents the scaling operation. The second property says that the two systems in Figure 8.4 are equivalent.

Example 8.5: Consider the same discrete-time system S of example 8.2, where input x produces output y such that

$$\forall n \in \mathbb{Z}, \quad y(n) = x(n) + 0.9x(n-1).$$

This system is linear. To show this, we must show that (8.11) and (8.12) hold. Suppose input $\hat{x} = ax$ produces output $\hat{y} = S(\hat{x})$. Then

$$\begin{aligned} \forall n, \quad \hat{y}(n) &= \hat{x}(n) + 0.9\hat{x}(n-1) \\ &= ax(n) + 0.9ax(n-1) \\ &= a(x(n) + 0.9x(n-1)) \\ &= ay(n). \end{aligned}$$

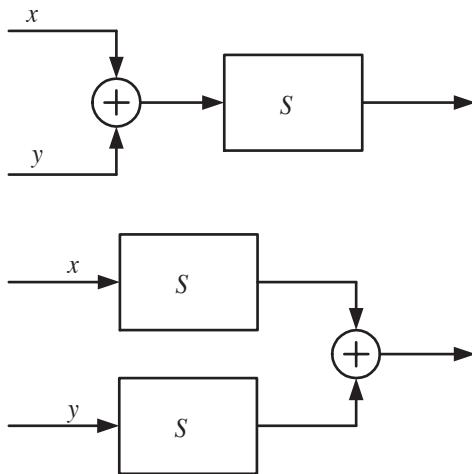


Figure 8.4: If S is linear, then these two systems are equivalent.

Thus, $S(ax) = aS(x)$, establishing (8.11).

To check (8.12), suppose input x_1 produces output y_1 and x_2 produces y_2 . Let $x = x_1 + x_2$ produce y . We must show that $y = y_1 + y_2$. We leave this as an exercise.

Example 8.6: In the continuous-time system *DelayAndSquare* or *DS* of example 8.3, an input x produces output y where

$$\forall t \in \mathbb{R}, \quad y(t) = (x(t-1))^2.$$

This system is not linear. To show this we must show that either (8.11) or (8.12) does not hold for *DS*. We will show that (8.11) does not hold. To show this, consider a scaled input $\hat{x} = ax$, for some complex number a . Suppose that this input produces output $\hat{y} = S(\hat{x})$. Then,

$$\forall t, \quad \hat{y}(t) = (\hat{x}(t-1))^2.$$

Since $\hat{x} = ax$,

$$\forall t, \quad \hat{y}(t) = (ax(t-1))^2 = a^2(x(t-1))^2 \neq ay(t) = a(x(t-1))^2.$$

In particular, take for example $a = 2$, $t = 0$, and x such that $\forall t$, $x(t) = 1$. These values result in

$$\hat{y}(t) = 4 \neq ay(t) = 2.$$

Example 8.7: In the time-reversal system RT of example 8.4,

$$RT : [\mathbb{R} \rightarrow \mathbb{R}] \rightarrow [\mathbb{R} \rightarrow \mathbb{R}],$$

any input x produces output y related by

$$\forall t \in \mathbb{R}, \quad y(t) = x(-t).$$

This system is linear. To show this we must show that (8.11) and (8.12) both hold. We first show that (8.11) holds; that is, for all $a \in \mathbb{R}$, $x \in [\mathbb{R} \rightarrow \mathbb{R}]$, and $t \in \mathbb{R}$,

$$RT(ax)(t) = (aRT(x))(t).$$

But this is certainly true, since the left and right sides both evaluate to $ax(-t)$. A similar argument is used to show (8.12).

Linearity is a mathematical fiction. No electronic system is linear in the strict sense. A system is designed to work with a range of input signals, and arbitrary scaling of the input does not translate into arbitrary scaling of the output. If you provide an input to your audio amplifier that is higher voltage than it is designed for, then it is not likely to just produce louder sounds. Its input circuits will get overloaded and signal distortion will result. Nonetheless, as a mathematical fiction, linearity is extremely convenient. It says that we can decompose the inputs to a system and study the effect of the system on the individual components.

8.1.3 Linearity and time-invariance

For time-domain systems, time-invariance is a useful (if fictional) property. For complex (or real) systems, linearity is a useful (if fictional) property. For complex (or real)

time-domain systems, the combination of these properties is extremely useful. Linear time-invariant (LTI) systems turn out to have particularly simple behavior with sinusoidal inputs.

Given a sinusoid at the input, the output of an LTI system will be a sinusoid with the same frequency, but possibly with different phase and amplitude.

It then follows that

Given an input that is described as a sum of sinusoids of certain frequencies, the output can be described as a sum of sinusoids with the same frequencies, but with (possible) phase and amplitude changes at each frequency.

A straightforward way to show that LTI systems have these properties starts by considering **complex exponentials** (for a review of complex numbers, see Appendix B). A continuous-time complex exponential is a signal $x \in [\mathbb{R} \rightarrow \mathbb{C}]$ where

$$\forall t \in \mathbb{R}, \quad x(t) = e^{i\omega t} = \cos(\omega t) + i \sin(\omega t).$$

Complex exponential functions have an interesting property that will prove useful to us. Specifically,

$$\forall t \in \mathbb{R} \text{ and } \tau \in \mathbb{R}, \quad x(t - \tau) = e^{i\omega(t-\tau)} = e^{-i\omega\tau} e^{i\omega t}.$$

This follows from the multiplication property of exponentials,

$$e^{b+c} = e^b e^c.$$

Since $D_\tau(x)(t) = x(t - \tau)$, we have that for the complex exponential x ,

$$D_\tau(x) = ax, \text{ where } a = e^{-i\omega\tau}. \quad (8.13)$$

In words, a delayed complex exponential is a scaled complex exponential, where the scaling constant is the complex number $a = e^{-i\omega\tau}$.

We will now show that if the input to a continuous-time LTI system is $e^{i\omega t}$, then the output will be $H(\omega)e^{i\omega t}$, where $H(\omega)$ is a constant (not a function of time) that depends on the frequency ω of the complex exponential. In other words, the output is only a scaled version of the input.

When the output of a system is only a scaled version of the input, the input is called an **eigenfunction**, which comes from the German word for “same.” The output is (almost) the same as the input.

Complex exponentials are eigenfunctions of LTI systems, as we will now show. This is the most important reason for the focus on complex exponentials in the study of signals and systems. This single property underlies much of the discipline of signal processing, and is used heavily in circuit analysis, communication systems, and control systems.

Given an LTI system $S : [\mathbb{R} \rightarrow \mathbb{C}] \rightarrow [\mathbb{R} \rightarrow \mathbb{C}]$, let x be an input signal where

$$\forall t \in \mathbb{R}, \quad x(t) = e^{i\omega t}$$

Recall that S is time invariant if for all $\tau \in \mathbb{R}$,

$$S \circ D_\tau = D_\tau \circ S.$$

Thus

$$S(D_\tau(x)) = D_\tau(S(x)).$$

From (8.13),

$$S(D_\tau(x)) = S(ax)$$

where $a = e^{-i\omega\tau}$, and from linearity,

$$S(ax) = aS(x)$$

so

$$aS(x) = D_\tau(S(x)). \quad (8.14)$$

Let $y = S(x)$ be the corresponding output signal. Substituting into (8.14) we get

$$ay = D_\tau(y).$$

In other words,

$$\forall t, \tau \in \mathbb{R}, \quad e^{-i\omega\tau}y(t) = y(t - \tau).$$

In particular, this is true for $t = 0$, so letting $t = 0$,

$$\forall \tau \in \mathbb{R}, \quad y(-\tau) = e^{-i\omega\tau}y(0).$$

Changing variables, letting $t = -\tau$, we note that this implies that

$$\forall t \in \mathbb{R}, \quad y(t) = e^{i\omega t}y(0).$$

Recall that $y(0)$ is the output evaluated at 0 when the input is $e^{i\omega t}$. It is a constant, in that it does not depend on t , so this establishes that the output is a complex exponential, just

like the input, except that it is scaled by $y(0)$. However, $y(0)$ does, in general, depend on ω , so we define the function $H: \mathbb{R} \rightarrow \mathbb{C}$ by

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = y(0) = (S(x))(0), \text{ where } \forall t \in \mathbb{R}, \quad x(t) = e^{i\omega t}. \quad (8.15)$$

That is, $H(\omega)$ is the output at time zero when the input is a complex exponential with frequency ω .

Using this notation, we write the output y as

$$\forall t \in \mathbb{R}, \quad y(t) = H(\omega)e^{i\omega t}$$

when the input is $e^{i\omega t}$. Note that $H(\omega)$ is a function of $\omega \in \mathbb{R}$, the frequency of the input complex exponential.

The function $H: \mathbb{R} \rightarrow \mathbb{C}$ is called the **frequency response**. It defines the response of the LTI system to a complex exponential input at any given frequency. It gives the scaling factor that the system imposes on that complex exponential.

For discrete-time systems, the situation is similar. By reasoning identical to that above, for an LTI system, if the input is a **discrete complex exponential**,

$$\forall n \in \mathbb{Z}, \quad x(n) = e^{i\omega n}$$

then the output is the same complex exponential scaled by a constant (a complex number that does not depend on time),

$$\forall n \in \mathbb{Z}, \quad y(n) = H(\omega)e^{i\omega n}$$

H is once again called the frequency response, and since it is a function of ω , and is possibly complex valued, it has the form $H: \mathbb{R} \rightarrow \mathbb{C}$.

There is one key difference, however, between discrete-time systems and continuous-time systems. Since n is an integer, notice that

$$e^{i\omega n} = e^{i(\omega+2\pi)n} = e^{i(\omega+4\pi)n},$$

and so on. That is, a discrete complex exponential with frequency ω is identical to a discrete complex exponential with frequency $\omega + 2K\pi$, for any integer K . The frequency response, therefore, must be identical at these frequencies, since the inputs are identical. That is

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = H(\omega + 2K\pi)$$

for any integer K . That is, a discrete-time frequency response is periodic with period 2π .

8.2 Finding and using the frequency response

We have seen that if the input to an LTI system is a complex exponential signal $x \in [\mathbb{R} \rightarrow \mathbb{C}]$ where

$$\forall t \in \mathbb{R}, \quad x(t) = e^{i\omega t} = \cos(\omega t) + i \sin(\omega t).$$

then the output is

$$\forall t \in \mathbb{R}, \quad y(t) = H(\omega) e^{i\omega t}. \quad (8.16)$$

where $H(\omega)$ is a (possibly complex-valued) number that is a property of the system. $H(\omega)$ is called the frequency response at frequency ω .

Example 8.8: Consider a delay system $S = D_T$, for some $T \in \mathbb{R}$. It is an LTI system, as is easy to verify by checking that (8.2), (8.11), and (8.12) are satisfied. Suppose the input to the delay system is the complex exponential x given by

$$\forall t \in \mathbb{R}, \quad x(t) = e^{i\omega t}.$$

Then the output y satisfies

$$\forall t \in \mathbb{R}, \quad y(t) = e^{i\omega(t-T)} = e^{-i\omega T} e^{i\omega t}.$$

Comparing this to (8.16) we see that the frequency response of the delay is

$$H(\omega) = e^{-i\omega T}.$$

Example 8.9: Consider a discrete-time M -sample delay system $S = D_M$. If $y = S(x)$ then y is given by

$$\forall n \in \mathbb{Z}, \quad y(n) = x(n - M). \quad (8.17)$$

This is an LTI system, as is easy to verify. We could find the frequency response exactly the same way as in the previous example, but instead we use a slightly different method. Since the system is LTI, we know that if the input is x such that

for all $n \in \mathbb{Z}$, $x(n) = e^{i\omega n}$, then the output is $H(\omega)e^{i\omega n}$, where H is the frequency response. By plugging this input and output into (8.17), we get

$$H(\omega)e^{i\omega n} = e^{i\omega(n-M)} = e^{i\omega n}e^{-i\omega M}.$$

Divide both sides by $e^{i\omega n}$ to get

$$H(\omega) = e^{-i\omega M}.$$

The techniques in the previous examples can be used to find the frequency response of more complicated systems. Simply replace the input x in a difference equation like (8.17) with $e^{i\omega n}$, and replace the output y with $H(\omega)e^{i\omega n}$, and then solve for $H(\omega)$.

Example 8.10: Consider a discrete-time, length two moving average, given by the difference equation

$$\forall n \in \mathbb{Z}, \quad y(n) = (x(n) + x(n-1))/2,$$

where x is the input and y is the output. When the input for all n is $e^{i\omega n}$, this becomes

$$H(\omega)e^{i\omega n} = (e^{i\omega n} + e^{i\omega(n-1)})/2.$$

Solving for $H(\omega)$, we find that the frequency response is

$$H(\omega) = (1 + e^{-i\omega})/2.$$

A similar approach can find the frequency response of a continuous-time system described by a differential equation.

Example 8.11: Consider a continuous-time system with input x and output y related by the differential equation

$$\forall t \in \mathbb{R}, \quad RC \frac{dy}{dt}(t) + y(t) = x(t), \quad (8.18)$$

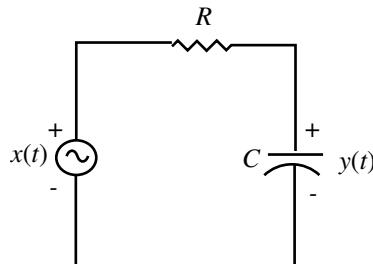


Figure 8.5: The RC circuit of example 8.11.

where R and C are real-valued constants. This differential equation describes the RC circuit of Figure 8.5, which consists of an R -ohm resistance in series with a C -farad capacitor. The circuit has input voltage x , provided by a voltage source, shown as a circle on the left. The output is the voltage y across the capacitor. Kirchhoff's voltage law gives the differential equation. It is easy to verify that this differential equation describes an LTI system.

We can determine the frequency response of this system by assuming that the input x is given by $\forall t \in \mathbb{R}$, $x(t) = e^{i\omega t}$, and finding the output. Since the system is LTI, the output will be given by $y(t) = H(\omega)e^{i\omega t}$. Plugging these values for x and y into (8.18) gives

$$RC(i\omega)H(\omega)e^{i\omega t} + H(\omega)e^{i\omega t} = e^{i\omega t}, \quad (8.19)$$

because

$$\frac{dy}{dt}(t) = i\omega H(\omega)e^{i\omega t}.$$

Dividing both sides of (8.19) by $e^{i\omega t}$ yields the frequency response of this circuit,

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \frac{1}{1 + iRC\omega}.$$

8.2.1 Linear difference and differential equations

The procedure of example 8.10 can be used to write down by inspection the frequency response of any high-order linear difference equation of the form, $\forall n \in \mathbb{Z}$,

$$a_0y(n) + a_1y(n-1) + \cdots + a_Ny(n-N) = b_0x(n) + b_1x(n-1) + \cdots + b_Mx(n-M). \quad (8.20)$$

The coefficients of this difference equation, a_0, \dots, a_N and b_0, \dots, b_M , are real constants. (They could also be complex.) This describes an LTI system, and a good way to recognize that a discrete-time system is LTI is to write it in this form. If the input for all n is $x(n) = e^{i\omega n}$, then the output for all n is $y(n) = H(\omega)e^{i\omega n}$. Plugging these values of input and output into (8.20) gives,

$$\begin{aligned} a_0H(\omega)e^{i\omega n} + a_1H(\omega)e^{i\omega(n-1)} &+ \cdots + a_NH(\omega)e^{i\omega(n-N)} \\ &= b_0e^{i\omega n} + b_1e^{i\omega(n-1)} + \cdots + b_Me^{i\omega(n-M)}. \end{aligned}$$

Recognizing that $e^{i\omega(n-m)} = e^{-im\omega}e^{i\omega n}$, we can divide both sides by $e^{i\omega n}$ and solve for $H(\omega)$ to get

$$\boxed{\forall \omega \in \mathbb{R}, \quad H(\omega) = \frac{b_0 + b_1e^{-i\omega} + \cdots + b_Me^{-iM\omega}}{a_0 + a_1e^{-i\omega} + \cdots + a_Ne^{-iN\omega}}} \quad (8.21)$$

Observe that the frequency response (8.21) is a ratio of two polynomials in $e^{-i\omega}$.

Example 8.12: Consider an LTI system given by the difference equation

$$\forall n \in \mathbb{Z}, \quad y(n) - y(n-3) = x(n) + 2x(n-1) + x(n-2).$$

Its frequency response is

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \frac{1 + 2e^{-i\omega} + e^{-i2\omega}}{1 - e^{-i3\omega}}.$$

In a similar way one can obtain the frequency response of any linear differential equation of the form,

$$\begin{aligned} \forall t \in \mathbb{R}, \quad a_N \frac{d^N y}{dt^N}(t) + \cdots + a_1 \frac{dy}{dt}(t) + a_0 y(t) = \\ b_M \frac{d^M x}{dt^M}(t) + \cdots + b_1 \frac{dx}{dt}(t) + b_0 x(t), \end{aligned} \quad (8.22)$$

where the coefficients a_N, \dots, a_0 and b_M, \dots, b_0 , are real (or complex) constants. This describes an LTI system, and a good way to recognize that a continuous-time system is LTI is to write it in this form. If the input for all t is $x(t) = e^{i\omega t}$, the output for all t is $y(t) = H(\omega)e^{i\omega t}$. Plugging these values of input and output into (8.22), and recognizing that

$$\frac{d^k}{dt^k} e^{i\omega t} = (i\omega)^k e^{i\omega t},$$

gives,

$$\begin{aligned} a_N(i\omega)^N H(\omega) e^{i\omega t} + \dots + a_1(i\omega) H(\omega) e^{i\omega t} + a_0 H(\omega) e^{i\omega t} = \\ b_M(i\omega)^M e^{i\omega t} + \dots + b_1(i\omega) e^{i\omega t} + b_0 e^{i\omega t}. \end{aligned}$$

We can divide both sides by $e^{i\omega t}$ to get

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \frac{b_M(i\omega)^M + \dots + b_1(i\omega) + b_0}{a_N(i\omega)^N + \dots + a_1(i\omega) + a_0} \quad (8.23)$$

Observe that the frequency response (8.23) is a ratio of two polynomials in $i\omega$.

Example 8.13: Consider the continuous-time system given by the differential equation

$$\forall t \in \mathbb{R}, \quad \frac{d^2y}{dt^2}(t) - 3\frac{dy}{dt}(t) + 2y(t) = \frac{dx}{dt} + x(t),$$

where x is the input and y is the output. It has frequency response

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \frac{i\omega + 1}{(i\omega)^2 - 3i\omega + 2}.$$

Complex exponentials as inputs are rather abstract. We have seen that with audio signals, sinusoidal signals are intrinsically significant because the human ear interprets the frequency of the sinusoid as its tone. Note that a real-valued sinusoidal signal can be given as a combination of exponential signals (see box on page 330),

$$\cos(\omega t) = (e^{i\omega t} + e^{-i\omega t})/2.$$

Thus, if this is the input to an LTI system with frequency response H , then the output will be

$$y(t) = (H(\omega)e^{i\omega t} + H(-\omega)e^{-i\omega t})/2. \quad (8.25)$$

Many (or most) LTI systems are not capable of producing complex-valued outputs when the input is real, so for such systems, this $y(t)$ must be real. This implies that

$$H(\omega) = H^*(-\omega). \quad (8.26)$$

To see why this is so, note that if $y(t)$ is real then so is $H(\omega)e^{i\omega t} + H(-\omega)e^{-i\omega t}$. But for this to be real, it must be that the imaginary parts of the two terms cancel,

$$\text{Im}\{H(\omega)e^{i\omega t}\} = -\text{Im}\{H(-\omega)e^{-i\omega t}\}. \quad (8.27)$$

Note that

$$\text{Im}\{H(\omega)e^{i\omega t}\} = \text{Re}\{H(\omega)\} \sin(\omega t) + \text{Im}\{H(\omega)\} \cos(\omega t).$$

Basics: Sinusoids in terms of complex exponentials

Euler's formula states that

$$e^{i\theta} = \cos(\theta) + i \sin(\theta).$$

The complex conjugate is

$$e^{-i\theta} = \cos(\theta) - i \sin(\theta).$$

Summing these,

$$e^{i\theta} + e^{-i\theta} = 2\cos(\theta)$$

or

$$\boxed{\cos(\theta) = (e^{i\theta} + e^{-i\theta})/2.}$$

Thus, for example,

$$\cos(\omega t) = (e^{i\omega t} + e^{-i\omega t})/2.$$

Similarly,

$$\boxed{\sin(\theta) = -i(e^{i\theta} - e^{-i\theta})/2.}$$

In appendix A we show that many useful trigonometric identities are easily derived from these simple relations.

Using a similar fact for the right side of (8.27), we get

$$\begin{aligned} & \operatorname{Re}\{H(\omega)\} \sin(\omega t) + \operatorname{Im}\{H(\omega)\} \cos(\omega t) \\ &= -\operatorname{Re}\{H(-\omega)\} \sin(-\omega t) - \operatorname{Im}\{H(-\omega)\} \cos(-\omega t). \end{aligned}$$

Tips and Tricks: Phasors

Consider a general continuous-time **sinusoidal signal**, $x(t) = A \cos(\omega t + \phi)$, for all $t \in \mathbb{R}$. Here A is the **amplitude**, ϕ is the **phase**, and ω is the **frequency** of the sinewave. (We call this a sinewave, even though we are using cosine to describe it.) The units of ϕ are radians. The units of ω are radians per second, assuming t is in seconds. This can be written

$$x(t) = \operatorname{Re}\{Ae^{i(\omega t + \phi)}\} = \operatorname{Re}\{Ae^{i\phi} e^{i\omega t}\} = \operatorname{Re}\{Xe^{i\omega t}\}$$

where $X = Ae^{i\phi}$ is called the **complex amplitude** or **phasor**. The representation

$$x(t) = \operatorname{Re}\{Xe^{i\omega t}\} \quad (8.24)$$

is called the phasor representation of x . It can be convenient. For example, consider summing two sinusoids with the same frequency,

$$x(t) = A_1 \cos(\omega t + \phi_1) + A_2 \cos(\omega t + \phi_2).$$

This is particularly easy using phasors, since

$$x(t) = \operatorname{Re}\{(X_1 + X_2)e^{i\omega t}\} = |X_1 + X_2| \cos(\omega t + \angle(X_1 + X_2))$$

where $X_1 = A_1 e^{i\phi_1}$ and $X_2 = A_2 e^{i\phi_2}$. Thus, addition of the sinusoids reduces to addition of two complex numbers.

The exponential $Xe^{i\omega t}$ in (8.24) is complex valued. If we represent it in a two-dimensional plane as in Figure 8.6, it will rotate in a counter-clockwise direction as t increases. The frequency of rotation will be ω radians per second. At time 0 it will be X , shown in gray. The real-valued sinewave $x(t)$ is the projection of $Xe^{i\omega t}$ on the real axis, namely

$$\operatorname{Re}\{Xe^{i\omega t}\} = |X| \cos(\omega t + \angle X).$$

The sum of two sinusoids with the same frequency is similarly depicted in Figure 8.7. The two phasors, X_1 and X_2 are put head to tail and then rotated together. A similar method can be used to add sinusoids of different frequencies, but then the two vectors will rotate at different rates.

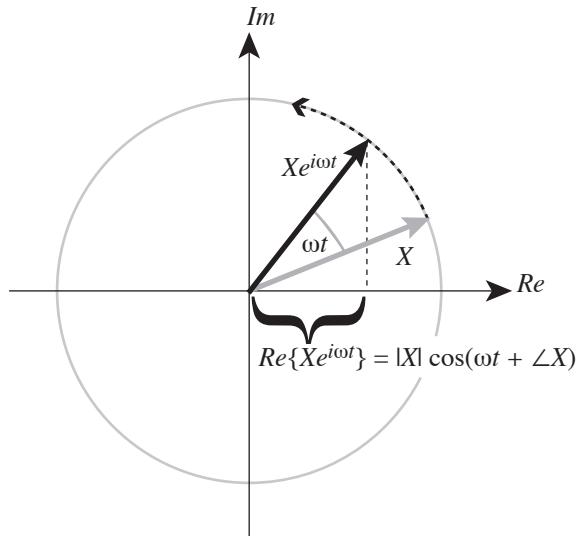


Figure 8.6: Phasor representation of a sinusoid.

If we evaluate this at $t = 0$ we get

$$\text{Im}\{H(\omega)\} = -\text{Im}\{H(-\omega)\},$$

and if we evaluate it at $t = \pi/(2\omega)$, we get

$$\text{Re}\{H(\omega)\} = \text{Re}\{H(-\omega)\},$$

which together imply (8.26).

Property (8.26) is called **conjugate symmetry**. The frequency response of a real system (one whose input and output signals are real-valued) is **conjugate symmetric**. Thus, combining (8.25) and (8.26), when the input is $x(t) = \cos(\omega t)$, the output is

$$\boxed{\forall t \in \mathbb{R}, \quad y(t) = \text{Re}\{H(\omega)e^{i\omega t}\}.}$$

If we write $H(\omega)$ in polar form,

$$H(\omega) = |H(\omega)|e^{i\angle H(\omega)},$$

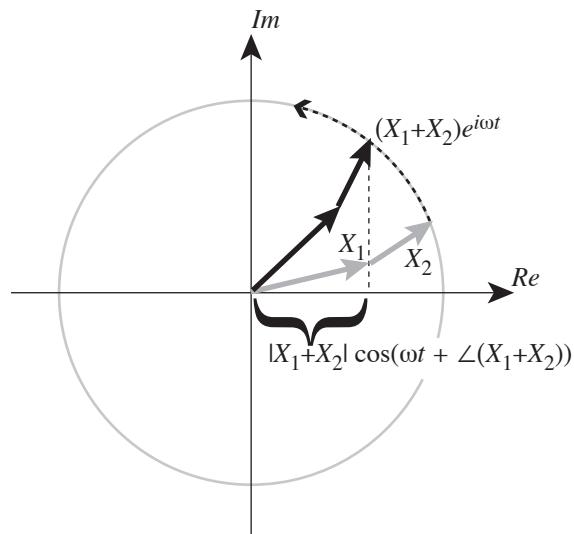


Figure 8.7: Phasor representation of the sum of two sinusoids with the same frequency.

then when the input is $\cos(\omega t)$, the output is

$$\boxed{\forall t \in \mathbb{R}, \quad y(t) = |H(\omega)| \cos(\omega t + \angle H(\omega)).}$$

Thus, $H(\omega)$ gives the **gain** $|H(\omega)|$ and **phase shift** $\angle H(\omega)$ that a sinusoidal input with frequency ω experiences. $|H(\omega)|$ is called the **magnitude response** of the system, and $\angle H(\omega)$ is called the **phase response**.

Example 8.14: The delay system $S = D_T$ of example 8.8 has frequency response

$$H(\omega) = e^{-i\omega T}.$$

The magnitude response is

$$|H(\omega)| = 1.$$

Thus, any cosine input into a delay yields a cosine output with the same amplitude (obviously). A filter with a constant unity magnitude response is called an **allpass filter**, because it passes all frequencies equally. A delay is a particularly simple form of an allpass filter.

The phase response is

$$\angle H(\omega) = -\omega T.$$

Thus, any cosine input with frequency ω yields a cosine output with the same frequency, but phase shift $-\omega T$.

Example 8.15: The M -sample discrete-time delay of example 8.9 is also an allpass filter. Its phase response is

$$\angle H(\omega) = -\omega M.$$

Example 8.16: The magnitude response of the length-two moving average considered in example 8.10 is

$$|H(\omega)| = |(1 + e^{-i\omega})/2|.$$

We can plot this using the following Matlab code, which (after adjusting the labels) results in Figure 8.8.

```
omega = [0:pi/250:pi];
H = (1 + exp(-i*omega))/2;
plot(omega, abs(H));
```

Notice that at frequency zero (a cosine with zero frequency has constant value), the magnitude response is 1. That is, a constant signal gets through the filter without any reduction in amplitude. This is expected, since the average of two neighboring samples of a constant signal is simply the value of the constant signal. Notice that the magnitude response decreases as the frequency increases. Thus, higher frequency signals have their amplitudes reduced more by the filter than lower frequency signals. Such a filter is called a **lowpass** filter because it passes lower frequencies better than higher frequencies.

Example 8.17: The RC circuit of example 8.11 has frequency response given by

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \frac{1}{1 + iRC\omega}.$$

We can express this in polar form, $H(\omega) = |H(\omega)|e^{i\angle H(\omega)}$ to get the magnitude and phase responses,

$$|H(\omega)| = \frac{1}{\sqrt{1 + (RC\omega)^2}}, \quad \angle H(\omega) = -\tan^{-1} RC\omega.$$

If for all t , $x(t) = \cos(\omega t)$, then $y(t) = |H(\omega)| \cos(\omega t - \angle H(\omega))$. Since $|H(\omega)| \rightarrow 0$ as $\omega \rightarrow \infty$, this RC circuit is a (not very good) low-pass filter.

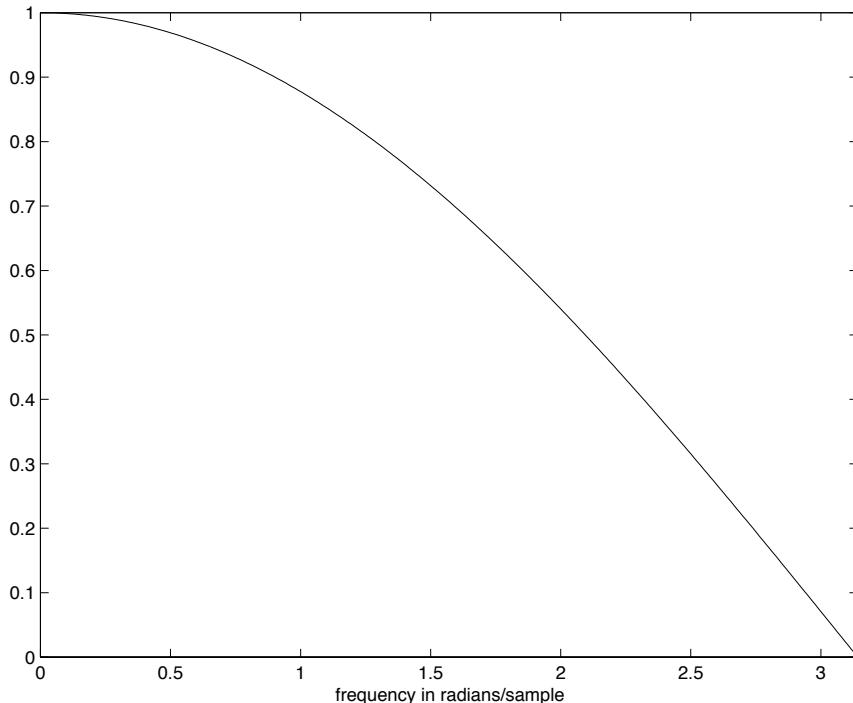


Figure 8.8: The magnitude response of a length-two moving average.

Often, we are given a frequency response, rather than some other description of an LTI system such as a difference equation. The frequency response, in fact, tells us everything we need to know about the system. The next example begins the exploration of that idea.

Example 8.18: Suppose that the frequency response H of a discrete-time LTI system *Filter* is given by

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \cos(2\omega)$$

where ω has units of radians/sample. Suppose that the input signal $x: \mathbb{Z} \rightarrow \mathbb{R}$ is such that for all $n \in \mathbb{Z}$,

$$x(n) = \begin{cases} +1 & n \text{ even} \\ -1 & n \text{ odd} \end{cases}$$

We can determine the output. All we have to do is notice that the input can be written as

$$x(n) = \cos(\pi n).$$

Thus, the input is a cosine with frequency π radians/sample. Hence, the output is

$$y(n) = |H(\pi)| \cos(\pi n + \angle H(\pi)) = \cos(\pi n) = x(n).$$

This input is passed unchanged by the system.

Suppose instead that the input is given by

$$x(n) = 5.$$

Once again, the input is a cosine, but this time with zero frequency,

$$x(n) = 5 \cos(0n).$$

Hence the output is

$$y(n) = |H(0)| \cdot 5 \cos(0n + \angle H(0)) = 5 = x(n).$$

This input is also passed unchanged by the system.

Suppose instead that the input is

$$x(n) = \cos(\pi n/2).$$

This input is given explicitly as a cosine, making our task easier. The output is

$$\begin{aligned} y(n) &= |H(\pi/2)| \cos(\pi n/2 + \angle H(\pi/2)) \\ &= \cos(\pi n/2 + \pi) \\ &= -\cos(\pi n/2) \\ &= -x(n). \end{aligned}$$

This input is inverted by the system.

Finally, suppose that the input is

$$x(n) = \cos(\pi n/4).$$

The output is

$$y(n) = |H(\pi/4)| \cos(\pi n/4 + \angle H(\pi/4)) = 0.$$

This input is filtered out by the system.

8.2.2 The Fourier series with complex exponentials

The Fourier series for a continuous-time, periodic signal $x : \mathbb{R} \rightarrow \mathbb{R}$ with period $p = 2\pi/\omega_0$, can be written as (see (7.4))

$$x(t) = A_0 + \sum_{k=1}^{\infty} A_k \cos(k\omega_0 t + \phi_k).$$

For reasons that we can now understand, the Fourier series is usually written in terms of complex exponentials rather than cosines. Since complex exponentials are eigenfunctions of LTI systems, this form of the Fourier series decomposes a signal into components that when processed by the system are only scaled.

Each term of the Fourier series expansion has the form

$$A_k \cos(k\omega_0 t + \phi_k)$$

which we can write (see box on page 330)

$$A_k \cos(k\omega_0 t + \phi_k) = A_k (e^{i(k\omega_0 t + \phi_k)} + e^{-i(k\omega_0 t + \phi_k)})/2.$$

So the Fourier series can also be written

$$x(t) = A_0 + \sum_{k=1}^{\infty} \frac{A_k}{2} (e^{i(k\omega_0 t + \phi_k)} + e^{-i(k\omega_0 t + \phi_k)}).$$

Observe that

$$e^{i(k\omega_0 t + \phi_k)} = e^{ik\omega_0 t} e^{i\phi_k},$$

and let

$$X_k = \begin{cases} A_0 & \text{if } k = 0 \\ 0.5A_k e^{i\phi_k} & \text{if } k > 0 \\ 0.5A_{-k} e^{-i\phi_{-k}} & \text{if } k < 0 \end{cases} \quad (8.28)$$

Then the Fourier series becomes

$$x(t) = \sum_{k=-\infty}^{\infty} X_k e^{ik\omega_0 t}.$$

(8.29)

This is the form in which one usually sees the Fourier series. Notice from (8.28) that the Fourier series coefficients are **conjugate symmetric**,

$$X_k = X_{-k}^*.$$

Of course, since (8.29) is an infinite sum, we need to worry about convergence (see box on page 295).

The **discrete-time Fourier series (DFS)** can be similarly written. If $x : \mathbb{Z} \rightarrow \mathbb{R}$ is a periodic signal with period $p = 2\pi/\omega_0$, then we can write

$$x(n) = \sum_{k=0}^{p-1} X_k e^{ik\omega_0 n} \quad (8.30)$$

for suitably defined coefficients X_k . Relating the coefficients X_k to the coefficients A_k and ϕ_k is a bit more difficult in the discrete-time case than in the continuous-time case (see box on page 347).

There are two differences between (8.29) and (8.30). First, the sum in the discrete-time case is finite, making it manageable by computer. Second, it is exact for any periodic waveform. There are no mathematically tricky cases, and no approximation needed.

8.2.3 Examples

The Fourier series coefficients A_k of a square wave are shown in figure 7.7 in the previous chapter. The magnitudes of the corresponding coefficients X_k for the Fourier series expansion of (8.29) are shown in figure 8.9. Since each cosine is composed of two complex exponentials, there are twice as many coefficients.

Notice the symmetry in the figure. There are frequency components shown at both positive and negative frequencies. Notice also that the amplitude of the components is half that in Figure 7.7, $|X_k| = |A_k|/2$. This is because there are now two components, one at negative frequencies and one at positive frequencies, that contribute.

8.3 Determining the Fourier series coefficients

We have seen in the previous chapter that determining the Fourier series coefficients by directly attempting to determine the amplitude of individual frequency components can be difficult, even when the individual frequency components are known. Usually, however, they are not known. A general formula for computing the coefficients for a continuous-time periodic signal is

$$X_m = \frac{1}{p} \int_0^p x(t) e^{-im\omega_0 t} dt. \quad (8.32)$$

The m -th Fourier series coefficient is obtained by multiplying x by a complex exponential with frequency $-m\omega_0$ and averaging. The validity of this equation is demonstrated in the box on page 349.

The discrete-time case is somewhat simpler. A discrete-time periodic signal x with period $p \in \mathbb{Z}$ has Fourier series coefficients given by

$$X_k = \frac{1}{p} \sum_{m=0}^{p-1} x(m) e^{-imk\omega_0}. \quad (8.33)$$

This can be shown by manipulations similar to those in the box on page 349. The practical importance in computing is much greater than that of the Fourier series for continuous-time signals. Since this sum is finite, the DFS coefficients can be easily computed precisely on a computer.

8.3.1 Negative frequencies

The Fourier series expansion for a periodic signal $x(t)$ is

$$x(t) = \sum_{k=-\infty}^{\infty} X_k e^{ik\omega_0 t}$$

This includes Fourier series coefficients for the constant term (when $k = 0$, $e^{ik\omega_0 t} = 1$), plus the fundamental and harmonics ($k \geq 1$). But it also includes terms that seem to correspond to negative frequencies. When $k \leq -1$, the frequency $k\omega_0$ is negative. These negative frequencies balance the positive ones so that the resulting sum is real-valued.

8.4 Frequency response and the Fourier series

Recall that if the input to an LTI system S is a complex exponential signal $x \in [\mathbb{R} \rightarrow \mathbb{C}]$ where

$$\forall t \in \mathbb{R}, \quad x(t) = e^{i\omega_0 t} = \cos(\omega_0 t) + i \sin(\omega_0 t).$$

then the output for all t is

$$y(t) = H(\omega_0)e^{i\omega_0 t},$$

where the complex number $H(\omega_0)$ is the frequency response of the system at the fundamental frequency ω_0 of the periodic input. It is equal to the output at time zero $y(0)$ when the input is $e^{i\omega_0 t}$. H itself is a function $H: \mathbb{R} \rightarrow \mathbb{C}$ that in principle can be evaluated for any frequency $\omega \in \mathbb{R}$, including negative frequencies.

Recall further that if an input x to the system S is a periodic signal with period p , then it can be represented as a Fourier series,

$$\forall t \in \mathbb{R}, \quad x(t) = \sum_{k=-\infty}^{\infty} X_k e^{ik\omega_0 t},$$

where $\omega_0 = 2\pi/p$. By linearity and time invariance of S , the output $y = S(x)$ for this periodic input x , is given by

$$\boxed{\forall t \in \mathbb{R}, \quad y(t) = \sum_{k=-\infty}^{\infty} H(k\omega_0)X_k e^{ik\omega_0 t}.}$$

Thus, linearity tells us that if the input is decomposed into a sum of components, then the output can be decomposed into a sum of components where each component is the response of the system to a single input component. Linearity together with time invariance tells us that each component, which is a complex exponential, is simply scaled. Thus, the output is given by a Fourier series with coefficients $X_k H(k\omega_0)$.

This major result is summarized below:

For an LTI system, if the input is given by a sum of complex exponentials, then the output can be given by a sum of the same complex exponentials, each one scaled by the frequency response evaluated at the corresponding frequency.

Among other things, this result tells us:

- There are no frequency components in the output that were not in the input. The output consists of the same frequency components as the input, but with each component individually scaled.
- LTI systems can be used to enhance or suppress certain frequency components. Such operations are called **filtering**.

- The frequency response function characterizes which frequencies are enhanced or suppressed, and also what phase shifts might be imposed on individual components by the system.

We will see many examples of filtering in the next chapter.

8.5 Frequency response of composite systems

In section 2.1.5 we studied several ways of composing systems (using block diagrams) to obtain more complex, composite systems. We will see in this section that when each block is an LTI system, the resulting composite system is also LTI. Moreover, we can easily obtain the frequency response of the composite system from the frequency response of each block. This provides a useful way to construct interesting and complex systems by assembling simpler components. This tool works equally well with discrete and continuous systems.

8.5.1 Cascade connection

Consider the composite system S obtained by the cascade connection of systems S_1 and S_2 in figure 8.10. Suppose S_1 and S_2 are LTI. We first show that $S = S_2 \circ S_1$ is LTI. To show that S is time-invariant, we must show that for any τ , $S \circ D_\tau = D_\tau \circ S$. But,

$$\begin{aligned} S \circ D_\tau &= S_2 \circ S_1 \circ D_\tau \\ &= S_2 \circ D_\tau \circ S_1, \text{ since } S_1 \text{ is time-invariant} \\ &= D_\tau \circ S_2 \circ S_1, \text{ since } S_2 \text{ is time-invariant} \\ &= D_\tau \circ S, \end{aligned}$$

as required.

We now show that S is linear. Let x be any input signal and a any complex number. Then

$$\begin{aligned} S(ax) &= (S_2 \circ S_1)(ax) \\ &= S_2(S_1(ax)) \\ &= S_2(aS_1(x)), \text{ since } S_1 \text{ is linear} \\ &= aS_2(S_1(x)), \text{ since } S_2 \text{ is linear} \\ &= aS(x). \end{aligned}$$

Lastly, if x and y are two input signals, then

$$\begin{aligned} S(x+y) &= (S_2 \circ S_1)(x+y) \\ &= S_2(S_1(x+y)) \\ &= S_2(S_1(x) + S_1(y)), \text{ since } S_1 \text{ is linear} \\ &= S_2(S_1(x)) + S_2(S_1(y)), \text{ since } S_2 \text{ is linear} \\ &= S(x) + S(y). \end{aligned}$$

This shows that S is linear.

We now compute the frequency response of S . Let $H_1(\omega), H_2(\omega), H(\omega)$ be the frequency response of S_1 , S_2 , and S , respectively, at the frequency ω . Consider the complex exponential input x given by

$$\forall t \in \mathbb{R}, \quad x(t) = e^{i\omega t}.$$

Then the signal $y = S_1(x)$ is a multiple of x , namely, $y = H_1(\omega)x$. In particular, y is a (scaled) complex exponential, and so $z = S_2(y)$ is given by

$$z = H_2(\omega)y = H_2(\omega)H_1(\omega)x.$$

But since $H(\omega)$ is the frequency response of S at the frequency ω , we also have

$$z = S(x) = H(\omega)x,$$

and so we obtain

$$\boxed{\forall \omega \in \mathbb{R}, \quad H(\omega) = H_2(\omega)H_1(\omega).} \quad (8.34)$$

The frequency response of the cascade connection is the product of the frequency responses of the components. Exactly the same formula applies in the discrete-time case. This is a remarkable result. First, suppose that the cascade connection of Figure 8.10 is reversed, i.e. consider the system $\tilde{S} = S_1 \circ S_2$. Then the frequency response of \tilde{S} is

$$\tilde{H}(\omega) = H_1(\omega)H_2(\omega) = H_2(\omega)H_1(\omega) = H(\omega).$$

That is, \tilde{S} and S have the same frequency response! This implies, in fact, that S and \tilde{S} are equivalent; they give the same output for the same input. Hence,

In any cascade connection of LTI systems, the order in which the systems are composed does not matter.

8.5.2 Feedback connection

The feedback arrangement shown in figure 8.11 is fundamental to the design of control systems. Typically, S_1 is some physical system, and S_2 is a controller that we design to get the physical system to do our bidding. The overall system S is called a **closed-loop** system. We first show that S is LTI if S_1 and S_2 are LTI, and we then calculate its frequency response.

Suppose x is the input signal, and define the signals u, z and y as shown. The circle with the plus sign represents the relationship $u = x + z$. The signals are then related by

$$\begin{aligned} y &= S_1(u) \\ &= S_1(x+z) \\ &= S_1(x) + S_1(z), \text{ since } S_1 \text{ is linear} \\ &= S_1(x) + S_1(S_2(y)), \end{aligned}$$

Note that this equation relates the input and output, but the output appears on both sides. We can rewrite this as

$$y - S_1(S_2(y)) = S_1(x). \quad (8.35)$$

Thus, given the input signal x , the output signal y is obtained by solving this equation. We will assume that for any signal x , (8.35) has a unique solution y . Then, of course, $y = S(x)$. We can use (8.35) and methods similar to the ones we used for the cascade example to show that S is LTI (see box on page 352).

We now compute the frequency response $H(\omega)$ of S at frequency ω . Let the frequency response of S_1 be H_1 , and of S_2 be H_2 . Suppose the input signal is the complex exponential

$$\forall t \in \mathbb{R}, \quad x(t) = e^{i\omega t}.$$

For this input, we know that $S_1(x) = H_1(\omega)x$ and $S_2(x) = H_2(\omega)x$. Since S is LTI, we know that the output signal y is given by

$$y = H(\omega)x.$$

Using this relation for y in (8.35) we get

$$\begin{aligned} H(\omega)x - S_1(S_2(H(\omega)x)) &= H(\omega)[x - S_1(S_2(x))], \text{ since } S_2, S_1 \text{ are linear} \\ &= H(\omega)[x - H_1(\omega)H_2(\omega)x] \\ &= H(\omega)[1 - H_1(\omega)H_2(\omega)]x \\ &= S_1(x) \\ &= H_1(\omega)x, \text{ by (8.35),} \end{aligned}$$

from which we get the frequency response of the feedback system,

$$\boxed{H(\omega) = \frac{H_1(\omega)}{1 - H_1(\omega)H_2(\omega)}} \quad (8.38)$$

This relation is at the foundation of linear feedback control design.

Example 8.19: Consider a discrete-time feedback system as in Figure 8.11 where S_1 simply scales the input by 0.9. That is, for all discrete-time input signals u , $S_1(u) = 0.9u$. Suppose further that S_2 is a one-sample delay. That is, $S_2 = D_1$. From example 8.9, the frequency response of S_2 is given by

$$\forall \omega \in \mathbb{R}, \quad H_2(\omega) = e^{-i\omega}.$$

The frequency response of S_1 is (trivially) given by

$$\forall \omega \in \mathbb{R}, \quad H_1(\omega) = 0.9.$$

Thus, the frequency response of the feedback composition is

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \frac{0.9}{1 - 0.9e^{-i\omega}}.$$

We can plot the magnitude of this using the following Matlab code, which (after adjusting the labels) results in Figure 8.12.

```
omega = [0:pi/250:pi];
H = 0.9./(1 - 0.9.*exp(-i*omega));
plot(omega, abs(H));
```

Notice that at zero frequency, the gain is 9, and that it rapidly drops off at higher frequencies. Thus, this system behaves as a lowpass filter.

Example 8.20: We can use formula (8.38) to obtain the frequency response of more complex composition, such as the one shown in Figure 8.13. To find the

frequency response of the composition S given on the left of the figure, we first express as the composition on the right where the system S_3 is given in the lower part of the figure. The frequency response H of S can now be obtained from formula (8.38) as

$$H(\omega) = \frac{H_1(\omega)H_3(\omega)}{1 - H_1(\omega)H_3(\omega)}.$$

The same formula also gives the frequency response H_3 of S_3 ,

$$H_3(\omega) = \frac{H_2(\omega)}{1 - H_2(\omega)},$$

which, upon substitution in the previous expression, yields,

$$H(\omega) = \frac{H_1(\omega)H_2(\omega)}{1 - H_2(\omega) - H_1(\omega)H_2(\omega)}.$$

8.6 Summary

Linear time-invariant systems have a particularly nice property: if the input is a sinusoid, then the output is a sinusoid of the same frequency. Moreover, if the input is a sum of two sinusoids, then the output will be a sum of two sinusoids with the same frequencies as the input sinusoids. Each sinusoid is scaled and shifted in phase by the system. The scaling and phase shift, as a function of frequency, is called the frequency response of the system.

It turns out that mathematically, this phenomenon is easiest to analyze using complex exponentials instead of real-valued sinusoids. The reason for this is that the phase shift and scaling together amount to simple multiplication of the complex exponential by a complex constant. If an input is represented as a sum of complex exponentials (a form of the Fourier series), then the output is simply the same Fourier series with each term of the series scaled by a complex constant. These scaling constants, viewed as a function of frequency, are the frequency response of the system.

Composing LTI system becomes particularly easy. The frequency response of the cascade of two LTI systems is simply the product of the frequency responses of the individual systems. This simple fact can be used to quickly ascertain the frequency response of complicated compositions.

Probing Further: Relating DFS coefficients

We have two discrete-time Fourier series expansions (see (8.30) and (7.8)),

$$x(n) = \sum_{k=0}^{p-1} X_k e^{ik\omega_0 n} \quad (8.31)$$

$$x(n) = A_0 + \sum_{k=1}^K A_k \cos(k\omega_0 n + \phi_k), \quad K = \begin{cases} (p-1)/2 & \text{if } p \text{ is odd} \\ p/2 & \text{if } p \text{ is even} \end{cases}$$

There is a relationship between the coefficients A_k , ϕ_k and X_k , but the relationship is more complicated than in the continuous-time case, given by (8.28). To develop that relationship, begin with the second of these expansions and write

$$x(n) = A_0 + \sum_{k=1}^K \frac{A_k}{2} (e^{i(k\omega_0 n + \phi_k)} + e^{-i(k\omega_0 n + \phi_k)}).$$

Note that since $\omega_0 = 2\pi/p$, then for all integers n , $e^{i\omega_0 pn} = 1$, so

$$e^{-i(k\omega_0 n + \phi_k)} = e^{-i(k\omega_0 n + \phi_k)} e^{i\omega_0 pn} = e^{i(\omega_0(p-k)n - \phi_k)}.$$

Thus

$$\begin{aligned} x(n) &= A_0 + \sum_{k=1}^K \frac{A_k}{2} e^{i\phi_k} e^{ik\omega_0 n} + \sum_{k=1}^K \frac{A_k}{2} e^{-i\phi_k} e^{i\omega_0(p-k)n} \\ &= A_0 + \sum_{k=1}^K \frac{A_k}{2} e^{i\phi_k} e^{ik\omega_0 n} + \sum_{m=K}^{p-1} \frac{A_{p-m}}{2} e^{-i\phi_{p-m}} e^{i\omega_0 mn}, \end{aligned}$$

by change of variables. Comparing this against (8.31),

$$X_k = \begin{cases} A_0 & \text{if } k = 0 \\ A_k e^{i\phi_k}/2 & \text{if } k \in \{1, \dots, K-1\} \\ A_k e^{i\phi_k}/2 + A_k e^{-i\phi_k}/2 = A_k \cos(\phi_k) & \text{if } k = K \\ A_{p-k} e^{-i\phi_{p-k}}/2 & \text{if } k \in \{K+1, \dots, p-1\} \end{cases}$$

This relationship is more complicated than (8.28). Fortunately, it is rare that we need to use both forms of the DFS, so we can usually just pick one of the two forms and work only with its set of coefficients.

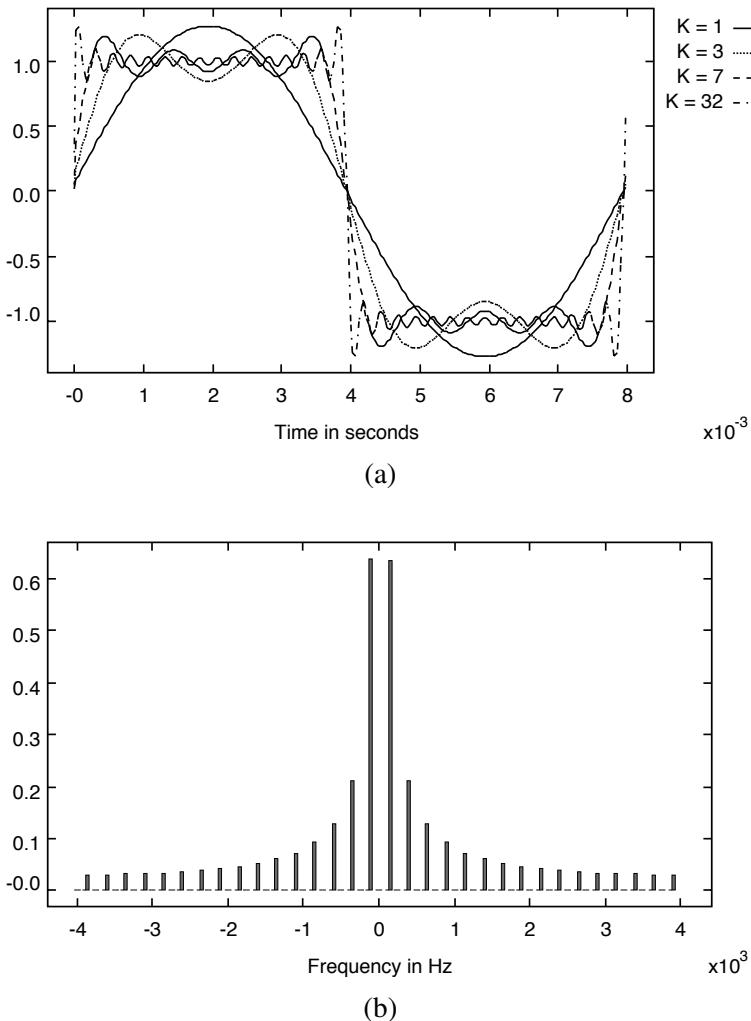


Figure 8.9: (a) Some finite Fourier series approximations to one cycle of a square wave. The number of Fourier series terms that are included in the approximation is $2K + 1$, so K is the magnitude of the largest index the terms. (b) The magnitude of the complex Fourier series coefficients shown as a function of frequency.

Probing Further: Formula for Fourier series coefficients

To see that (8.32) is valid, try substituting for $x(t)$ its Fourier series expansion,

$$x(t) = \sum_{k=-\infty}^{\infty} X_k e^{ik\omega_0 t}$$

to get

$$X_m = \frac{1}{p} \int_0^p \sum_{k=-\infty}^{\infty} X_k e^{ik\omega_0 t} e^{-im\omega_0 t} dt.$$

Exchange the integral and sum (assuming this is valid, see box on page 350) to get

$$X_m = \frac{1}{p} \sum_{k=-\infty}^{\infty} X_k \int_0^p e^{ik\omega_0 t} e^{-im\omega_0 t} dt.$$

The exponentials can be combined to get

$$X_m = \frac{1}{p} \sum_{k=-\infty}^{\infty} X_k \int_0^p e^{i(k-m)\omega_0 t} dt.$$

In the summation, where k varies over all integers, there will be exactly one term of the summation where $k = m$. In that term, the integral evaluates to p . For the rest of the terms, $k \neq m$. Separating these two situations, we can write

$$X_m = X_m + \frac{1}{p} \sum_{k=-\infty, k \neq m}^{\infty} X_k \int_0^p e^{i(k-m)\omega_0 t} dt,$$

where the first term X_m is the value of the term in the summation where $k = m$. For each remaining term of the summation, the integral evaluates to zero, thus establishing our result. To show that the integral evaluates to zero, let $n = k - m$, and note that $n \neq 0$.

Then

$$\int_0^p e^{in\omega_0 t} dt = \int_0^p \cos(n\omega_0 t) dt + i \int_0^p \sin(n\omega_0 t) dt$$

Since $\omega_0 = 2\pi/p$, these two integrals exactly span one or more complete cycles of the cosine or sine, and hence integrate to zero.

Probing Further: Exchanging integrals and summations

The demonstration of the validity of the formula for the Fourier series coefficients in the box on page 349 relies on being able to exchange an integral and an infinite summation. The infinite summation can be given as a limit of a sequence of functions

$$x_N(t) = \sum_{k=-N}^N X_k e^{ik\omega_0 t}.$$

Thus, we wish to exchange the integral and limit in

$$X_m = \frac{1}{p} \int_0^p (\lim_{N \rightarrow \infty} x_N(t)) dt.$$

A sufficient condition for being able to perform the exchange is that the limit converges uniformly in the interval $[0, p]$. A sufficient condition for uniform convergence is that x is continuous and that its first derivative is piecewise continuous.

See R. G. Bartle, *The Elements of Real Analysis*, Second Edition, John Wiley & Sons, 1976, p. 241.

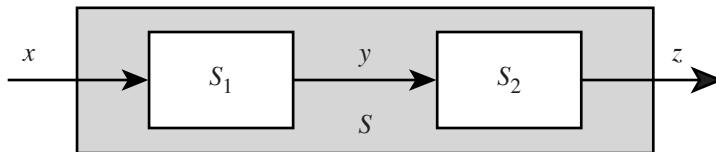


Figure 8.10: The cascade connection of the two LTI systems is the system $S = S_2 \circ S_1$. The frequency response is related by $\forall \omega, H(\omega) = H_1(\omega)H_2(\omega)$.

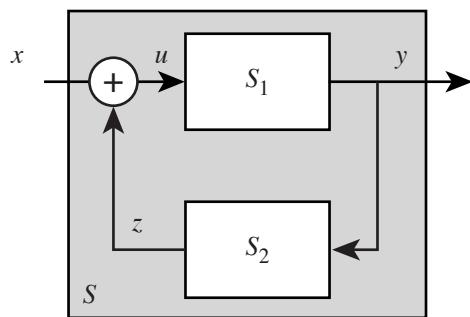


Figure 8.11: The feedback connection of the two LTI systems S_1, S_2 is the LTI system S . The frequency response is related by $\forall \omega \in \mathbb{R}, H(\omega) = H_1(\omega)/[1 - H_1(\omega)H_2(\omega)]$.

Probing Further: Feedback systems are LTI

To show that S in Figure 8.11 is time-invariant we must show that for any $\tau \in \mathbb{R}$,

$$S(D_\tau(x)) = D_\tau(S(x)) = D_\tau(y), \quad (8.36)$$

that is, we must show that $D_\tau(y)$ is the output of S when the input is $D_\tau(x)$. Now the left-hand side of (8.35) with y replaced by $D_\tau(y)$ is

$$\begin{aligned} D_\tau(y) - S_1(S_2(D_\tau(y))) &= D_\tau(y) - D_\tau(S_1(S_2(y))), \\ &\quad \text{since } S_1 \text{ and } S_2 \text{ are time-invariant} \\ &= D_\tau(y - S_1(S_2(y))), \text{ since } D_\tau \text{ is linear,} \\ &= D_\tau(S_1(x)), \text{ by (8.35)} \\ &= S_1(D_\tau(x)), \text{ since } S_1 \text{ is time-invariant} \end{aligned}$$

so that $D_\tau(y)$ is indeed the solution of (8.35) when the input is $D_\tau(x)$. This proves (8.36). Linearity is shown similarly. Let a be any complex number. To show that ay is the output when the input is ax , we evaluate the left-hand side of (8.35) at ay ,

$$\begin{aligned} ay - S_1(S_2(ay)) &= ay - aS_1(S_2(y)), \text{ since } S_2 \text{ and } S_1 \text{ are linear} \\ &= a[y - S_1(S_2(y))] \\ &= aS_1(x), \text{ by (8.35)} \\ &= S_1(ax), \text{ since } S_1 \text{ is linear} \end{aligned}$$

which shows that $S(ax) = aS(x)$.

Now suppose w is another input and $z = S(w)$ is the corresponding output. I.e.,

$$z - S_1(S_2(z)) = S_1(w). \quad (8.37)$$

We evaluate the left-hand side of (8.35) at $y+z$, using that S_2 and S_1 are linear,

$$\begin{aligned} (y+z) - S_1(S_2(y+z)) &= [y - S_1(S_2(y))] + [z - S_1(S_2(z))], \\ &= S_1(x) + S_1(w), \text{ by (8.35) and (8.37)} \\ &= S_1(x+w), \text{ since } S_1 \text{ is linear} \end{aligned}$$

and so $S(x+w) = y+z = S(x)+S(z)$.

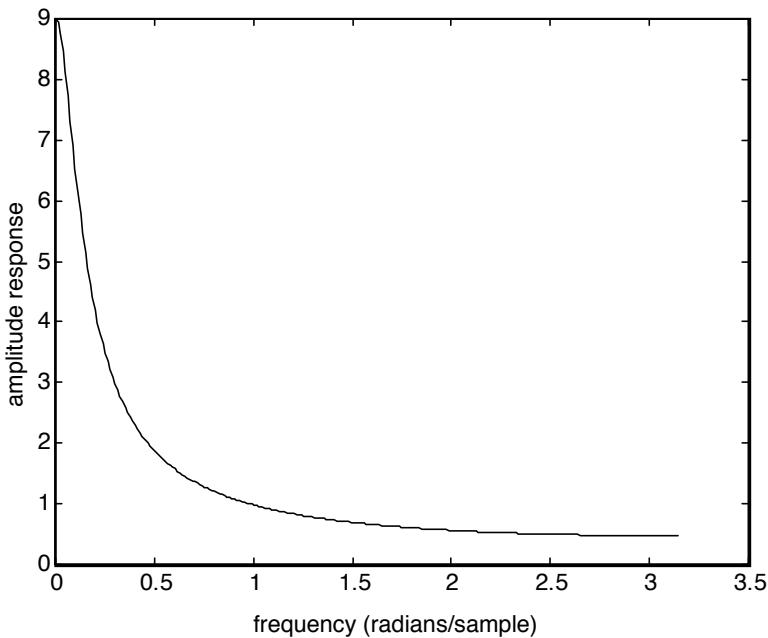


Figure 8.12: The magnitude response of the feedback composition of example 8.19.

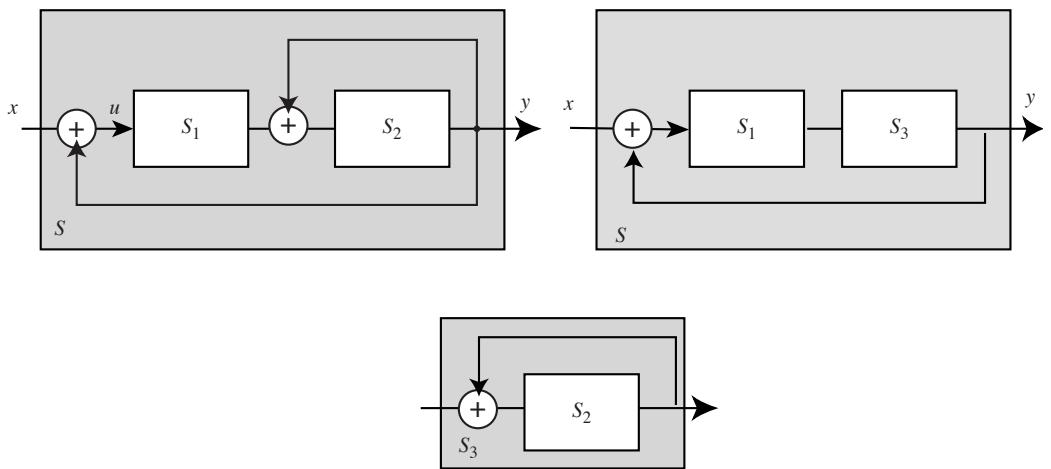


Figure 8.13: The composition on the left can be expressed as the one on the right, where S_3 is the system at the bottom.

Exercises

Each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **E** Find $A \in \mathbb{C}$ so that

$$\forall t \in \text{Reals}, \quad Ae^{i\omega t} + A^* e^{-i\omega t} = \cos(\omega t + \pi/4),$$

where A^* is the complex conjugate of A .

2. **E** Plot the function $s: \mathbb{R} \rightarrow \mathbb{R}$ given by

$$\forall x \in \mathbb{R}, \quad s(x) = \text{Im}\{e^{(-x+i2\pi x)}\}.$$

You are free to choose a reasonable interval for your plot, but be sure it includes $x = 0$.

3. **E** This exercise explores the fact that a delay in a sinewave causes a phase shift. That is, for any real numbers τ and ω , there is a phase shift $\phi \in \mathbb{R}$ such that for all $t \in \mathbb{R}$,

$$\sin(\omega(t - \tau)) = \sin(\omega t - \phi).$$

Give ϕ in terms of τ, ω . What are the units of τ, ω, ϕ ? **Hint:** The argument to the sin function has units of radians.

4. **E** Let $x: \mathbb{R} \rightarrow \mathbb{R}$. Show that x is periodic with period p if and only if $D_p(x) = x$. Now show that if S is a time-invariant system and x is a periodic signal, then $S(x)$ is also periodic with period p .

5. **E** Analogously to D_τ in (8.1) and D_M in Section 8.1.3, define formally the following variants:

- (a) A shift operator $S_{v,h}$ that shifts an image v units vertically and h units horizontally, where $v \in \mathbb{R}$ and $h \in \mathbb{R}$.
- (b) A shift operator $S_{m,n}$ that shifts a discrete image m units vertically and n units horizontally, where $m \in \mathbb{Z}$ and $n \in \mathbb{Z}$.

6. E Consider a discrete-time system $D: [\mathbb{Z} \rightarrow \mathbb{R}] \rightarrow [\mathbb{Z} \rightarrow \mathbb{R}]$, where if $y = D(x)$ then

$$\forall n \in \mathbb{Z}, \quad y(n) = x(n-1).$$

- (a) Is D linear? Justify your answer.
(b) Is D time-invariant? Justify your answer.
7. E Consider a continuous-time system $TimeScale: [\mathbb{R} \rightarrow \mathbb{R}] \rightarrow [\mathbb{R} \rightarrow \mathbb{R}]$, where if $y = TimeScale(x)$ then

$$\forall t \in \mathbb{R}, \quad y(t) = x(2t).$$

- (a) Is $TimeScale$ linear? Justify your answer.
(b) Is $TimeScale$ time-invariant? Justify your answer.
8. E Consider the continuous-time signal x where

$$\forall t \in \mathbb{R}, \quad x(t) = 1 + \cos(\pi t) + \cos(2\pi t).$$

Suppose that x is the input to an LTI system with frequency response given by

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \begin{cases} e^{i\omega} & \text{if } |\omega| < 4 \text{ radians/second} \\ 0 & \text{otherwise} \end{cases}$$

Find the output y of the system.

9. T Suppose that the continuous-time signal $x: \mathbb{R} \rightarrow \mathbb{R}$ is periodic with period p . Let the fundamental frequency be $\omega_0 = 2\pi/p$. Suppose that the Fourier series coefficients for this signal are known constants A_0, A_1, A_2, \dots and ϕ_1, ϕ_2, \dots . Give the Fourier series coefficients A'_0, A'_1, A'_2, \dots and ϕ'_1, ϕ'_2, \dots for each of the following signals:

- (a) ax , where $a \in \mathbb{R}$ is a constant;
(b) $D_\tau(x)$, where $\tau \in \mathbb{R}$ is a constant and D_τ is the delay system; and
(c) $S(x)$, where S is an LTI system with frequency response H given by

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \begin{cases} 1; & \text{if } \omega = 0 \\ 0; & \text{otherwise} \end{cases}$$

(Note that this is a highly unrealistic frequency response.)

- (d) Let $y: \mathbb{R} \rightarrow \mathbb{R}$ be another periodic signal with period p . Suppose y has Fourier series coefficients $A''_0, A''_1, A''_2, \dots$ and $\phi''_1, \phi''_2, \dots$. Give the Fourier series coefficients of $x + y$.
10. **E** Consider discrete-time systems with input $x: \mathbb{Z} \rightarrow \mathbb{R}$ and output $y: \mathbb{Z} \rightarrow \mathbb{R}$. Each of the following defines such a system. For each, indicate whether it is linear (L), time-invariant (TI), both (LTI), or neither (N).

- (a) $\forall n \in \mathbb{Z}, \quad y(n) = x(n) + 0.9y(n-1)$
- (b) $\forall n \in \mathbb{Z}, \quad y(n) = \cos(2\pi n)x(n)$
- (c) $\forall n \in \mathbb{Z}, \quad y(n) = \cos(2\pi n/9)x(n)$
- (d) $\forall n \in \mathbb{Z}, \quad y(n) = \cos(2\pi n/9)(x(n) + x(n-1))$
- (e) $\forall n \in \mathbb{Z}, \quad y(n) = x(n) + 0.1(x(n))^2$
- (f) $\forall n \in \mathbb{Z}, \quad y(n) = x(n) + 0.1(x(n-1))^2$

11. **E** Suppose that the frequency response of a discrete-time LTI system S is given by

$$H(\omega) = |\sin(\omega)|$$

where ω has units of radians/sample. Suppose the input is the discrete-time signal x given by $\forall n \in \mathbb{Z}, \quad x(n) = 1$. Give a *simple* expression for $y = S(x)$.

12. **T** Find the smallest positive integer n such that

$$\sum_{k=0}^n e^{i5k\pi/6} = 0.$$

Hint: Note that the term being summed is a periodic function of k . What is its period? What is the sum of a complex exponential over one period?

13. **T** Consider a continuous-time periodic signal x with fundamental frequency $\omega_0 = 1$ radian/second. Suppose that the Fourier series coefficients (see (7.4)) are

$$A_k = \begin{cases} 1 & k = 0, 1, \text{ or } 2 \\ 0 & \text{otherwise} \end{cases}$$

and for all $k \in \mathbb{N}_0$, $\phi_k = 0$.

- (a) Find the Fourier series coefficients X_k for all $k \in \mathbb{Z}$ (see (8.29)).

- (b) Consider a continuous-time LTI system *Filter*: $[\mathbb{R} \rightarrow \mathbb{R}] \rightarrow [\mathbb{R} \rightarrow \mathbb{R}]$, with frequency response

$$H(\omega) = \cos(\pi\omega/2).$$

Find $y = \text{Filter}(x)$. I.e., give a simple expression for $y(t)$ that is valid for all $t \in \mathbb{R}$.

- (c) For y calculated in (b), find the fundamental frequency in radians per second. I.e., find the largest $\omega'_0 > 0$ such that

$$\forall t \in \mathbb{R}, \quad y(t) = y(t + 2\pi/\omega'_0)$$

14. T Consider a continuous-time LTI system S . Suppose that when the input x is given by

$$\forall t \in \text{Reals}, \quad x(t) = \begin{cases} 1, & \text{if } 0 \leq t < 1 \\ 0, & \text{otherwise} \end{cases}$$

then the output $y = S(x)$ is given by

$$\forall t \in \text{Reals}, \quad y(t) = \begin{cases} 1, & \text{if } 0 \leq t < 2 \\ 0, & \text{otherwise} \end{cases}$$

Give an expression and a sketch for the output of the same system if the input is

(a)

$$\forall t \in \text{Reals}, \quad x'(t) = \begin{cases} 1, & \text{if } 0 \leq t < 1 \\ -1, & \text{if } 1 \leq t < 2 \\ 0, & \text{otherwise} \end{cases}$$

(b)

$$\forall t \in \text{Reals}, \quad x'(t) = \begin{cases} 1, & \text{if } 0 \leq t < 1/2 \\ 0, & \text{otherwise} \end{cases}$$

15. T Suppose that the frequency response H of a discrete-time LTI system *Filter* is given by:

$$\forall \omega \in [-\pi, \pi], \quad H(\omega) = |\omega|.$$

where ω has units of radians/sample. Note that since a discrete-time frequency response is periodic with period 2π , this definition implicitly gives $H(\omega)$ for all $\omega \in \mathbb{R}$. Give simple expressions for the output y when the input signal $x : \mathbb{Z} \rightarrow \mathbb{R}$ is such that $\forall n \in \mathbb{Z}$ each of the following is true:

- (a) $x(n) = \cos(\pi n/2)$.

(b) $x(n) = 5$.

(c) $x(n) = \begin{cases} +1, & n \text{ even} \\ -1, & n \text{ odd} \end{cases}$

16. T Consider a continuous-time LTI system S . Suppose that when the input is given by

$$x(t) = \begin{cases} \sin(\pi t) & 0 \leq t < 1 \\ 0 & \text{otherwise} \end{cases}$$

then the output $y = S(x)$ is given by

$$y(t) = \begin{cases} \sin(\pi t) & 0 \leq t < 1 \\ \sin(\pi(t-1)) & 1 \leq t < 2 \\ 0 & \text{otherwise} \end{cases}$$

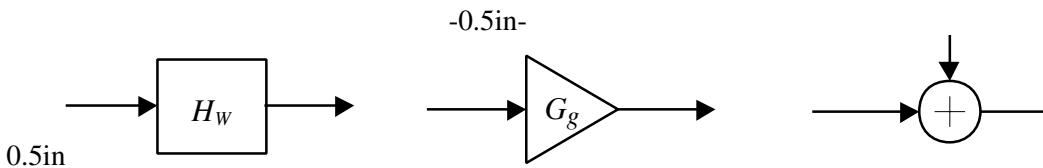
for all $t \in \mathbb{R}$.

- (a) Carefully sketch these two signals.

- (b) Give an expression and a sketch for the output of the same system if the input is

$$x(t) = \begin{cases} \sin(\pi t) & 0 \leq t < 1 \\ -\sin(\pi(t-1)) & 1 \leq t < 2 \\ 0 & \text{otherwise} \end{cases} .$$

17. T Suppose you are given the building blocks shown below for building block diagrams:



These blocks are defined as follows:

- An LTI system $H_W : [\mathbb{R} \rightarrow \mathbb{R}] \rightarrow [\mathbb{R} \rightarrow \mathbb{R}]$ that has a rectangular frequency response given by

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \begin{cases} 1 & -W < \omega < W \\ 0 & \text{otherwise} \end{cases}$$

where W is a parameter you can set.

- A gain block $G_g: [\mathbb{R} \rightarrow \mathbb{R}] \rightarrow [\mathbb{R} \rightarrow \mathbb{R}]$ where if $y = g(x)$, then

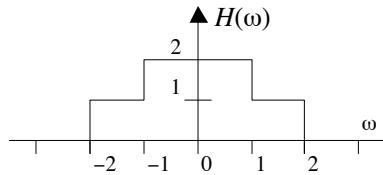
$$\forall t \in \mathbb{R}, \quad y(t) = gx(t)$$

where $g \in \mathbb{R}$ is a parameter you can set.

- An adder, which can add two continuous-time signals. Specifically, $Add: [\mathbb{R} \rightarrow \mathbb{R}] \times [\mathbb{R} \rightarrow \mathbb{R}] \rightarrow [\mathbb{R} \rightarrow \mathbb{R}]$ such that if $y = Add(x_1, x_2)$ then

$$\forall t \in \mathbb{R}, \quad y(t) = x_1(t) + x_2(t).$$

Use these building blocks to construct a system with the frequency response shown below:



18. T Let u be a discrete-time signal given by

$$\forall n \in \mathbb{Z}, \quad u(n) = \begin{cases} 1 & 0 \leq n \\ 0 & \text{otherwise} \end{cases}$$

This is the **unit step** signal, which we saw before in (2.16). Suppose that a discrete-time system H that is known to be LTI is such that if the input is u , the output is $y = H(u)$ given by

$$\forall n \in \mathbb{Z}, \quad y(n) = nu(n).$$

This is called the **step response** of the system. Find a simple expression for the output $w = H(p)$ when the input is p given by

$$\forall n \in \mathbb{Z}, \quad p(n) = \begin{cases} 2 & 0 \leq n < 8 \\ 0 & \text{otherwise} \end{cases}$$

Sketch w .

19. T Suppose you are given the Fourier series coefficients $\dots, X_{-1}, X_0, X_1, X_2, \dots$ for a periodic signal $x: \mathbb{R} \rightarrow \mathbb{R}$ with period p . Find the fundamental frequency and the Fourier series coefficients of the following signals in terms of those of x .

- (a) y such that $\forall t \in \mathbb{R}$, $y(t) = x(at)$, for some positive real number a .
- (b) w such that $\forall t \in \mathbb{R}$, $w(t) = x(t)e^{i\omega_0 t}$, where $\omega_0 = 2\pi/p$.
- (c) z such that $\forall t \in \mathbb{R}$, $z(t) = x(t) \cos(\omega_0 t)$, where $\omega_0 = 2\pi/p$.
20. **E** Analogously to the box on page 349, show that the formula (8.33) for the discrete Fourier series coefficients is valid.
21. **C** Consider a system *Square*: $[\mathbb{R} \rightarrow \mathbb{R}] \rightarrow [\mathbb{R} \rightarrow \mathbb{R}]$, where if $y = \text{Square}(x)$ then
- $$\forall t \in \mathbb{R}, \quad y(t) = (x(t))^2.$$
- (a) Show that this system is memoryless.
- (b) Show that this system is not linear.
- (c) Show that this system is time invariant.
- (d) Suppose that the input x is given by

$$\forall t \in \mathbb{R}, \quad x(t) = \cos(\omega t),$$

for some fixed ω . Show that the output y contains a component at frequency 2ω .

9

Filtering

Contents

9.1	Convolution	365
9.1.1	Convolution sum and integral	367
9.1.2	Impulses	371
9.1.3	Signals as sums of weighted delta functions	372
9.1.4	Impulse response and convolution	375
9.2	Frequency response and impulse response	378
9.3	Causality	382
9.4	Finite impulse response (FIR) filters	382
	<i>Probing Further: Causality</i>	383
9.4.1	Design of FIR filters	385
9.4.2	Decibels	391
	<i>Probing Further: Decibels</i>	394
9.5	Infinite impulse response (IIR) filters	395
9.5.1	Designing IIR filters	396
9.6	Implementation of filters	398
9.6.1	Matlab implementation	398
9.6.2	Signal flow graphs	400
	<i>Probing Further: Java implementation of an FIR filter</i>	401
	<i>Probing Further: FIR filter in a programmable DSP</i>	402
9.7	Summary	403
	Exercises	406

Linear time invariant systems have the property that if the input is described as a sum of sinusoids, then the output is a sum of sinusoids of the same frequencies. Each sinusoidal component will typically be scaled differently, and each will be subjected to a phase change, but the output will not contain any sinusoidal components that are not also present in the input. For this reason, an LTI system is often called a **filter**. It can filter out frequency components of the input, and also enhance other components, but it cannot introduce components that are not already present in the input. It merely changes the relative amplitudes and phases of the frequency components that are present in the inputs.

LTI systems arise in two circumstances in an engineering context. First, they may be used as a model of a physical system. Many physical systems are accurately modeled as LTI systems. Second, they may present an ideal for an engineered system. For example, they may specify the behavior that an electronic system is expected to exhibit.

Consider for example an audio system. The human ear hears frequencies in the range of about 30 to 20,000 Hz, so a specification for a high fidelity audio system typically requires that the frequency response be constant (in magnitude) over this range. The human ear is relatively insensitive to phase, so the same specification may say nothing about the phase response (the argument, or angle of the frequency response). An audio system is free to filter out frequencies outside this range.

Consider an acoustic environment, a physical context such as a lecture hall where sounds are heard. The hall itself alters the sound. The sound heard by your ear is not identical to the sound created by the lecturer. The room introduces echoes, caused by reflections of the sound by the walls. These echoes tend to occur more for the lower frequency components in the sound than the higher frequency components because the walls and objects in the room tend to absorb higher frequency sounds better. Thus, the lower frequency sounds bounce around in the room, reinforcing each other, while the higher frequency sounds, which are more quickly absorbed, become relatively less pronounced. In an extreme circumstance, in a room where the walls are lined with shag carpeting, for example, the higher frequency sounds are absorbed so effectively that the sound gets muffled by the room.

The room can be modeled by an LTI system where the frequency response $H(\omega)$ is smaller in magnitude for large ω than for small ω . This is a simple form of **distortion** introduced by a **channel** (the room), which in this case carries a sound from its transmitter (the lecturer) to its receiver (the listener). This form of distortion is called **linear distortion**, a shorthand for linear, time-invariant distortion (the time invariance is left implicit).

A public address system in a lecture hall may compensate for the acoustics of the room by boosting the high frequency content in the sound. Such a compensator is called an **equalizer** because it corrects for distortion in the channel so that all frequencies are received equally well by the receiver.

In a communications system, a channel may be a physical medium, such as a pair of wires, that carries an electrical signal. That physical medium distorts the signal, and this distortion is often reasonably well approximated as linear and time invariant. An equalizer in the receiver compensates for this distortion. Unlike the audio example, however, such an equalizer often needs to compensate for the phase response, not just the magnitude response. Because the human ear is relatively insensitive to phase distortion, a public address system equalizer need not compensate for phase distortion. But the wire pair may be carrying a signal that is not an audio signal. It may be, for example, a modem signal.

Images may also be processed by LTI systems. Consider the three images shown in Figure 9.1. The top image is the original, undistorted image. The lower left image is blurred, as might result for example from unfocused optics. The lower right image is, in a sense, the opposite of the blurred image. Whereas the blurred image deemphasizes the patterns in the outfit, for example, the right image deemphasizes the regions of constant value, changing them all to a neutral gray.

For images, time is not the critical variable. Its role is replaced by two spatial variables, one in the horizontal direction and one in the vertical direction. Thus, instead of LTI, we might talk about an image processing system being a **linear, space-invariant (LSI)** system. The blurred image is constructed from the original by an LSI system that eliminates high (spatial) frequencies, passing unaltered the low frequencies. Such a system is called a **lowpass** filter. The lower right image is constructed from the original by an LSI system that eliminates low frequencies, passing unaltered the high frequencies. Such a system is called a **highpass** system. Both images were created using Adobe Photoshop, although the blurred image could have been just as easily created by a defocused lens.

9.1 Convolution

The frequency response of a system is a declarative description of the system. It tells us what it is, not how it works. It tells us, for example, that it is a lowpass filter, but it does not tell us whether it is a defocused lens or a computer program, much less telling us how the computer program works. In this chapter, we explore imperative descriptions



Figure 9.1: An image and two versions that have been distorted by a linear, space-invariant system.

of systems, and build up to detailed descriptions of software that can implement certain kinds of LTI (or LSI) systems. These imperative descriptions are based on **convolution**.

9.1.1 Convolution sum and integral

For discrete-time signals the convolution operator is called the convolution sum, and for continuous-time signals it is called the convolution integral. We define these two operators now and note some important properties.

Let $x, y \in [\mathbb{Z} \rightarrow \mathbb{R}]$ be two discrete-time signals. The **convolution** of x and y is the discrete-time signal, denoted $x * y$, given by the **convolution** sum,

$$\forall n \in \mathbb{Z}, \quad (x * y)(n) = \sum_{k=-\infty}^{\infty} x(k)y(n-k). \quad (9.1)$$

We note two properties. First, the order in the convolution does not matter, $x * y = y * x$. Indeed, if in (9.1) we change the variables in the summation, letting $m = n - k$, we get

$$\begin{aligned} \forall n \in \mathbb{Z}, \quad (x * y)(n) &= \sum_{k=-\infty}^{\infty} x(k)y(n-k) \\ &= \sum_{m=-\infty}^{\infty} x(n-m)y(m). \end{aligned}$$

Thus,

$$(x * y)(n) = (y * x)(n). \quad (9.2)$$

This property is called **commutativity** of the convolution operator.¹

Another property of convolution is **linearity**. That is, if x, y_1, y_2 are three signals and a_1 and a_2 are real numbers, then

$$x * (a_1 y_1 + a_2 y_2) = a_1(x * y_1) + a_2(x * y_2), \quad (9.3)$$

which may be checked directly by applying definition (9.1) to both sides.

¹Matrix multiplication is an example of an operator that is not commutative, while matrix addition is. Since the sum of two matrices M and N (of the same size) does not depend on the order, i.e., $M + N = N + M$, the matrix sum is a commutative operator. However, the product of two matrices depends on the order, i.e., it is not always true that $M \times N = N \times M$, so the matrix product is not commutative.

We now use the convolution sum to define some LTI systems. Fix a discrete-time signal h , and define the system

$$S: [\mathbb{Z} \rightarrow \mathbb{R}] \rightarrow [\mathbb{Z} \rightarrow \mathbb{R}]$$

by

$$\forall x \in [\mathbb{Z} \rightarrow \mathbb{R}], \quad S(x) = h * x.$$

Thus the output signal $y = S(x)$ corresponding to the input signal x is given by

$$\forall n \in \mathbb{Z}, \quad y(n) = \sum_{k=-\infty}^{\infty} h(k)x(n-k).$$

We now show that S is LTI. The linearity of S follows immediately from the linearity property of the convolution. To show time-invariance, we must show that for any integer M , and any input signal x ,

$$D_M(h * x) = h * (D_M(x)),$$

where D_M is a **delay** by M . But this is easy to see, since for all n ,

$$\begin{aligned} (D_M(h * x))(n) &= (h * x)(n - M) \\ &= \sum_{k=-\infty}^{\infty} h(k)x(n - M - k), \text{ by definition (9.1)} \\ &= \sum_{k=-\infty}^{\infty} h(k)z(n - k), \text{ where } z = D_M(x) \\ &= (h * z)(n). \end{aligned}$$

Thus every discrete-time signal h defines an LTI system via convolution. In the next section we will see the converse result, that every LTI system is defined by convolution with some signal h .

Example 9.1: Consider a discrete-time signal h defined by

$$\forall n \in \mathbb{Z}, \quad h(n) = \begin{cases} 1/3 & \text{if } n \in \{0, 1, 2\} \\ 0 & \text{otherwise} \end{cases}$$

This is shown in Figure 9.2. Let us define a system S as follows. If the input is x , then the output is

$$y = S(x) = h * x.$$

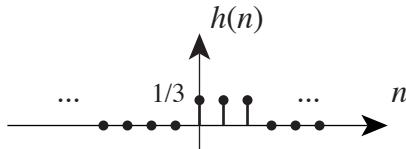


Figure 9.2: Signal in example 9.1.

I.e.,

$$\begin{aligned} \forall n \in \mathbb{Z}, \quad y(n) &= \sum_{k=-\infty}^{\infty} h(k)x(n-k) \\ &= \sum_{k=0}^2 (1/3)x(n-k) \\ &= (x(n) + x(n-1) + x(n-2))/3. \end{aligned} \quad (9.4)$$

This system calculates the three-point moving average!

We now turn to the continuous time case. Let $x, y \in [\mathbb{R} \rightarrow \mathbb{R}]$ be two continuous-time signals. The **convolution** of x and y is the continuous-time signal, denoted $x * y$, given by the **convolution integral**

$$\forall t \in \mathbb{R}, \quad (x * y)(t) = \int_{-\infty}^{\infty} x(\tau)y(t - \tau)d\tau. \quad (9.5)$$

By a change of variable in the integral we can check that convolution again is commutative, i.e.,

$$\boxed{\forall t \in \mathbb{R}, \quad (x * y)(t) = (y * x)(t),} \quad (9.6)$$

and it is linear; i.e. if x, y_1, y_2 are three continuous-time signals and a_1, a_2 are real numbers, then

$$\boxed{x * (a_1 y_1 + a_2 y_2) = a_1(x * y_1) + a_2(x * y_2).} \quad (9.7)$$

Again fix $h \in [\mathbb{R} \rightarrow \mathbb{R}]$, and define the system

$$S: [\mathbb{R} \rightarrow \mathbb{R}] \rightarrow [\mathbb{R} \rightarrow \mathbb{R}]$$

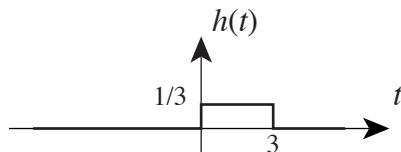


Figure 9.3: Signal in example 9.2.

by

$$\forall x \in [\mathbb{R} \rightarrow \mathbb{R}], \quad S(x) = h * x.$$

Then in exactly the same way as for the discrete-time case, we can show that S is LTI.

Example 9.2: Consider a continuous-time signal h defined by

$$\forall t \in \mathbb{R}, \quad h(t) = \begin{cases} 1/3 & \text{if } t \in [0, 3] \\ 0 & \text{otherwise} \end{cases}$$

This is shown in Figure 9.3. Let us define a system S as follows. If the input is x , then the output is

$$y = S(x) = h * x.$$

I.e,

$$\begin{aligned} \forall t \in \mathbb{R}, \quad y(t) &= \int_{-\infty}^{\infty} h(\tau)x(t - \tau)d\tau \\ &= \frac{1}{3} \int_0^3 x(t - \tau)d\tau. \end{aligned} \tag{9.8}$$

This system is the length-three continuous-time moving average!

Note that we are using the same symbol ‘*’ for the convolution sum and the convolution integral. The context will determine which operator is intended.

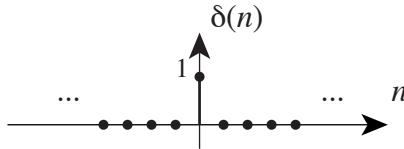


Figure 9.4: The Kronecker delta function, a discrete-time impulse.

9.1.2 Impulses

Intuitively, an impulse is a signal that is zero everywhere except at time zero. In the discrete-time case, the **Kronecker delta function**,

$$\delta: \mathbb{Z} \rightarrow \mathbb{R}$$

is defined by

$$\boxed{\forall n \in \mathbb{Z}, \quad \delta(n) = \begin{cases} 1 & \text{if } n = 0 \\ 0 & \text{otherwise} \end{cases}} \quad (9.9)$$

Its graph is shown in Figure 9.4.

The continuous-time case, which is called the **Dirac delta function**, is mathematically much more difficult to work with. Like the Kronecker delta function, it is zero everywhere except at zero. But unlike the Kronecker delta function, its value is infinite at zero. We will not concentrate on its subtleties, but rather just introduce it and assert some results without fully demonstrating their validity. The Dirac delta function is defined to be

$$\delta: \mathbb{R} \rightarrow \mathbb{R}_{++}$$

where $\mathbb{R}_{++} = \mathbb{R} \cup \{\infty, -\infty\}$, and

$$\forall t \in \mathbb{R} \text{ where } t \neq 0, \quad \delta(t) = 0$$

and where the following property is satisfied for any $\varepsilon > 0$ in \mathbb{R}_{++} ,

$$\int_{-\varepsilon}^{\varepsilon} \delta(t) dt = 1$$

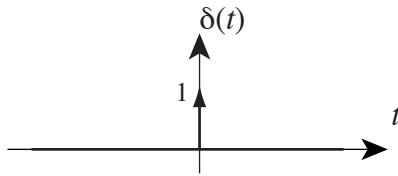


Figure 9.5: The Dirac delta function, a continuous-time impulse.

For the latter property to be satisfied, clearly no finite value at $t = 0$ would suffice. This is why the value must be infinite at $t = 0$. Notice that the Kronecker delta function has a similar property,

$$\sum_{n=-a}^a \delta(n) = 1$$

for any integer $a > 0$, but that in this case, the property is trivial. There is no mathematical subtlety.

The Dirac delta function is usually depicted as in Figure 9.5. In any figure, of course, the infinite value at $t = 0$ cannot be shown directly. The figure suggests that infinite value with a vertical arrow. Next to the arrow is the **weight** of the delta function, ‘1’ in this case. In general, a Dirac delta function can be multiplied by any real constant a . Of course, this does not change its value at $t = 0$, which is infinite, nor does it change its value at $t \neq 0$, which is zero. What it does change is its integral,

$$\int_{-\varepsilon}^{\varepsilon} a\delta(t)dt = a.$$

Thus, although the impulse is still infinitely narrow and infinitely high, the area under the impulse has been scaled by a .

9.1.3 Signals as sums of weighted delta functions

Any discrete-time signal $x: \mathbb{Z} \rightarrow \mathbb{R}$ can be expressed as a sum of weighted Kronecker delta functions,

$\forall n \in \mathbb{Z}, \quad x(n) = \sum_{k=-\infty}^{\infty} x(k)\delta(n-k).$

(9.10)

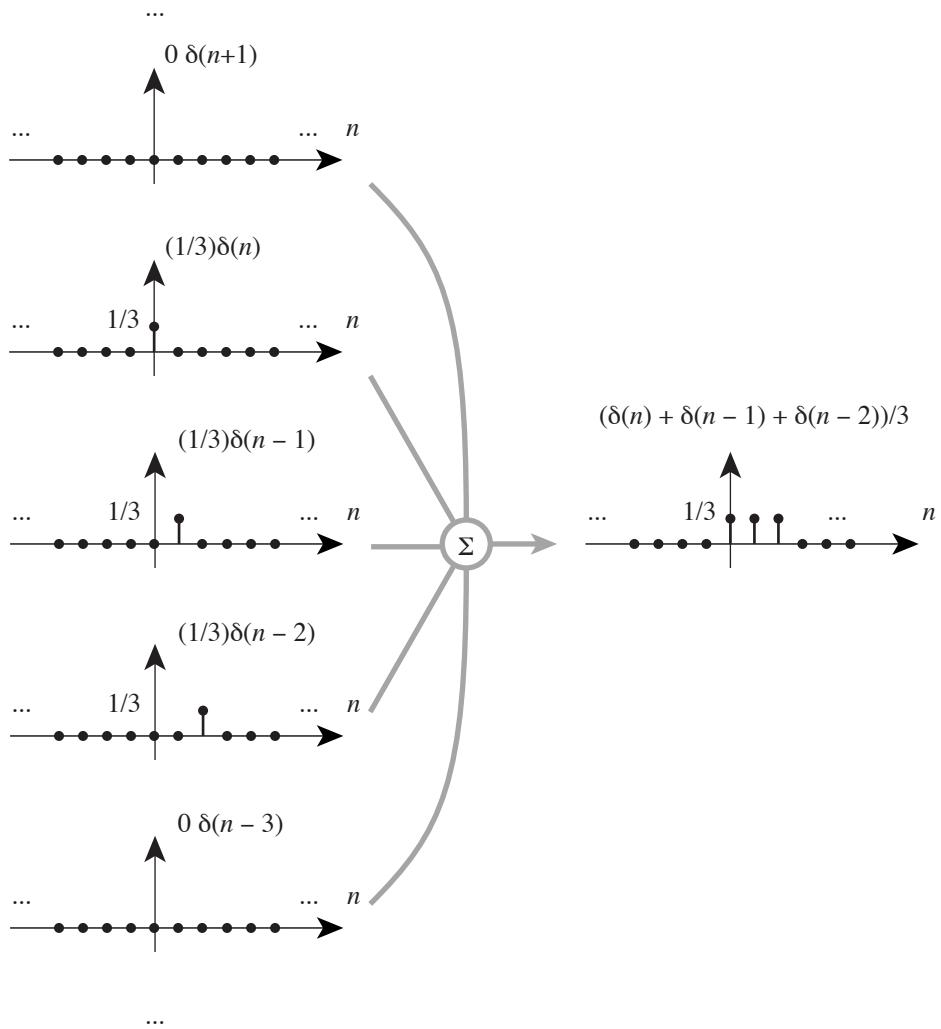


Figure 9.6: A discrete-time signal is a sum of weighted delta functions.

The k th term in the sum is $x(k)\delta(n - k)$. This term, by itself, defines a signal that is zero everywhere except at $n = k$, where it has value $x(k)$. This signal is called a **weighted delta function** because it is a (time shifted) delta function with a specified weight. Thus, any discrete-time signal is a sum of weighted delta functions, much the way that the Fourier series describes a signal as a sum of weighted complex exponential functions.

Example 9.3: The signal h in example 9.1 can be written in terms of Kronecker delta functions,

$$\forall n \in \mathbb{Z}, \quad h(n) = (\delta(n) + \delta(n - 1) + \delta(n - 2))/3.$$

This has the form of (9.10), and is illustrated in Figure 9.6. It is described as a sum of signals where each signal contains only a single weighted impulse.

Equation (9.10) is sometimes called the **sifting property** of the Kronecker delta function because it “sifts out” the value of a function x at some integer n . That is, the infinite sum reduces to a single number. This property can often be used to eliminate infinite summations in more complicated expressions.

The continuous-time version of this is similar, except that the sum becomes an integral (integration, after all, is just sum over a continuum). Given any signal $x: \mathbb{R} \rightarrow \mathbb{R}$,

$$\boxed{\forall t \in \mathbb{R}, \quad x(t) = \int_{-\infty}^{\infty} x(\tau)\delta(t - \tau)d\tau.} \quad (9.11)$$

Although this is mathematically much more subtle than the discrete-time case, it is very similar in structure. It describes a signal x as a sum (or more precisely, an integral) of weighted Dirac delta functions.

Example 9.4: The signal h in Figure 9.3 and example 9.2 can be written as a sum (an integral, actually) of weighted Dirac delta functions,

$$\begin{aligned} \forall t \in \mathbb{R}, \quad h(t) &= \int_{-\infty}^{\infty} h(\tau)\delta(t - \tau)d\tau \\ &= \int_0^3 (1/3)\delta(t - \tau)d\tau. \end{aligned}$$

This has the form of (9.11).

Equation (9.11) is sometimes called the **sifting property** of the Dirac delta function, because it sifts out from the function x the value at a given time t . The sifting property can often be used to eliminate integrals, since it replaces an integral with a single value.

9.1.4 Impulse response and convolution

Consider a discrete-time LTI system $S: [\mathbb{Z} \rightarrow \mathbb{R}] \rightarrow [\mathbb{Z} \rightarrow \mathbb{R}]$. Define its **impulse response** h to be the output signal when the input signal is the Kronecker delta function (an impulse), $h = S(\delta)$, that is,

$$\forall n \in \mathbb{Z}, \quad h(n) = (S(\delta))(n).$$

Now let x be any input signal, and let $y = S(x)$ be the corresponding output signal. In (9.10), x is given as sum of components, where each component is a weighted delta function. Since S is LTI, the output can be given as a sum of the responses to these components. Each component is a signal $x(k)\delta(n-k)$ for fixed k , and the response to this signal is $x(k)h(n-k)$. The response to a scaled and delayed impulse will be a scaled and delayed impulse response. Thus, the overall output is

$$\boxed{\forall n \in \mathbb{Z}, \quad y(n) = \sum_{k=-\infty}^{\infty} x(k)h(n-k) = (x * h)(n) = (h * x)(n).}$$

Thus, the output of any discrete-time LTI system is given by the convolution of the input signal and the impulse response.

Example 9.5: The three-point moving average system S of example 9.1 has impulse response

$$\forall n \in \mathbb{Z}, \quad h(n) = (\delta(n) + \delta(n-1) + \delta(n-2))/3.$$

This can be determined from (9.4) by just letting the input be $x = \delta$. The impulse response, after all, is defined to be the output when the input is an impulse. The impulse response is shown in Figure 9.2.

Consider now a continuous-time LTI system $S: [\mathbb{R} \rightarrow \mathbb{R}] \rightarrow [\mathbb{R} \rightarrow \mathbb{R}]$. Define its **impulse response** to be the output signal h when the input signal is the Dirac delta function, $h = S(\delta)$, i.e.,

$$\forall t \in \mathbb{R}, \quad h(t) = S(\delta)(t).$$

Now let x be any input signal and let $y = S(x)$, be the corresponding output signal. By the sifting property we can express x as the sum (integral) of weighted delta functions,

$$x(t) = \int_{-\infty}^{\infty} x(\tau)\delta(t - \tau)d\tau.$$

Since S is LTI, the output is a sum (integral) of the responses to each of the components (the integrand for fixed τ), or

$$\boxed{\forall t \in \mathbb{R}, \quad y(t) = \int_{-\infty}^{\infty} x(\tau)h(t - \tau)d\tau = (x * h)(t) = (h * x)(t).} \quad (9.12)$$

Thus,

The output of any continuous-time LTI system is given by the convolution of the input signal and the impulse response.

Example 9.6: The length-three continuous-time moving average system S of example 9.2 has impulse response

$$\forall t \in \mathbb{R}, \quad h(t) = \begin{cases} 1/3 & \text{if } t \in [0, 3] \\ 0 & \text{otherwise} \end{cases}$$

This can be determined from (9.8) by just letting the input be $x = \delta$ and then using the sifting property of the delta function. The impulse response, after all, is defined to be the output when the input is an impulse. The impulse response is shown in Figure 9.3. In general, a moving average has an impulse response with this rectangular shape.

Example 9.7: Consider an M -step discrete-time delay system, as in example 8.9, where the output y is given in terms of the input x by the difference equation

$$\forall n \in \mathbb{Z}, \quad y(n) = x(n - M). \quad (9.13)$$

The impulse response can be found by letting $x = \delta$, to get

$$h(n) = \delta(n - M).$$

The output can be given as a convolution of the input and the impulse response,

$$y(n) = \sum_{k=-\infty}^{\infty} x(k)\delta(n - M - k) = x(n - M),$$

using the sifting property. Of course, this agrees with (9.13).

Example 9.8: Consider a T second continuous-time delay system, where the output y is given in terms of the input x by the equation

$$\forall t \in \mathbb{R}, \quad y(t) = x(t - T). \quad (9.14)$$

The impulse response can be found by letting $x = \delta$, to get

$$h(t) = \delta(t - T).$$

The output can be given as a convolution of the input and the impulse response,

$$y(t) = \int_{-\infty}^{\infty} x(\tau)\delta(t - T - \tau)d\tau = x(t - T),$$

using the sifting property. Of course, this agrees with (9.14).

Example 9.9: Suppose that we have two LTI systems (discrete or continuous time) with impulse responses h_1 and h_2 , and we connect them in a cascade structure as shown in Figure 9.7. We can find the impulse response of the cascade composition by letting the input be an impulse, $x = \delta$. Then the output of the first system will be its impulse response, $w = h_1$. This provides the input to the second system, so its

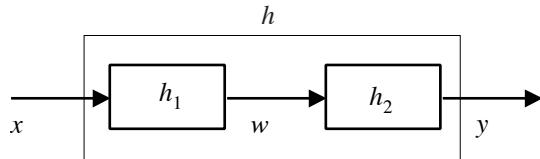


Figure 9.7: A cascade combination of two discrete-time LTI systems.

output will be $y = h_1 * h_2$. Thus, the overall impulse response is the convolution of the two impulse responses,

$$h = h_1 * h_2.$$

We also know from the previous chapter that the frequency responses relate in a very simple way, namely

$$H(\omega) = H_1(\omega)H_2(\omega).$$

We will find that, in general, convolution in the time domain is equivalent to multiplication in the frequency domain.

9.2 Frequency response and impulse response

If a discrete-time LTI system has impulse response h , then the output signal y corresponding to the input signal x is given by the convolution sum,

$$\forall n \in \mathbb{Z}, \quad y(n) = \sum_{m=-\infty}^{\infty} h(m)x(n-m).$$

In particular, suppose the input is the complex exponential function

$$\forall n \in \mathbb{Z}, \quad x(n) = e^{i\omega n},$$

for some real ω . Then the output signal is

$$\forall n \in \mathbb{Z}, \quad y(n) = \sum_{m=-\infty}^{\infty} h(m)e^{i\omega(n-m)} = e^{i\omega n} \sum_{m=-\infty}^{\infty} h(m)e^{-i\omega m}.$$

Recall further that when the input is a complex exponential with frequency ω , then the output is given by

$$\forall n \in \mathbb{Z}, \quad y(n) = H(\omega)e^{i\omega n}$$

where $H(\omega)$ is the frequency response. Comparing these two expressions for the output we see that the frequency response is related to the impulse response by

$$\boxed{\forall \omega \in \mathbb{R}, \quad H(\omega) = \sum_{m=-\infty}^{\infty} h(m)e^{-i\omega m}.} \quad (9.15)$$

This expression allows us, in principle, to calculate the frequency response from the impulse response. Equation (9.15) gives us a way to transform h , a time-domain function, into H , a frequency domain function. Equation (9.15) is called a **discrete-time Fourier transform (DTFT)**. Equivalently, we say that H is the DTFT of h . So the frequency response of a discrete-time system is the DTFT of its impulse response.

Example 9.10: Consider the M -step delay from example 9.7. Its impulse response is

$$\forall n \in \mathbb{Z}, \quad h(n) = \delta(n - M).$$

We can find the frequency response by calculating the DTFT,

$$\begin{aligned} \forall \omega \in \mathbb{R}, \quad H(\omega) &= \sum_{m=-\infty}^{\infty} h(m)e^{-i\omega m} \\ &= \sum_{m=-\infty}^{\infty} \delta(m - M)e^{-i\omega m} \\ &= e^{-i\omega M} \end{aligned}$$

where the last step follows from the sifting property. This same result was obtained more directly in example 8.9. Note that the magnitude response is particularly simple,

$$|H(\omega)| = 1.$$

This is intuitive. An M -step delay does not change the magnitude of any complex exponential input. It only shifts its phase.

Notice from (9.15) that

$$\boxed{\text{If } h \text{ is real-valued then } H^*(-\omega) = H(\omega)} \quad (9.16)$$

(just conjugate both sides of (9.15) and evaluate at $-\omega$). This property is called **conjugate symmetry**. It implies

$$|H(-\omega)| = |H(\omega)|. \quad (9.17)$$

This says that for any LTI system with a real-valued impulse response, a complex exponential with frequency ω experiences the same amplitude change as a complex exponential with frequency $-\omega$.

Notice further from (9.15) that

$$\boxed{\forall \omega \in \mathbb{R}, \quad H(\omega + 2\pi) = H(\omega)}. \quad (9.18)$$

I.e., the DTFT is periodic with period 2π . This says that a complex exponential with frequency ω experiences the same amplitude and phase change as a complex exponential with frequency $\omega + 2\pi$. This should not be surprising since the two complex exponentials are in fact identical,

$$\forall n \in \mathbb{Z}, \quad e^{i(\omega+2\pi)n} = e^{i\omega n} e^{i2\pi n} = e^{i\omega n},$$

because $e^{i2\pi n} = 1$ for any integer n .

The continuous-time version proceeds in the same way. Let S be a continuous-time system with impulse response h . Then the output signal y corresponding to an input signal x is given by

$$\forall t \in \mathbb{R}, \quad y(t) = \int_{-\infty}^{\infty} x(\tau)h(\tau)d\tau.$$

In particular, if the input signal is the complex exponential,

$$\forall t \in \mathbb{R}, \quad x(t) = e^{i\omega t},$$

then the output signal is

$$y(t) = \int_{-\infty}^{\infty} e^{i\omega(t-\tau)}h(\tau)d\tau = e^{i\omega t} \int_{-\infty}^{\infty} e^{-i\omega\tau}h(\tau)d\tau.$$

The output is also given by $y(t) = H(\omega)e^{i\omega t}$ where $H(\omega)$ is the frequency response, and so we have

$$\boxed{H(\omega) = \int_{-\infty}^{\infty} h(t)e^{-i\omega t}dt.} \quad (9.19)$$

So, given its impulse response, we can calculate the frequency response of a continuous-time LTI system by evaluating the integral (9.19). Like the DTFT, this integral transforms a time-domain signal h into a frequency-domain signal H . It is called the **continuous-time Fourier transform** (CTFT), or more commonly, simply the **Fourier transform** (FT). Thus the frequency response H of a continuous-time LTI system is just the CTFT of its impulse response h .

Example 9.11: Consider the T second delay from example 9.8. Its impulse response is

$$h(t) = \delta(t - T).$$

We can find the frequency response by calculating the CTFT,

$$\begin{aligned} H(\omega) &= \int_{-\infty}^{\infty} h(t) e^{-i\omega t} dt \\ &= \int_{-\infty}^{\infty} \delta(t - T) e^{-i\omega t} dt \\ &= e^{-i\omega T} \end{aligned}$$

where the last step follows from the sifting property. Note that the magnitude response is particularly simple,

$$|H(\omega)| = 1.$$

This is intuitive. A T second delay does not change the magnitude of any complex exponential input. It only shifts its phase.

Notice from (9.19) that the CTFT is also conjugate symmetric if h is real,

$$H^*(-\omega) = H(\omega) \quad (9.20)$$

$$|H(-\omega)| = |H(\omega)|. \quad (9.21)$$

9.3 Causality

A system is **causal** if the output value at a particular time depends only on the input values at that time or before. For LTI systems, if we examine the convolution sum,

$$y(n) = \sum_{m=-\infty}^{\infty} h(m)x(n-m),$$

for a causal system it must be true that $h(m) = 0$ for all $m < 0$. Were this not true, there would be non-zero terms in the sum with $m < 0$, and those terms would involve a future sample of the input, $x(n-m)$. Conversely, if $h(m) = 0$ for all $m < 0$, then the system is causal since the sum for $y(n)$ will involve only previous input values, $x(n), x(n-1), x(n-2), \dots$.

Causality is an important practical property of a system that receives its data in **real time** (physical time). Such systems cannot possibly look ahead in time, at least not until someone invents a time machine. However, there are many situations where causality is irrelevant. A system that processes stored data, such as digital audio of a compact disk or audio files in a computer, has no difficulty looking ahead in “time.”

9.4 Finite impulse response (FIR) filters

Consider an LTI system $S: [\mathbb{Z} \rightarrow \mathbb{R}] \rightarrow [\mathbb{Z} \rightarrow \mathbb{R}]$ with impulse response $h: \mathbb{Z} \rightarrow \mathbb{R}$ that has the properties

$$h(n) = 0 \text{ if } n < 0, \quad \text{and} \quad h(n) = 0 \text{ if } n \geq L,$$

where L is some positive integer. Such a system is called a **finite impulse response (FIR)** system because the interesting part (the non-zero part) of the impulse response is finite in extent. Because of that property, the convolution sum becomes a finite sum,

$$y(n) = \sum_{m=-\infty}^{\infty} x(n-m)h(m) = \sum_{m=0}^{L-1} x(n-m)h(m). \quad (9.22)$$

L is the length of the impulse response.

This sum, since it is finite, is convenient to work with. It can be used to define a procedure for computing the output of an FIR system given its input. This makes it easy to implement on a computer. We will see that it is also reasonably straightforward to implement certain **infinite impulse response (IIR)** filters on a computer.

Probing Further: Causality

We can give a much more general and formal definition of causality that does not require a system to be LTI. Consider a system $S: [A \rightarrow B] \rightarrow [A \rightarrow B]$ that operates on signals of type $[A \rightarrow B]$. Assume A is an ordered set and B is any ordinary set. An ordered set is one with relations “ $<$ ” and “ $>$ ” where for any two elements a and b , one of the following assertions must be true:

$$a = b, \quad a > b, \text{ or } a < b.$$

Examples of ordered sets are \mathbb{Z} and \mathbb{R} .

An example of a set that is not an ordered set is $\mathbb{Z} \times \mathbb{Z}$ where we define the ordering relation “ $<$ ” so that $(a, b) < (c, d)$ if $a < c$ and $b < c$, and we similarly define “ $>$ ”. Under these definitions, for the elements $(1, 2)$ and $(2, 1)$, none of the above assertions is true, so the set is not ordered.

However, we could define the ordering relation “ $<$ ” so that $(a, b) < (c, d)$ if one of the following is true:

$$a < c \text{ or}$$

$$a = c, \text{ and } b < c.$$

The relation “ $>$ ” could be similarly defined. Under these definitions, the set is ordered.

Define a function $\text{Prefix}_t: [A \rightarrow B] \rightarrow [A_t \rightarrow B]$ that extracts a portion of a signal up to $t \in A$. Formally, $A_t \subset A$ such that $a \in A_t$ if $a \in A$ and $a \leq t$. Then for all $x \in [A \rightarrow B]$ and for all $t \in A_t$, $(\text{Prefix}_t(x))(t) = x(t)$.

A system S is causal if for all $t \in A$ and for all $x, y \in [A \rightarrow B]$

$$\text{Prefix}_t(x) = \text{Prefix}_t(y) \Rightarrow \text{Prefix}_t(S(x)) = \text{Prefix}_t(S(y)).$$

The symbol “ \Rightarrow ” reads “implies.” In words, the system is causal if when two input signals have the same prefix up to time t , it follows that the two corresponding output signals have the same prefix up to time t .

A continuous-time finite impulse response could be defined, but in practice, continuous-time systems rarely have finite impulse responses, so there is not as much motivation for doing so. Moreover, even though the convolution integral acquires finite limits, this does not make it any more computable. Computing integrals on a computer is a difficult proposition whether the limits are finite or not.

Example 9.12: We have seen in example 9.1 a 3-point moving average. An L -point moving average system with input x has output y given by

$$y(n) = \frac{1}{L} \sum_{m=0}^{L-1} x(n-m).$$

The output at index n is the average of the most recent L inputs. Such a filter is widely used on Wall Street to try to detect trends in stock market prices. We can study its properties. First, it is easy to see that it is an LTI system. In fact, it is an FIR system with impulse response

$$h(n) = \begin{cases} 1/L & \text{if } 0 \leq n < L \\ 0 & \text{otherwise} \end{cases}$$

To see this, just let $x = \delta$. The frequency response is the DTFT,

$$H(\omega) = \sum_{m=-\infty}^{\infty} h(m)e^{-i\omega m} = \frac{1}{L} \sum_{m=0}^{L-1} e^{-i\omega m}.$$

We can write the frequency response as

$$H(\omega) = \frac{1}{L} \left(\frac{1 - e^{-i\omega L}}{1 - e^{-i\omega}} \right)$$

where we have let $a = e^{-i\omega}$, and we have used the useful identity

$$\sum_{m=0}^{L-1} a^m = \frac{1 - a^L}{1 - a}$$

(9.23)

You can verify the identity by multiplying both sides by $1 - a$. We can plot the magnitude of the frequency response using Matlab as follows (for $L = 4$):

```

1 L = 4;
2 w = [-pi:pi/250:pi];
3 H = (1/L)*(1-exp(-i*w*L))./(1-exp(-i*w));
4 plot(w, abs(H));
5 xlabel('frequency in radians/sample');

```

This issues a “divide by zero” warning, but yields a correct plot nonetheless. The magnitude of the frequency response at $\omega = 0$ is 1, as you can verify using [L'Hôpital's rule](#).

The plot is shown in Figure 9.8, together with plots for $L = 8$ and $L = 16$. Notice that the plot shows only the frequency range $-\pi < \omega < \pi$. Since the DTFT is periodic with period 2π , this plot simply repeats outside this range.

Notice that in all three cases shown in Figure 9.8, the frequency response has a lowpass characteristic. A constant component (zero frequency) in the input passes through the filter unattenuated. Certain higher frequencies, such as $\pi/2$, are completely eliminated by the filter. However, if the intent was to design a lowpass filter, then we have not done very well. Some of the higher frequencies are attenuated only by a factor of about 1/10 (for the 16 point moving average) or 1/3 (for the four point moving average). We can do better than that with more intelligent filter design.

9.4.1 Design of FIR filters

The moving average system in example 9.12 exhibits a lowpass frequency response, but not a particularly good lowpass frequency response. A great deal of intellectual energy has historically gone into finding ways to choose the impulse response of an FIR filter. The subject is quite deep. Fortunately, much of the work that has been done is readily available in the form of easy-to-use software, so one does not need to be knowledgeable about these techniques to be able to design good FIR filters.

Example 9.13: Matlab’s filter design facilities in its DSP toolbox provide some well-studied algorithms for filter design. For example,

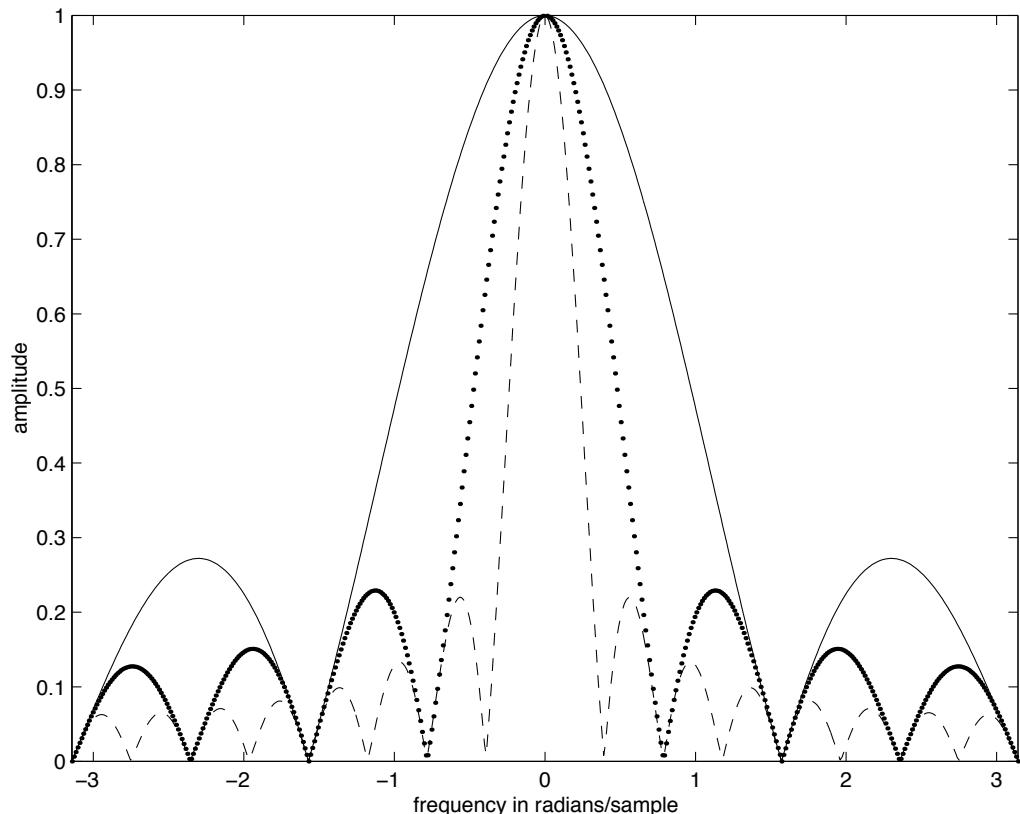


Figure 9.8: The magnitude response of the moving average filter with lengths $L = 4$ (solid line), 8 (dotted line), and 16 (dashed line).

```
>> h = remez(7, [0, 0.125, 0.25, 1], [1, 1, 0, 0])

h =
Columns 1 through 6
    0.0849    0.1712    0.1384    0.1912
    0.1912    0.1384

Columns 7 through 8
    0.1712    0.0849
```

This returns the impulse response of a length 8 FIR lowpass filter. The arguments to the `remez` function specify the filter by outlining approximately the desired frequency response. You can use Matlab's on-line help to get the details, but in brief, the arguments above define a **passband** (a region of frequency where the gain is roughly 1) and a **stopband** (a region of frequency where the gain is roughly 0). The first argument, 7 specifies that the length of the filter should be 8 (you will have to ask The MathWorks why this is off by one). The second argument, $[0, 0.125, 0.25, 1]$, specifies that the first frequency band begins at 0 and extends to 0.125π radians/sample, and that the second band begins at 0.25π and extends to π radians/sample. (The π factor is left off.) The unspecified band, from 0.125π to 0.25π , is a "don't care" region, a **transition band** that allows for a gradual transition between the passband and the stopband.

The last argument, $[1, 1, 0, 0]$, specifies that the first band should have a magnitude frequency response of approximately 1, and that the second band should have a magnitude frequency response of approximately 0.

The frequency response of this filter can be directly calculated and plotted using the following (rather brute force) Matlab code:

```
1   w = [-pi:pi/250:pi];
2   H = h(1) + ...
3       h(2)*exp(-i*w) + ...
4       h(3)*exp(-i*2*w) + ...
5       h(4)*exp(-i*3*w) + ...
6       h(5)*exp(-i*4*w) + ...
7       h(6)*exp(-i*5*w) + ...
8       h(7)*exp(-i*6*w) + ...
9       h(8)*exp(-i*7*w);
```

```
10 plot(w, abs(H));
```

The result is shown in Figure 9.9, where it is plotted together with the magnitude response of a moving average filter with the same length. Notice that the attenuation in the stopband is better for the filter designed using the `remez` function than for the moving average filter. Also notice that it is not zero, despite our request that it be zero, and that the passband gain is not one, despite our request that it be one.

The `remez` function used in this example applies an optimization algorithm called the Parks-McClellan algorithm, which is based on the Remez exchange algorithm (hence the name of the function). This algorithm ensures that the sidelobes (the humps in the stopband) are of equal size. This turns out to minimize their maximum size. The Parks-McClellan algorithm is widely used for designing FIR filters.

In this example, the `remez` function is unable to deliver a filter that meets our request. The gain in the stopband is not zero, and the gain in the passband is not one. Generally, this is the problem with filter design (and much of the rest of life); we cannot have what we want. We can get closer by using more resources (also as in much of life). In this case, that means designing a filter with a longer impulse response. Since the impulse response is longer, the filter will be more costly to implement. This is because the finite summation in (9.22) will have more terms.

Example 9.14: Consider for example the impulse response returned by

```
h = remez(63, [0, 0.125, 0.25, 1], [1, 1, 0, 0]);
```

This has length 64. The magnitude frequency response of this can be calculated using the following Matlab code (plotted in Figure 9.10):

```
1 H = fft(h, 1024);
2 magnitude = abs([H(513:1024), H(1:512)]);
3 plot([-pi:pi/512:pi-pi/1024], magnitude);
```

The frequency response achieved in this example appears in Figure 9.10 to exactly match our requirements. However, this plot is somewhat deceptive. It suggests that the mag-

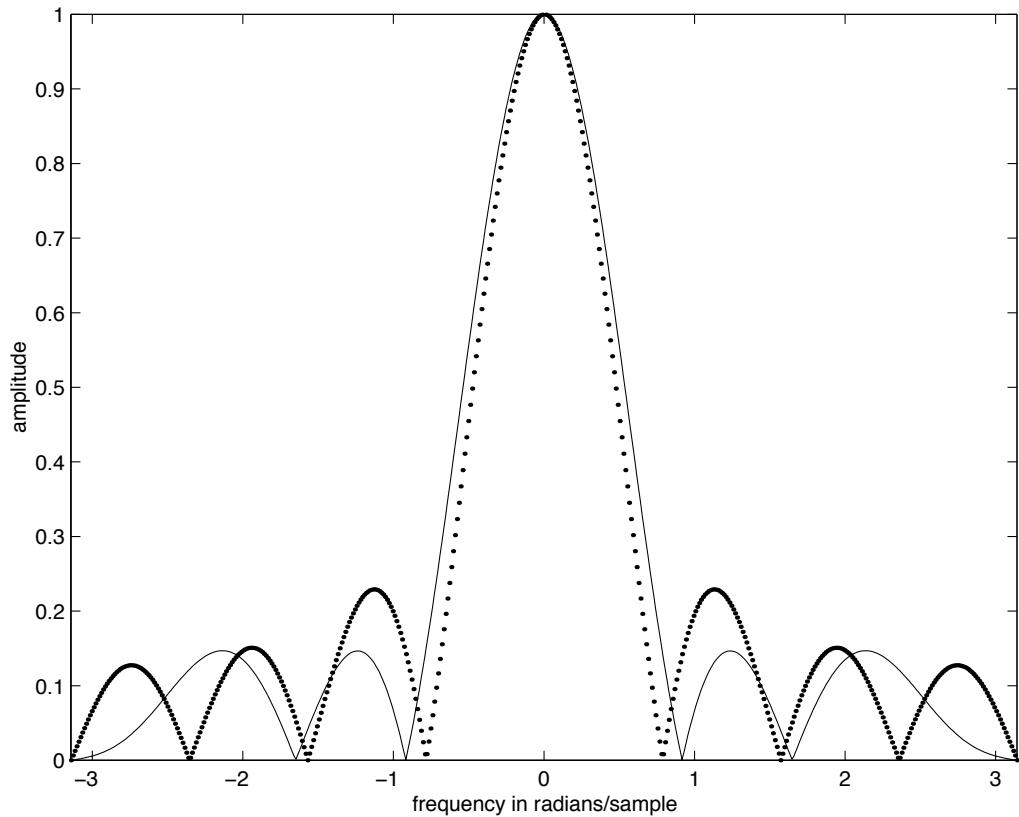


Figure 9.9: Magnitude response an FIR filter designed using the Parks-McClellan algorithm (the Matlab `remez` function), compared to an ordinary moving average.

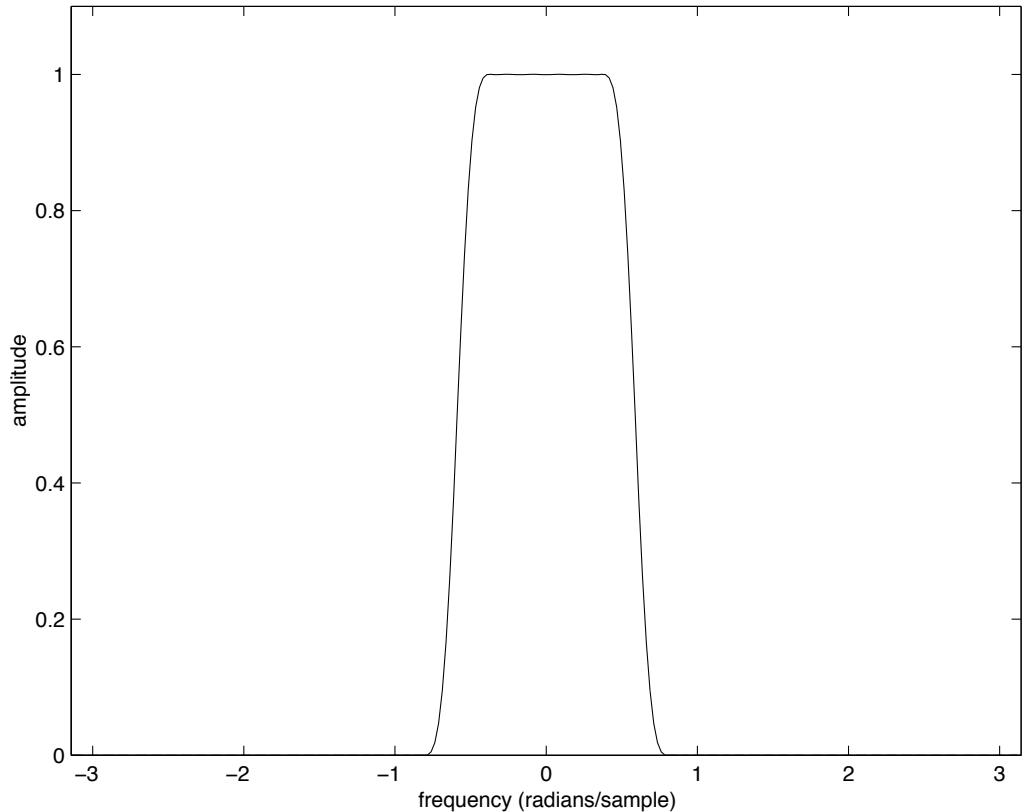


Figure 9.10: Magnitude frequency response of a 64-point lowpass FIR filter designed with the Parks-McClellan algorithm.

nitude frequency response in the stopband is in fact zero. However, it is not, except at certain discrete frequencies. If you zoom in sufficiently on the plot, you will see that. Instead of zooming such plots, engineers usually construct such plots using a logarithmic vertical axis, as explained in the next subsection.

9.4.2 Decibels

The amplitude response of a filter is the magnitude of the frequency response. It specifies the **gain** experienced by a complex exponential at that frequency. This gain is simply the ratio of the output amplitude to the input amplitude. Since it is the ratio of two amplitudes with same units, the gain itself is unitless.

It is customary in engineering to give gains in a logarithmic scale. Specifically, if the gain of a filter at frequency ω is $|H(\omega)|$, then we give instead

$$G(\omega) = 20 \log_{10}(|H(\omega)|). \quad (9.24)$$

This has units of **decibels**, written **dB**. The multiplication by 20 and the use of base 10 logarithms is by convention (see box on page 394).

Example 9.15: The plot in Figure 9.10 is redone using the following Matlab commands,

```

1 H = fft(h, 1024);
2 dB = 20*log10(abs([H(513:1024), H(1:512)]));
3 plot([-pi:pi/512:pi-pi/1024], dB);

```

After some adjustment of the axes, the yields the plot in Figure 9.11. Notice that in the passband, the gain is 0 dB. This is because $\log_{10}(1) = 0$. Zero decibels corresponds to a gain of unity. In the stopband, the gain is almost -70 dB, a very respectable attenuation. If this were an audio signal, then frequency components in the stopband would probably not be audible as long as there is some signal in the passband to mask them. They are 70 dB weaker than the components in the passband, which translates into a factor of 3162 smaller in amplitude, since

$$20\log_{10}(1/3162) \approx -70.$$

We can find the gain given decibels by solving (9.24) for $|H(\omega)|$ in terms of $G(\omega)$ to get

$$|H(\omega)| = 10^{G(\omega)/20}.$$

In this case, in the stopband

$$|H(\omega)| = 10^{-70/20} \approx 1/3162.$$

Notice that $20\log(0) = -\infty$. Thus, whenever the gain is zero, the gain in decibels is $-\infty$. The downward spikes in figure 9.11 occur at frequencies where the gain is zero, or $-\infty$ dB. The spikes do not necessarily precisely show this because the plot does not necessarily evaluate the gain at precisely the frequency that yields zero, hence the ragged bottoms.

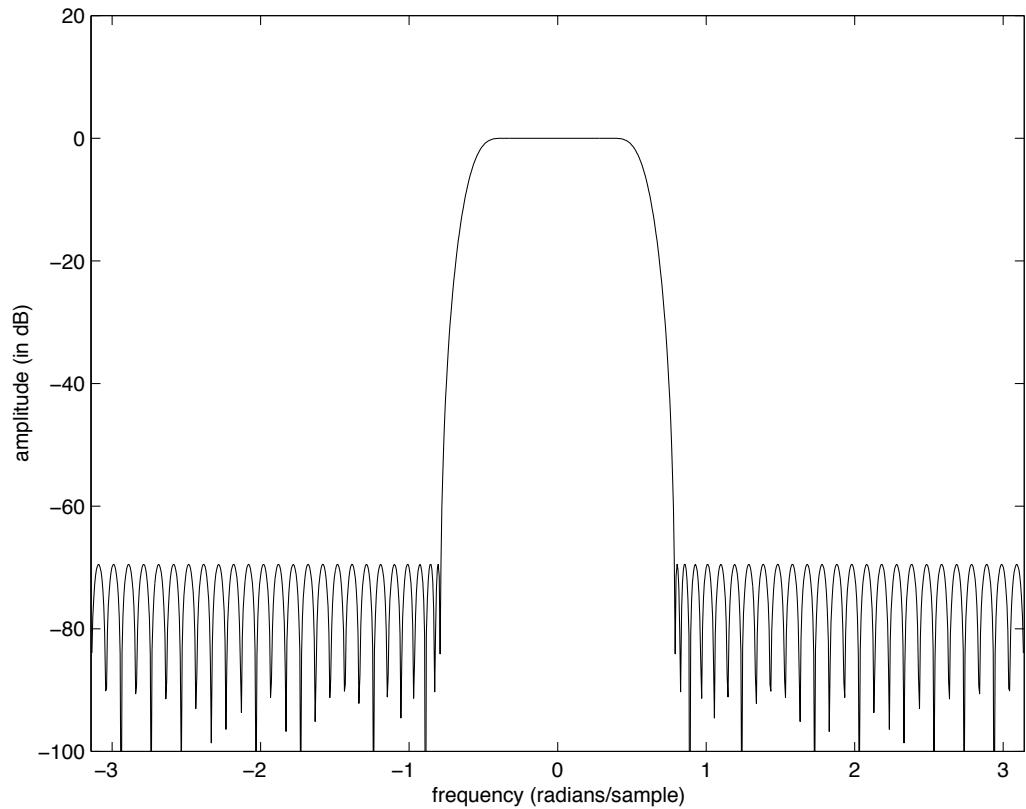


Figure 9.11: Magnitude frequency response in decibels of a 64-point lowpass FIR filter designed with the Parks-McClellan algorithm.

Probing Further: Decibels

The term “decibel” is literally one tenth of a **bel**, which is named after Alexander Graham Bell. This unit of measure was originally developed by telephone engineers at Bell Telephone Labs to designate the ratio of the **power** of two signals.

Power is a measure of energy dissipation (work done) per unit time. It is measured in **watts** for electronic systems. One bel is defined to be a factor of 10 in power. Thus, a 1000 watt hair dryer dissipates 1 bel, or 10 dB, more power than a 100 watt light bulb. Let $p_1 = 1000$ watts be the power of the hair dryer and $p_2 = 100$ be the power of the light bulb. Then the ratio is

$$\log_{10}(p_1/p_2) = 1 \text{ bel}, \quad \text{or}$$

$$10\log_{10}(p_1/p_2) = 10 \text{ dB}.$$

Comparing against (9.24) we notice a discrepancy. There, the multiplying factor is 20, not 10. That is because the ratio in (9.24) is a ratio of amplitudes, not powers. In electronic circuits, if an amplitude represents the voltage across a resistor, then the power dissipated by the resistor is proportional to the *square* of the amplitude. Let a_1 and a_2 be two such amplitudes. Then the ratio of their powers is

$$10\log_{10}(a_1^2/a_2^2) = 20\log_{10}(a_1/a_2).$$

Hence the multiplying factor of 20 instead of 10. A 3 dB power ratio amounts to a factor of 2 in power. In amplitudes, this is a ratio of $\sqrt{2}$. The edge of the passband of a bandpass filter is often defined to be the frequency at which the power drops to half, which is the frequency where the gain is 3 dB below the passband gain. The magnitude frequency response here is $1/\sqrt{2}$ times the passband gain.

In audio, decibels are used to measure sound pressure. A statement like “a jet engine at 10 meters produces 120 dB of sound,” by convention, compares sound pressure to a defined reference of 20 micropascals, where a pascal is a pressure of 1 newton per square meter. For most people, this is approximately the threshold of hearing at 1 kHz. Thus, a sound at 0 dB is barely audible. A sound at 10 dB has 10 times the power. A sound at 100 dB has 10^{10} times the power. The jet engine, therefore, would probably make you deaf without ear protection.

9.5 Infinite impulse response (IIR) filters

The equation for an FIR filter (9.22) is a difference equation relating the output at index n to the inputs at indices $n - L + 1$ through n . A more general form of this difference equation includes more indices of the output,

$$\forall n \in \mathbb{Z}, \quad y(n) = \sum_{m=0}^{L-1} x(n-m)b(m) + \sum_{m=1}^{M-1} y(n-m)a(m) \quad (9.25)$$

where L and M are positive integers, and $b(m)$ and $a(m)$ are **filter coefficients**, which are usually real valued. If all the a coefficients are zero, then this reduces to an FIR filter with impulse response $b = h$. However, if any a coefficient is non-zero, then the impulse response of this filter will never completely die out, since the output keeps getting recycled to affect future outputs. Such a filter is called an **infinite impulse response** or **IIR** filter, or sometimes a **recursive filter**.

Example 9.16: Consider a causal LTI system defined by the difference equation

$$\forall n \in \mathbb{Z}, \quad y(n) = x(n) + 0.9y(n-1).$$

We can find the impulse response by letting $x = \delta$, the Kronecker delta function. Since the system is causal, we know that $h(n) = 0$ for $n < 0$ (see page 382). Thus,

$$\begin{aligned} y(n) &= 0 && \text{if } n < 0 \\ y(0) &= 1 \\ y(1) &= 0.9 \\ y(2) &= 0.9^2 \\ y(3) &= 0.9^3 \end{aligned}$$

Noticing the pattern, we conclude that

$$y(n) = (0.9)^n u(n),$$

where u is the **unit step**, seen before in (2.16),

$$u(n) = \begin{cases} 1 & \text{if } n \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (9.26)$$

The output y and the magnitude of the frequency response (in dB) are plotted in Figure 9.12. Notice that this filter has about 20 dB of gain at DC, dropping to about -6 dB at π radians/sample.

9.5.1 Designing IIR filters

Designing IIR filters amounts to choosing the a and b coefficients for (9.25). As with FIR filters, how to choose these coefficients is a well-studied subject, and the results of this study are (for the most part) available in easy-to-use software. There are four widely used methods for calculating these coefficients, resulting in four types of filters called **Butterworth**, **Chebyshev 1**, **Chebyshev 2**, and **elliptic** filters.

Example 9.17: We can design one of each of the four types of filters using the Matlab commands `butter`, `cheby1`, `cheby2`, `ellip`. The arguments for each of these specify either a **cutoff frequency**, which is the frequency at which the filter achieves -3 dB gain, or in the case of `cheby2`, the edge of the stopband. For example, to get lowpass filters with a gain of about 1 from 0 to $\pi/8$ radians/sample, and a stopband at higher frequencies, we can use the following commands:

```
N = 5;
Wn = 0.125;
[B1, A1] = butter(N, Wn);
[B2, A2] = cheby1(N, 1, Wn);
[B3, A3] = cheby2(N, 70, 0.25);
[B4, A4] = ellip(N, 1, 70, Wn);
```

The returned values are vectors containing the a and b coefficients of (9.25). The magnitude frequency response of the resulting filters is shown in Figure 9.13. In that figure, we show only positive frequencies, since the magnitude frequency response is symmetric. We also only show the frequency range from 0 to π , since the frequency response is periodic with period 2π . Notice that the Butterworth filter has the most gradual **rolloff** from the passband to the stopband. Thus, for a given filter order, a Butterworth filter yields the weakest lowpass characteristic of the four. The elliptic filter has the sharpest rolloff. The Butterworth filter, on the other hand, has the smoothest characteristic. The Chebyshev 1 filter has **ripple** in the passband, the Chebyshev 2 filter has ripple in the stopband, and the elliptic filter has ripple in both.

In the above Matlab commands, N is the filter **order**, equal to L and M in (9.25). It is a constraint of these filter design techniques that $L = M$ in (9.25). Wn is the cutoff frequency, as a fraction of π radians/sample. A cutoff frequency of 0.125

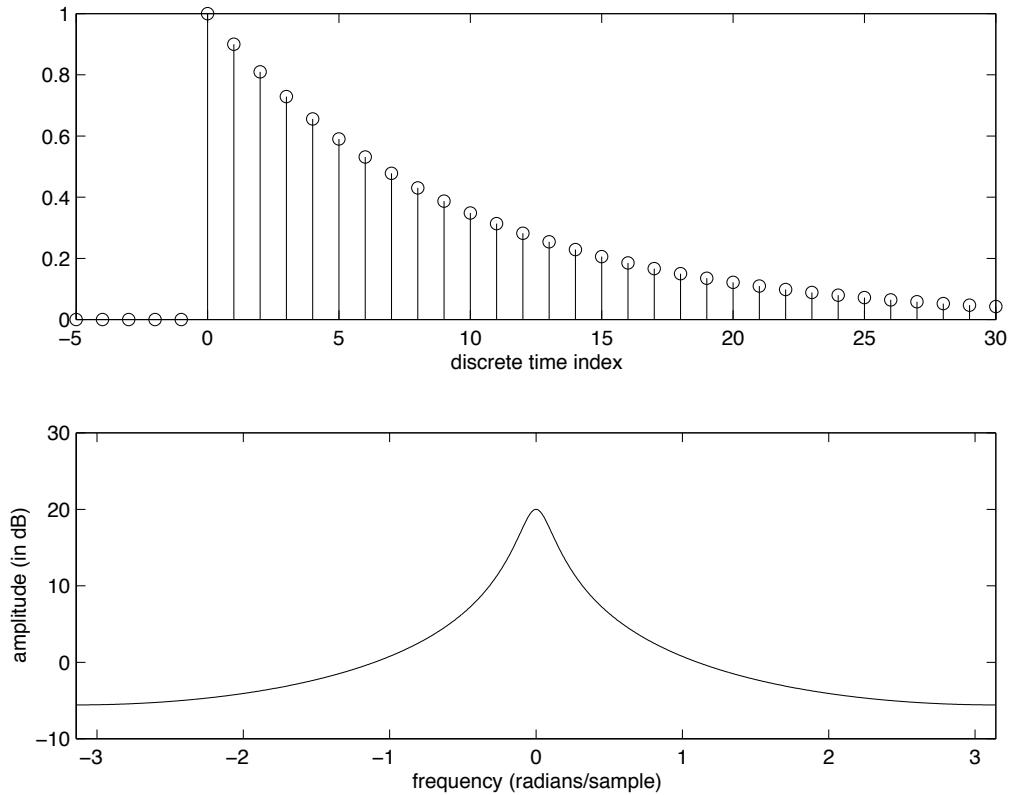


Figure 9.12: Impulse response (top) and magnitude frequency response in dB (bottom) of a simple causal IIR filter.

means $0.125\pi = \pi/8$ radians/sample. The “1” argument in the `cheby1` command specifies the amount of passband ripple that we are willing to tolerate (in dB). The 70 in the `cheby2` and `ellip` commands specifies the amount of stopband attenuation that we want (in dB). Finally, the 0.25 in the `cheby2` line specifies the edge of the stopband.

9.6 Implementation of filters

We now have several ways to describe an LTI system (a filter). We can give a state-space description, a frequency response, an impulse response, or a difference equation such as (9.25) or (9.22). All are useful. The state-space description and the difference equations prove the most useful when constructing the filter.

A realization of a filter in hardware or software is called an **implementation**. Do not confuse **filter design** with **filter implementation**. The term “filter design” is used in the community to refer to the choice of frequency response, impulse response, or coefficients for a difference equation, not to how the frequency response is implemented in hardware or software. In this section, we talk about implementation.

The output y of an FIR filter with impulse response h and input x is given by (9.22). The output of an IIR filter with coefficients a and b is given by (9.25). Each of these difference equations defines a procedure for calculating the output given the input. We discuss various ways of implementing these procedures.

9.6.1 Matlab implementation

If x is finite, and we can interpret it as an infinite signal that is zero outside the specified range. Then we can compute the output of an FIR filter using Matlab’s `conv` function, and the output of an IIR filter using `filter`.

Example 9.18: Consider an FIR filter with an impulse response of length L . If x is a vector containing the P values of the input, and h is a vector containing the L values of the impulse response, then

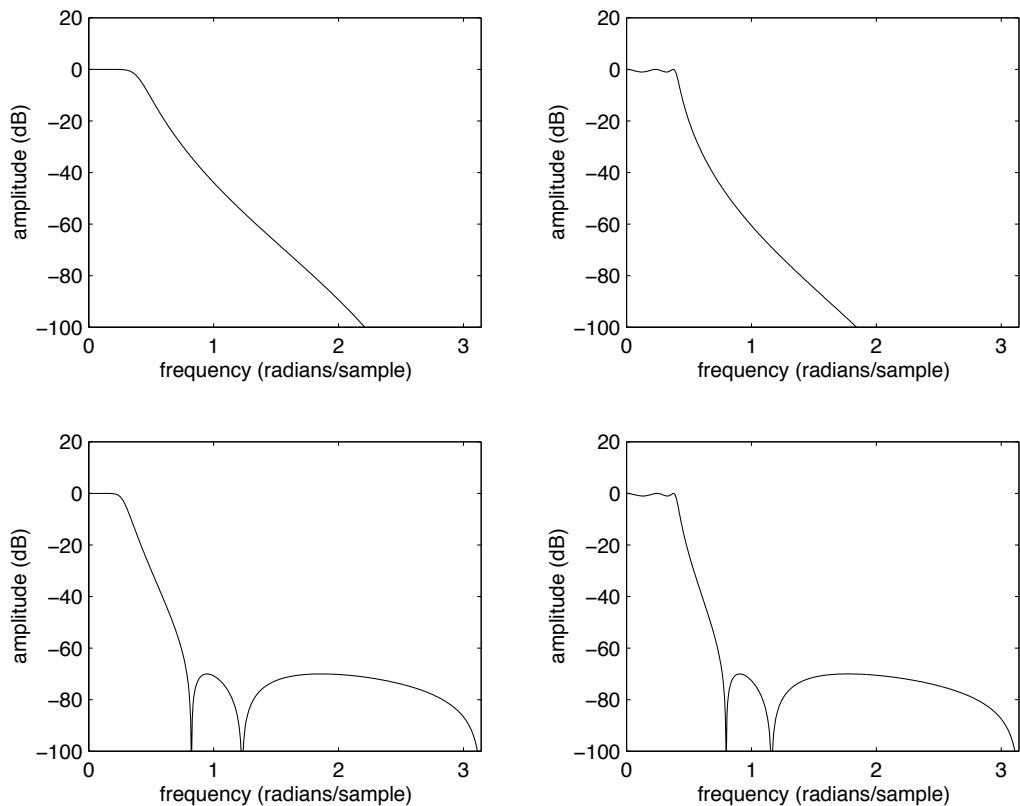


Figure 9.13: Four frequency responses for 5-th order IIR filters of type Butterworth (upper left), Chebyshev 1 (upper right), Chebyshev 2 (lower left), and Elliptic (lower right).

```
y = conv(x, h);
```

yields a vector containing $L + P - 1$ values of the output.

This strategy, of course, only works for finite input data, since Matlab requires that the input be available in a finite vector.

Discrete-time filters can be implemented using standard programming languages and using assembly languages on specialized processors (see boxes). These implementations do not have the limitation that the input be finite.

9.6.2 Signal flow graphs

We can describe the computations in a discrete-time filter using a block diagram with three visual elements, a unit delay, a multiplier, and an adder. In the convolution sum for an FIR filter,

$$y(n) = \sum_{m=0}^{L-1} h(m)x(n-m),$$

notice that at each n we need access to $x(n)$, $x(n-1)$, $x(n-2)$, \dots , $x(n-L+1)$. We can maintain this set of values by cascading a set of **unit delay** elements to form a **delay line**, as shown in figure 9.14.

For each integer n , the output sample is the values in the delay line scaled by $h(0)$, $h(1)$, \dots , $h(L-1)$. To obtain the values in the delay line, we simply tap the delay line, as shown in Figure 9.15. The triangular boxes denote **multipliers** that multiply by a constant ($h(m)$, in this case). The circles with the plus signs denote **adders**. The structure in Figure 9.15 is called a **tapped delay line** description of an FIR filter.

Diagrams of the type shown in Figure 9.15 are called **signal flow graphs** because they describe computations by focusing on the flow of signals between operators. Signal flow graphs can be quite literal descriptions of digital hardware that implements a filter. But what they really describe is the computation, irrespective of whether the implementation is in hardware or software.

An IIR filter can also be described using a signal flow graph. Consider the difference equation in (9.25). A signal flow graph description of this equation is shown in Figure 9.16. Notice that the left side is structurally equivalent to the tapped delay line, but stood

Probing Further: Java implementation of an FIR filter

The following Java class implements an FIR filter:

```

1  class FIR {
2      private int length, count = 0;
3      private double[] delayLine, impResp;
4      FIR(double[] coefs) {
5          length = coefs.length;
6          impResp = coefs;
7          delayLine = new double[length];
8      }
9      double getOutputSample(double inputSample) {
10         delayLine[count] = inputSample;
11         double result = 0.0;
12         int index = count;
13         for (int i=0; i<length; i++) {
14             result += impResp[i] * delayLine[index--];
15             if (index < 0) index = length-1;
16         }
17         if (++count >= length) count = 0;
18         return result;
19     }
20 }
```

A class in Java has both data members and methods. The methods are procedures that operate on the data, and may or may not take arguments or return values. In this case, there are two procedures, “FIR” and “getOutputSample.” The first, lines 4-8, is a constructor, which is a procedure that is called to create an FIR filter. It takes one argument, an array of double-precision floating-point numbers that specify the impulse response of the filter. The second, lines 9-19, takes a new input sample as an argument and returns a new output sample. It also updates the delay line using circular buffering, where the “count” member is used to keep track of where each new input sample should go. It gets incremented (line 17) each time the `getOutputSample()` method is called. When it exceeds the length of the buffer, it gets reset to zero. At all times, it contains the L most recently received input data samples. The most recent one is at `index` `count` in the buffer. The second most recent is at `count - 1`, or if that is negative, at `length - 1`. Line 15 makes sure that the variable `index` remains within the buffer as we iterate through the loop.

Probing Further: FIR filter in a programmable DSP

The following section of code is the assembly language for a programmable DSP, which is a specialized microprocessor designed to implement signal processing functions efficiently in embedded systems (such as cellular telephones, digital cordless telephones, digital audio systems, etc.). This particular code is for the Motorola DSP56000 family of processors.

```

1  fir      movep          x:input,x:(r0)
2      clr a            x:(r0)-,x0      y:(r4)+,y0
3      rep m0
4      mac x0,y0,a      x:(r0)-,x0      y:(r4)+,y0
5      macr x0,y0,a     (r0) +
6      movep a,x:output
7      jmp fir

```

This processor has two memory banks called *x* and *y*. The code assumes that each input sample can be successively read from a memory location called *input*, and that the impulse response is stored in *y* memory beginning at an address stored in register *r4*. Moreover, it assumes that register *r0* contains the address of a section of *x* memory to use for storing input samples (the delay line), and that this register has been set up to perform modulo addressing. Modulo addressing means that if it increments or decrements beyond the range of its buffer, then the address wraps around to the other end of the buffer. Finally, it assumes that the register *m0* contains an integer specifying the number of samples in the impulse response minus one.

The key line (the one that does most of the work) is line 4. It follows a *rep* instruction, which causes that one line to be repeatedly executed the number of times specified by register *m0*. Line 4 multiplies the data in register *x0* by that in *y0* and adds the result to *a* (the accumulator). Such an operation is called a multiply and accumulate or *mac* operation. At the same time, it loads *x0* with an input sample from the delay line, in *x* memory at a location given by *r0*. It also loads register *y0* with a sample from the impulse response, stored in *y* memory at a location given by *r4*. At the same time, it increments *r0* and decrements *r4*. This one-line instruction, which carries out several operations in parallel, is obviously highly tuned to FIR filtering. Indeed, FIR filtering is a major function of processors of this type.

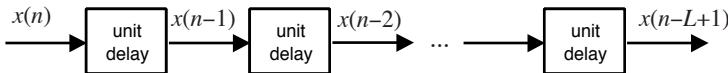


Figure 9.14: A delay line.

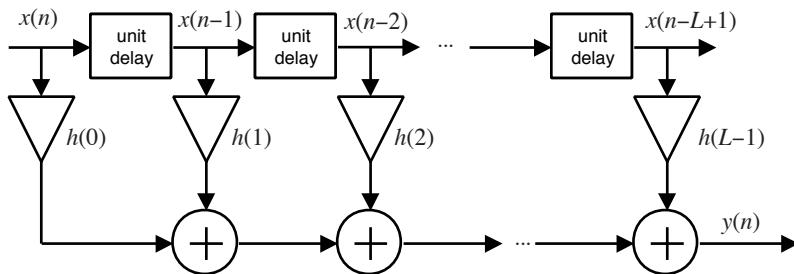


Figure 9.15: A tapped delay line realization of an FIR filter, described as a signal flow graph.

on end. The right side represents the **feedback** in the filter, or the **recursion** that makes it an IIR filter rather than an FIR filter.

The filter structure in Figure 9.16 can be simplified somewhat by observing that since the left and right sides are LTI systems, their order can be reversed without changing the output. Once the order is reversed, the two delay lines can be combined into one, as shown in Figure 9.17. There are many other structures that can be used to realize IIR filters.

The relative advantages of one structure over another is a fairly deep topic, depending primarily on an understanding of the effects of finite precision arithmetic. It is beyond the scope of this text.

9.7 Summary

The output of an LTI system does not contain any frequencies that are not also present in the input. Because of this property, LTI systems are often called filters. This chapter considers how filters might be implemented. The convolution sum (for discrete-time systems) and convolution integral (for continuous-time systems) give descriptions of how to

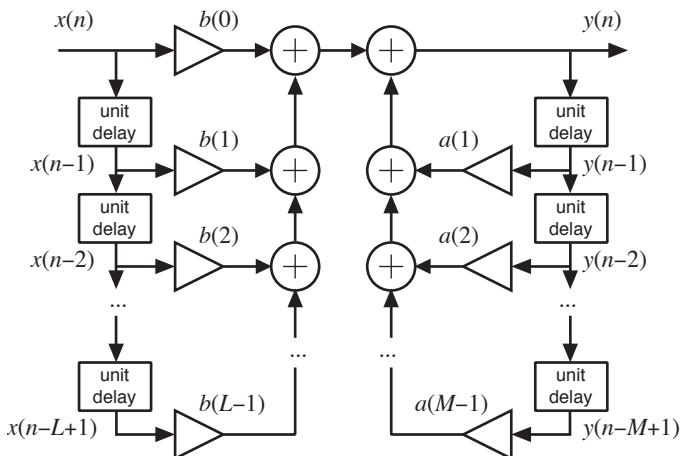


Figure 9.16: A signal flow graph describing an IIR filter. This is called a **direct form 1** filter structure.

calculate an output given an input signal. This description highlights the usefulness of the response that a system has to an idealized impulse, because the output is given by the convolution of the input and the impulse response. The frequency response, moreover, is shown to be Fourier transform of the impulse response, where the Fourier transform is a generalization of the Fourier series considered in previous chapters. Fourier transforms are considered in much more depth in the next chapter.

This chapter also considers the design of filters, by which we mean the selection of a suitable frequency response. Engineers are, as usual, forced to compromise to get an acceptable response at an acceptable computational cost. The response is assessed by considering how effectively it performs the desired filtering operation, and the cost is assessed by considering the arithmetic calculation that must be realized to implement the filter. The chapter closes with a discussion of alternative ways of realizing the arithmetic calculation.

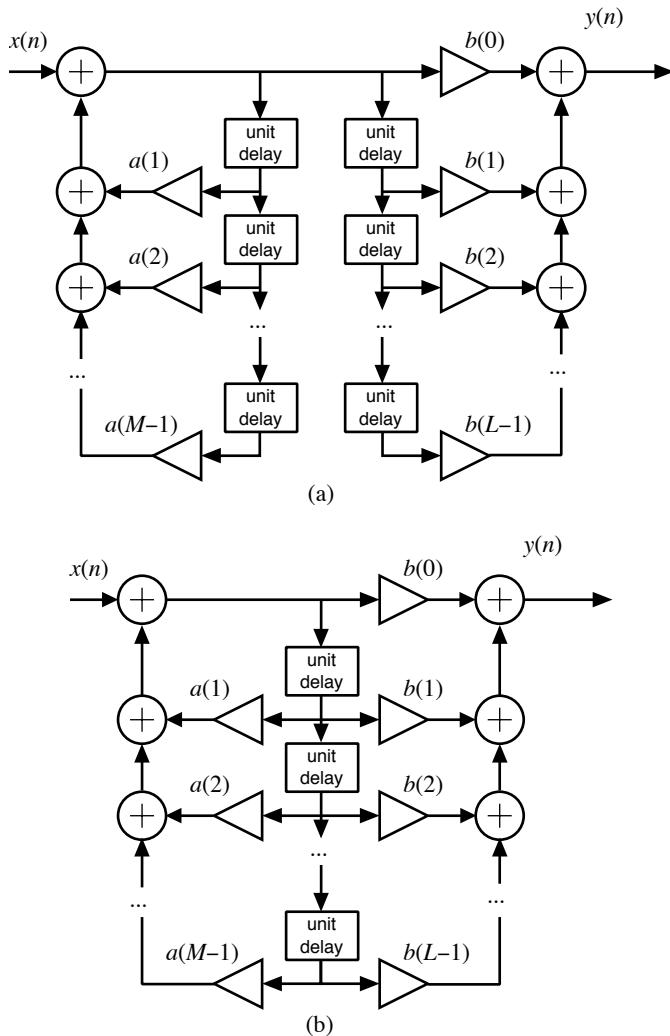


Figure 9.17: (a) A signal flow graph equivalent to that in Figure 9.16, obtained by reversing the left and right components. (b) A signal flow graph equivalent to that in (a) obtained by merging the two delay lines into one. This is called a **direct form 2 filter structure**.

Exercises

Each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **E** Consider an LTI discrete-time system *Filter* with impulse response

$$h(n) = \sum_{k=0}^7 \delta(n - k),$$

where δ is the Kronecker delta function.

- (a) Sketch $h(n)$.
 - (b) Suppose the input signal $x: \mathbb{Z} \rightarrow \mathbb{R}$ is such that $\forall n \in \mathbb{Z}$, $x(n) = \cos(\omega n)$, where $\omega = \pi/4$ radians/sample. Give a simple expression for $y = \text{Filter}(x)$.
 - (c) Give the value of $H(\omega)$ for $\omega = \pi/4$, where H is the frequency response.
2. **E** Consider the continuous-time moving average system S , whose impulse response is shown in Figure 9.3. Find its frequency response. The following fact from calculus may be useful:
- $$\int_a^b e^{c\omega} cd\omega = e^{cb} - e^{ca}$$
- for real a and b and complex c . Use Matlab to plot the magnitude of this frequency response over the range -5 Hz to 5 Hz. Note the symmetry of the magnitude response, as required by (9.21).
3. **E** Consider a continuous-time LTI system with impulse response given by

$$\forall t \in \mathbb{R}, \quad h(t) = \delta(t - 1) + \delta(t - 2),$$

where δ is the Dirac delta function.

- (a) Find a simple equation relating the input x and output y of this system.
- (b) Find the frequency response of this system.

- (c) Use Matlab to plot the magnitude frequency response of this system in the range -5 to 5 Hz.
4. E Consider a discrete-time LTI system with impulse response h given by

$$\forall n \in \mathbb{Z}, \quad h(n) = \delta(n) + 2\delta(n-1)$$

- (a) Plot the impulse response.
 (b) Find and sketch the output when the input is u , the unit step, given by (9.26).
 (c) Find and sketch the output when the input is a ramp,

$$r(n) = \begin{cases} n & \text{if } n \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

- (d) Find the frequency response.
 (e) Show that the frequency response is periodic with period 2π .
 (f) Show that the frequency response is conjugate symmetric.
 (g) Give a simplified expression for the magnitude response.
 (h) Give a simplified expression for the phase response.
 (i) Suppose that the input x is given by

$$\forall n \in \mathbb{Z}, \quad x(n) = \cos(\pi n/2 + \pi/6) + \sin(\pi n + \pi/3).$$

Find the output y .

5. E Consider the sawtooth signal shown in Figure 9.18. This is a periodic, continuous-time signal. Suppose it is filtered by an LTI system with frequency response

$$H(\omega) = \begin{cases} 1 & \text{if } |\omega| \leq 2.5 \text{ radians/second} \\ 0 & \text{otherwise} \end{cases}$$

What is the output?

6. E Suppose that the following difference equation relates the input x and output y of a discrete-time, causal LTI system S ,

$$y(n) + \alpha y(n-1) = x(n) + x(n-1),$$

for some constant α .

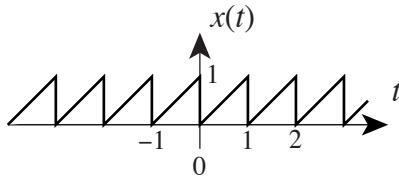


Figure 9.18: A sawtooth signal.

- (a) Find the impulse response h .
 - (b) Find the frequency response H .
 - (c) Find a sinusoidal input with non-zero amplitude such that the output is zero.
 - (d) Use Matlab to create a plot of the magnitude of the frequency response, assuming $\alpha = -0.9$.
 - (e) Find a state-space description for this system (define the state s and find A, b, c^T, d).
 - (f) Suppose $\alpha = 1$. Find the impulse response and frequency response. Make sure your answer makes sense (check it against the original difference equation).
7. T Each of the statements below refers to a discrete-time system S with input x and output y . Determine whether the statement is true or false. The signal u below is the unit step, given by (9.26). The signal δ below is the Kronecker delta function.
- (a) Suppose you know that if x is a sinusoid then y is a sinusoid. Then you can conclude that S is LTI.
 - (b) Suppose you know that S is LTI, and that if $x(n) = \cos(\pi n/2)$, then $y(n) = 2\cos(\pi n/2)$. Then you have enough information to determine the frequency response.
 - (c) Suppose you know that S is LTI, and that if $x(n) = \delta(n)$, then

$$y(n) = (0.9)^n u(n).$$

Then you have enough information to determine the frequency response.

- (d) Suppose you know that S is LTI, and that if $x(n) = u(n)$, then $y(n) = (0.9)^n u(n)$. Then you have enough information to determine the frequency response.

- (e) Suppose you know that S is causal, and that input $x(n) = \delta(n)$ produces output $y(n) = \delta(n) + \delta(n-1)$, and input $x'(n) = \delta(n-2)$ produces output $y'(n) = 2\delta(n-2) + \delta(n-3)$. Then you can conclude that S is not LTI.
- (f) Suppose you know that S is causal, and that if $x(n) = \delta(n) + \delta(n-2)$ then $y(n) = \delta(n) + \delta(n-1) + 2\delta(n-2) + \delta(n-3)$. Then you can conclude that S is not LTI.

8. T Consider the continuous-time systems S_k given by, $\forall t \in \mathbb{R}$,

$$\begin{aligned}(S_1(x))(t) &= x(t-2), \\ (S_2(x))(t) &= x(t+2), \\ (S_3(x))(t) &= x(t)-2, \\ (S_4(x))(t) &= x(2-t), \\ (S_5(x))(t) &= x(2t), \\ (S_6(x))(t) &= t^2x(t),\end{aligned}$$

- (a) Which of these systems is linear?
 (b) Which of these systems is time invariant?
 (c) Which of these systems is causal?

9. T Consider an LTI discrete-time system *Filter* with impulse response

$$\forall n \in \mathbb{Z}, \quad h(n) = \delta(n) + \delta(n-2),$$

where δ is the Kronecker delta function.

- (a) Sketch h .
 (b) Find the output when the input is u , the unit step, given by (9.26).
 (c) Find the output when the input is a ramp,

$$r(n) = \begin{cases} n & \text{if } n \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

- (d) Suppose the input signal x is such that

$$\forall n \in \mathbb{Z}, \quad x(n) = \cos(\omega n),$$

where $\omega = \pi/2$ radians/sample. Give a simple expression for $y = \text{Filter}(x)$.

- (e) Give an expression for $H(\omega)$ that is valid for all ω , where H is the frequency response.
- (f) Sketch the magnitude of the frequency response. Can you explain your answer in part (b)?
- (g) Is there any other frequency at which a sinusoidal input with a non-zero amplitude will yield an output that is zero?

10. **T** Consider an LTI discrete-time system *Filter* with impulse response

$$h(n) = \delta(n) - \delta(n-1)$$

where δ is the Kronecker delta function.

- (a) Sketch $h(n)$.
- (b) Suppose the input signal $x: \mathbb{Z} \rightarrow \mathbb{R}$ is such that $\forall n \in \mathbb{Z}, x(n) = 1$. Give a simple expression for $y = \text{Filter}(x)$.
- (c) Give an expression for $H(\omega)$ that is valid for all ω , where H is the frequency response.
- (d) Sketch the magnitude of the frequency response. Can you explain your answer in part (b)?

11. **T** Consider a discrete-time LTI system with impulse response h given by

$$\forall n \in \mathbb{Z}, \quad h(n) = \delta(n-1)/2 + \delta(n+1)/2$$

And consider the periodic discrete-time signal given by

$$\forall n \in \mathbb{Z}, \quad x(n) = 2 + \sin(\pi n/2) + \cos(\pi n).$$

- (a) Is the system causal?
- (b) Find the frequency response of the system. Check that your answer is periodic with period 2π .
- (c) For the given signal x , find the fundamental frequency ω_0 and the Fourier series coefficients X_k in the Fourier series expansion,

$$x(n) = \sum_{k=-\infty}^{\infty} X_k e^{i\omega_0 kn}.$$

Give the units of the fundamental frequency.

- (d) Assuming the input to the system is x as given, find the output.
12. T Consider a continuous-time LTI system S . Suppose that when the input is the continuous-time **unit step**, given by

$$u(t) = \begin{cases} 1, & t \geq 0 \\ 0, & t < 0 \end{cases} \quad (9.27)$$

then the output $y = S(u)$ is given by

$$y(t) = \begin{cases} 1, & 0 \leq t < 1 \\ 0, & \text{otherwise} \end{cases}$$

This output y is called the **step response** because it is the response to a unit step.

- (a) Express y in terms of sums and differences of u and $D_1(u)$, where D_1 is the delay operator.
- (b) Give a signal flow graph that produces this result $y = S(u)$ when the input is u .
Note: We know that if two LTI systems have the same impulse response, then they are the same system. It is a fact, albeit a non-trivial one to demonstrate, that if two LTI systems have the same step response, then they are also the same system. Thus, your signal flow graph implements S .
- (c) Use your signal flow graph to determine what the output y' of S is when the input is

$$x(t) = \begin{cases} 1, & 0 \leq t \leq 1 \\ 0, & \text{otherwise} \end{cases}$$

Plot your answer.

- (d) What is the frequency response $H(\omega)$ of S ?
13. T Suppose a discrete-time LTI system S has impulse response

$$h(n) = u(n)/2^n = \begin{cases} 1/2^n & \text{if } n \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

where u is the unit step function (9.26).

- (a) What is the step response of this system? The step response is defined to be the output when the input is the unit step. **Hint:** The identity (9.23) might be helpful.

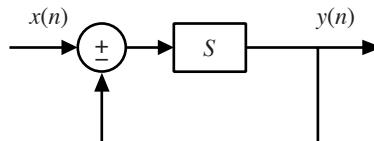


Figure 9.19: Feedback composition.

- (b) What is the frequency response? Plot the magnitude and phase response (you may use Matlab, or do it by hand). **Hint:** The following variant of the identity (9.23) might be useful. If $|a| < 1$,

$$\sum_{m=0}^{\infty} a^m = \frac{1}{1-a}.$$

This follows immediately from (9.23) by letting L go to infinity.

- (c) Suppose S is put in cascade with another identical system. What is the frequency response of the cascade composition?
(d) Suppose S is arranged in a feedback composition as shown in figure 9.19. What is the frequency response of the feedback composition?

10

The Four Fourier Transforms

Contents

10.1 Notation	414
10.2 The Fourier series (FS)	415
<i>Probing Further: Showing inverse relations</i>	417
10.3 The discrete Fourier transform (DFT)	421
10.4 The discrete-Time Fourier transform (DTFT)	424
10.5 The continuous-time Fourier transform	428
10.6 Fourier transforms vs. Fourier series	434
10.6.1 Fourier transforms of finite signals	434
10.6.2 Fourier analysis of a speech signal	435
10.6.3 Fourier transforms of periodic signals	438
10.7 Properties of Fourier transforms	444
10.7.1 Convolution	444
10.7.2 Conjugate symmetry	449
10.7.3 Time shifting	450
10.7.4 Linearity	453
10.7.5 Constant signals	455
10.7.6 Frequency shifting and modulation	456
10.8 Summary	458
<i>Probing Further: Multiplying signals</i>	459
Exercises	460

In chapter 7 we saw that the Fourier series describes a periodic signal as a sum of complex exponentials. In chapter 8 we saw that if the input to an LTI system is a sum of complex exponentials, then the frequency response of the LTI system describes its response to each of the component exponentials. Thus we can calculate the system response to any periodic input signal by combining the responses to the individual components.

In chapter 9 we saw that the response of the LTI system to any input signal can also be obtained as the convolution of the input signal and the impulse response. The impulse response and the frequency response give us the same information about the system, but in different forms. The impulse response and the frequency response are related by the Fourier transform, where in chapter 9 we saw both discrete time and continuous time versions.

In this chapter, we will see that for discrete-time systems, the frequency response can be described as a sum of weighted complex exponentials (the DTFT), where the weights turn out to be the impulse response samples. We will see that the impulse response is, in fact, a Fourier series representation of the frequency response, with the roles of time and frequency reversed from the uses of the Fourier series that we have seen so far.

This reappearance of the Fourier series is not a coincidence. In this chapter, we explore this pattern by showing that the Fourier series is a special case of a family of representations of signals that are collectively called **Fourier transforms**. The Fourier series applies specifically to continuous-time, periodic signals. The discrete Fourier series applies to discrete-time, periodic signals. We complete the story with the continuous-time Fourier transform (CTFT), which applies to continuous-time signals that are not periodic, and the discrete-time Fourier transform (DTFT), which applies to discrete-time signals that are not periodic.

10.1 Notation

We define the following four sets of signals:

- $\text{ContSignals} = [\mathbb{R} \rightarrow \mathbb{C}]$. Since \mathbb{R} is included in \mathbb{C} , ContSignals includes continuous-time signals whose range is \mathbb{R} , and so we won't need to consider these separately.

ContSignals includes continuous-time signals, but we are not insisting that the domain be interpreted as time. Indeed, sometimes the domain could be interpreted as

space, if we are dealing with images. In this chapter we will see that it is useful sometimes to interpret the domain as frequency.

- $\text{DiscSignals} = [\mathbb{Z} \rightarrow \mathbb{C}]$.

This includes discrete-time signals whose domain is time or sample number, but again we are not insisting that the domain be interpreted as time.

- $\text{ContPeriodic}_p \subset \text{ContSignals}$.

This set is defined to contain all continuous signals that are periodic with period p , where p is a real number.

- $\text{DiscPeriodic}_p \subset \text{DiscSignals}$.

This set is defined to contain all discrete signals that are periodic with period p , where p is an integer.

Note that whenever we talk about periodic signals we could equally well talk about finite signals, where the domain of the finite signal is that of one cycle of the periodic signal.

10.2 The Fourier series (FS)

A periodic signal $x \in \text{ContPeriodic}_p$ may be described as a weighted sum of complex exponentials. This sum is the **continuous-time Fourier series** representation of x ,

$$\boxed{\forall t \in \mathbb{R}, \quad x(t) = \sum_{m=-\infty}^{\infty} X_m e^{im\omega_0 t}}, \quad (10.1)$$

where $\omega_0 = 2\pi/p$ (radians/second). The Fourier series coefficients are given by

$$\boxed{\forall m \in \mathbb{Z}, \quad X_m = \frac{1}{p} \int_0^p x(t) e^{-im\omega_0 t} dt}. \quad (10.2)$$

Observe that the sequence of Fourier series coefficients given by (10.2) can be regarded as a signal $X \in \text{DiscSignals}$, where

$$\forall m \in \mathbb{Z}, \quad X(m) = X_m.$$

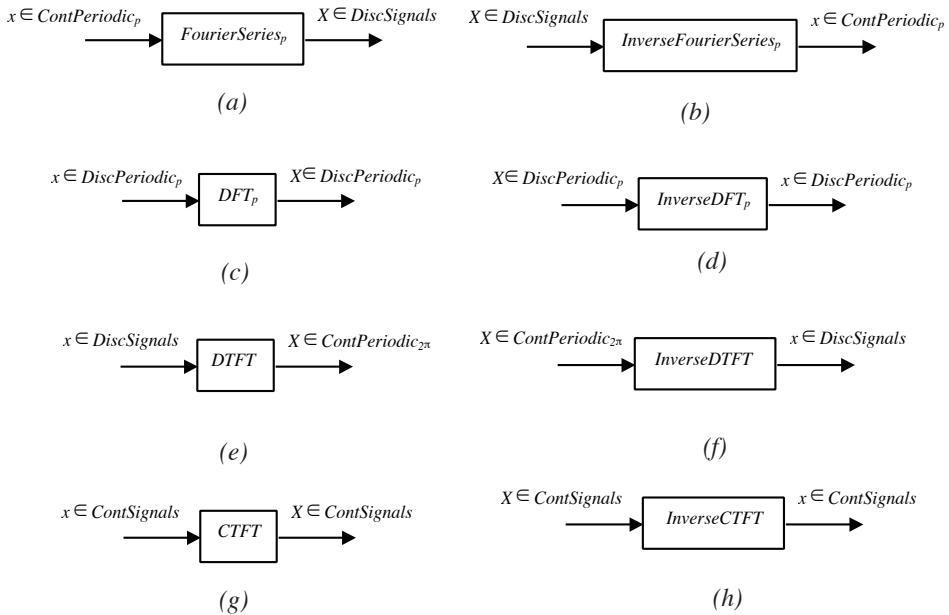


Figure 10.1: Fourier transforms as systems.

So we can define a system FourierSeries_p with domain ContPeriodic_p and range DiscSignals such that if the input is the periodic signal x , the output is its Fourier series coefficients, X . That is,

$$\text{FourierSeries}_p : \text{ContPeriodic}_p \rightarrow \text{DiscSignals}.$$

This system is the first of four forms of the Fourier transform, and is depicted graphically in Figure 10.1(a). Its inverse is a system

$$\text{InverseFourierSeries}_p : \text{DiscSignals} \rightarrow \text{ContPeriodic}_p,$$

depicted in Figure 10.1(b).

The two systems, FourierSeries_p and $\text{InverseFourierSeries}_p$, are **inverses** of each other, because (see box on page 417)

$$\forall x \in \text{ContPeriodic}_p, (\text{InverseFourierSeries}_p \circ \text{FourierSeries}_p)(x) = x \quad (10.3)$$

$$\forall X \in \text{DiscSignals}, (\text{FourierSeries}_p \circ \text{InverseFourierSeries}_p)(X) = X \quad (10.4)$$

Probing Further: Showing inverse relations

In this chapter, and in previous chapters, we have given formulas that describe time-domain functions in terms of frequency-domain functions, and vice versa. By convention, a formula that gives the frequency-domain function in terms of the time-domain function is called a **Fourier transform**, and the formula that gives the time-domain function in terms of the frequency-domain function is called an **inverse Fourier transform**. As shown in Figure 10.1, these transforms can be viewed as systems that take as inputs signals in one domain and return signals in the other. We discuss four distinct Fourier transforms and their corresponding inverses. In each case, it is possible to show that the Fourier transform and its inverse are in fact inverses of one another, as stated in (10.3) and (10.4). We prove the second relation, (10.4), to illustrate how this is done. Similar proofs can be carried out for all four types of Fourier transforms, although sometimes these proofs require you to be adept at manipulating Dirac delta functions, which requires significant mathematical skill.

Let $X \in DiscSignals$ be the Fourier series for some $x \in ContPeriodic_p$. That is, $x = InverseFourierSeries_p(X)$. Let $Y = FourierSeries_p(x)$. We now show that $Y = X$, i.e. $Y_m = X_m$ for all m .

$$\begin{aligned}
 Y_m &= \frac{1}{p} \int_0^p x(t) e^{-im\omega_0 t} dt, \text{ by (10.2)} \\
 &= \frac{1}{p} \int_0^p \left[\sum_{k=-\infty}^{\infty} X_k e^{ik\omega_0 t} \right] e^{-im\omega_0 t} dt, \text{ by (10.1)} \\
 &= \sum_{k=-\infty}^{\infty} \frac{1}{p} X_k \int_0^p e^{i(k-m)\omega_0 t} dt \\
 &= \frac{1}{p} X_m \int_0^p dt + \sum_{k \neq m} \frac{1}{p} X_k \int_0^p e^{i(k-m)\omega_0 t} dt \\
 &= X_m, \quad \text{since for } k \neq m, \\
 &\quad \int_0^p e^{i(k-m)\omega_0 t} dt = 0.
 \end{aligned}$$

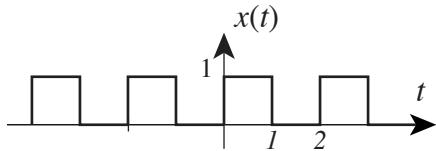


Figure 10.2: A square wave.

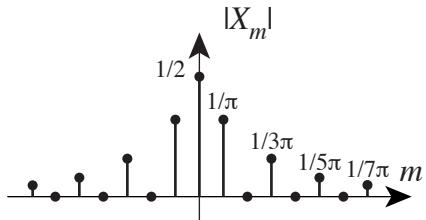


Figure 10.3: Magnitude of the Fourier series coefficients of a square wave.

Example 10.1: Consider a **square wave** $x \in \text{ContPeriodic}_2$, shown in Figure 10.2. It is periodic with period $p = 2$, so its fundamental frequency is $\omega_0 = 2\pi/2 = \pi$ radians/second. We can find its continuous-time Fourier series coefficients using (10.2) as follows,

$$\begin{aligned} X_m &= \frac{1}{2} \int_0^2 x(t) e^{-im\pi t} dt \\ &= \frac{1}{2} \int_0^1 e^{-im\pi t} dt. \end{aligned}$$

Notice that when $m = 0$, this integral is easy to evaluate because $e^0 = 1$, so

$$X_0 = 1/2.$$

The following fact from calculus will help us solve the integral when $m \neq 0$,

$$\int_a^b e^{c\omega} c d\omega = e^{cb} - e^{ca} \quad (10.5)$$

for real a and b and complex c . Letting $c = -im\pi$, the integral becomes

$$\begin{aligned} X_m &= \frac{1}{2c} \int_0^1 e^{ct} c dt \\ &= \frac{-1}{2im\pi} (e^{-im\pi} - e^0) \\ &= \frac{i}{2m\pi} (e^{-im\pi} - 1) \end{aligned}$$

where the last step follows from multiplying top and bottom by i , observing that $i^2 = -1$, and observing that $e^0 = 1$. Notice that

$$e^{-im\pi} = \begin{cases} 1 & \text{if } m \text{ is even} \\ -1 & \text{if } m \text{ is odd} \end{cases}$$

Thus, when $m \neq 0$,

$$X_m = \begin{cases} 0 & \text{if } m \text{ is even} \\ -i/m\pi & \text{if } m \text{ is odd} \end{cases}$$

The magnitude of these Fourier series coefficients is plotted in Figure 10.3. Notice that the magnitudes of the coefficients decay rather slowly as m gets large (they decay as $1/m$). This accounts for the persistent overshoot (Gibbs phenomenon) seen in Figure 7.7. Finite Fourier series approximations of this periodic square wave are not particularly good because the size of the Fourier series coefficients decays slowly.

Signal	Fourier Series	Reference
$\forall t \in \mathbb{R},$ $x(t) = e^{i\omega_0 t},$ where $\omega_0 \neq 0.$	$\forall m \in \mathbb{Z},$ $X_m = \begin{cases} 1 & \text{if } m = 1 \\ 0 & \text{otherwise} \end{cases}$	Exercise 2
$\forall t \in \mathbb{R},$ $x(t) = \cos(\omega_0 t),$ where $\omega_0 \neq 0.$	$\forall m \in \mathbb{Z},$ $X_m = \begin{cases} 1/2 & \text{if } m = 1 \\ 0 & \text{otherwise} \end{cases}$	Exercise 2
$\forall t \in \mathbb{R},$ $x(t) = \sin(\omega_0 t),$ where $\omega_0 \neq 0.$	$\forall m \in \mathbb{Z},$ $X_m = \begin{cases} 1/2i & \text{if } m = 1 \\ -1/2i & \text{if } m = -1 \\ 0 & \text{otherwise} \end{cases}$	Exercise 2
$\forall t \in \mathbb{R},$ $x(t) = 1$	$\forall m \in \mathbb{Z},$ $X_m = \begin{cases} 1 & \text{if } m = 0 \\ 0 & \text{otherwise} \end{cases}$	Exercise 2
Square wave: $\forall t \in [0, p],$ $x(t) = \begin{cases} 1 & \text{if } t < T \text{ or } t > p - T \\ 0 & \text{otherwise} \end{cases}$	$\forall m \in \mathbb{Z},$ $X_m = \frac{\sin(m\omega_0 T)}{(m\pi)}$	Exercise 3
Impulse train: $\forall t \in \mathbb{R},$ $x(t) = \sum_{n=-\infty}^{\infty} \delta(t - np)$	$\forall m \in \mathbb{Z},$ $X_m = 1/p$	Exercise 4

Table 10.1: Fourier series coefficients of periodic signals. In all cases, $\omega_0 = 2\pi/p$, where p is the period. We can obtain Fourier transforms for each of these signals by using (10.16).

Other examples of Fourier series coefficients for various signals are given in table 10.1.

10.3 The discrete Fourier transform (DFT)

The **discrete-time Fourier series (DFS)** expansion for $x \in DiscPeriodic_p$ is (see (8.30))

$$\forall n \in \mathbb{Z}, \quad x(n) = \sum_{k=0}^{p-1} X_k e^{ik\omega_0 n}, \quad (10.6)$$

where $\omega_0 = 2\pi/p$ (radians/sample). The Fourier series coefficients can be found using the formula

$$\forall k \in \mathbb{Z}, \quad X_k = \frac{1}{p} \sum_{m=0}^{p-1} x(m) e^{-imk\omega_0}. \quad (10.7)$$

For historical reasons, the **discrete Fourier transform (DFT)** is the DFS with slightly different scaling. It is defined by

$$\forall n \in \mathbb{Z}, \quad x(n) = \frac{1}{p} \sum_{k=0}^{p-1} X'_k e^{ik\omega_0 n}, \quad (10.8)$$

$$\forall k \in \mathbb{Z}, \quad X'_k = \sum_{m=0}^{p-1} x(m) e^{-imk\omega_0}. \quad (10.9)$$

Obviously, the DFT coefficients are related to the DFS coefficients by

$$X'_k = pX_k.$$

This scaling is somewhat unfortunate, since it means that the DFT coefficients do not have the same units as the signal x , but the scaling is firmly established in the literature, so we stick to it. We omit the prime when it is clear whether we are talking about the Fourier transform instead of the Fourier series.

Observe that $X' = DFT_p(x)$ is a discrete signal that is itself periodic with period p . To verify this, note that for any integer N and for all integers k ,

$$\begin{aligned}
 X'_{k+Np} &= \sum_{m=0}^{p-1} x(m) e^{-im(k+Np)\omega_0} \\
 &= \sum_{m=0}^{p-1} x(m) e^{-imk\omega_0} e^{-imNp\omega_0} \\
 &= \sum_{m=0}^{p-1} x(m) e^{-imk\omega_0} e^{-imN2\pi}, \text{ since } \omega_0 = 2\pi/p \\
 &= \sum_{m=0}^{p-1} x(m) e^{-imk\omega_0} \\
 &= X'_k.
 \end{aligned}$$

Note that (10.9) looks like a discrete Fourier series expansion of the periodic function X' . That is, the periodic function is described as a sum of complex exponentials. The only substantial difference, comparing with (10.6), is the sign of the exponent. This sign difference can be easily removed with a change of variables. By doing so, you can discover that $x(-m)$ is the m -th Fourier series coefficient for the function $X'!$ The DFT is rather special, therefore, in that both the time and frequency domain representations of a function are Fourier series, and both are periodic.

The DFT therefore is the function

$$DFT_p: DiscPeriodic_p \rightarrow DiscPeriodic_p,$$

given by (10.9). The inverse DFT is the function

$$InverseDFT_p: DiscPeriodic_p \rightarrow DiscPeriodic_p,$$

given by (10.8). As in (10.3), (10.4), DFT_p and $InverseDFT_p$ are inverses of each other. This can be verified using methods similar to those in the box on page 417. The DFT and its inverse are computed by systems that we can represent as shown in Figure 10.1(c) and (d).

The DFT is the most useful form of the Fourier transform for computation, because the system DFT_p is easily implemented on a computer. Both summations (10.8) and (10.9) are finite. Moreover, there is an algorithm called the **fast Fourier transform (FFT)** that

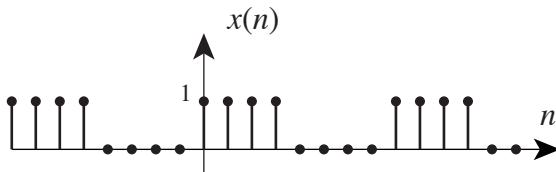


Figure 10.4: A discrete square wave.

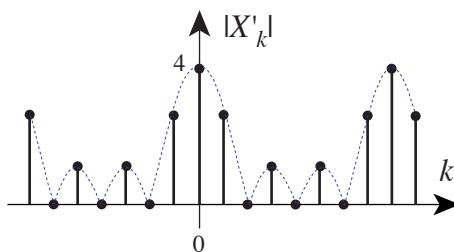


Figure 10.5: Magnitude of the DFT of a discrete square wave.

calculates these summations with far fewer arithmetic operations than the most direct method. Moreover, because the sums are finite, the DFT always exists. There are no mathematical problems with convergence.

Example 10.2: Consider a **discrete square wave** $x \in DiscPeriodic_8$, shown in Figure 10.4. It is periodic with period $p = 8$, so its fundamental frequency is $\omega_0 = 2\pi/8 = \pi/4$ radians/sample. We can find its DFT using (10.9) as follows,

$$\begin{aligned} X'_k &= \sum_{m=0}^7 x(m)e^{-imk\omega_0} \\ &= \sum_{m=0}^3 e^{-imk\pi/4}. \end{aligned}$$

Notice that when $k = 0$, this sum is easy to evaluate because $e^0 = 1$, so

$$X'_0 = 4.$$

Moreover, when k is any multiple of 8, we get $X'_k = 4$, as it should, since the DFT is periodic with period 8. The following identity will help us simplify the summation when $k \neq 0$ nor any multiple of 8,

$$\boxed{\sum_{m=0}^N a^m = \frac{1-a^{N+1}}{1-a}.} \quad (10.10)$$

(To demonstrate the validity of this identity, just multiply both sides by $1 - a$.) Letting $N = 3$ and $a = e^{-ik\pi/4}$, we get that for $k \neq 0$ nor any multiple of 8,

$$X'_k = \frac{1 - e^{-ik\pi}}{1 - e^{-ik\pi/4}}.$$

Notice that the numerator is particularly simple, since

$$1 - e^{-ik\pi} = \begin{cases} 0 & \text{if } k \text{ is even} \\ 2 & \text{if } k \text{ is odd} \end{cases}$$

The magnitude of these DFT coefficients is plotted in figure 10.5.

Other examples of discrete Fourier transform coefficients for various signals are given in table 10.2.

10.4 The discrete-Time Fourier transform (DTFT)

We have shown in Section 9.2 that the frequency response H of an LTI system is related to the impulse response h by

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \sum_{m=-\infty}^{\infty} h(m)e^{-i\omega m}.$$

H is called the **discrete-time Fourier transform (DTFT)** of h . For any $x \in DiscSignals$ (not just an impulse response), its DTFT is defined to be

$$\boxed{\forall \omega \in \mathbb{R}, \quad X(\omega) = \sum_{m=-\infty}^{\infty} x(m)e^{-i\omega m}.} \quad (10.11)$$

Signal	DFT	Reference
$\forall n \in \mathbb{Z},$ $x(n) = e^{j2\pi fn},$ where $f \neq 0.$	$\forall k \in \mathbb{Z},$ $X'_k = \begin{cases} p & \text{if } k \in A \\ 0 & \text{otherwise} \end{cases}$	Exercise 5
$\forall n \in \mathbb{Z},$ $x(n) = \cos(2\pi fn),$ where $f \neq 0.$	$\forall k \in \mathbb{Z},$ $X'_k = \begin{cases} p/2 & \text{if } k \in A \\ p/2 & \text{if } k \in B \\ 0 & \text{otherwise} \end{cases}$	Exercise 5
$\forall n \in \mathbb{Z},$ $x(n) = \sin(i2\pi fn),$ where $f \neq 0.$	$\forall k \in \mathbb{Z},$ $X'_k = \begin{cases} p/2i & \text{if } k \in A \\ -p/2i & \text{if } k \in B \\ 0 & \text{otherwise} \end{cases}$	Exercise 5
$\forall n \in \mathbb{Z},$ $x(n) = 1$	$\forall k \in \mathbb{Z},$ $X'_k = \begin{cases} p & \text{if } k \in C \\ 0 & \text{otherwise} \end{cases}$	Exercise 5
Square wave: $\forall n \in \{0, 1, \dots, p-1\},$ $x(n) = \begin{cases} 1 & \text{if } n \leq M \text{ or } n \geq p-M \\ 0 & \text{otherwise} \end{cases}$	$\forall k \in \mathbb{Z},$ $X'_k = \frac{\sin(k(M+0.5)\omega_0)}{\sin(k\omega_0/2)}$	Exercise 6
Impulse train: $\forall n \in \mathbb{Z},$ $x(n) = \sum_{k=-\infty}^{\infty} \delta(n-kp)$	$\forall k \in \mathbb{Z},$ $X'_k = 1$	Exercise 7

Table 10.2: Discrete Fourier transform of periodic signals. The fundamental frequency is $\omega_0 = 2\pi/p$, where p is the period. For the complex exponential and sinusoidal signals, the frequency f must be rational, and is related to the period p by $f = m/p$ for some integer m (see Section 7.6.1). The following sets are used in this table: $A = \{\dots, m-2p, m-p, m, m+p, m+2p, \dots\}$, $B = \{\dots, -m-2p, -m-p, -m, -m+p, -m+2p, \dots\}$, and $C = \{\dots, -2p, -p, 0, p, 2p, \dots\}$.

Of course, this definition is only valid for those x and those ω where the sum converges (it is not trivial mathematically to characterize this).

Notice that the function X is periodic with period 2π . That is, $X(\omega) = X(\omega + 2\pi N)$ for any integer N , because

$$e^{-i\omega t} = e^{-i(\omega+2\pi N)t}$$

for any integer N . Thus, $X \in \text{ContPeriodic}_{2\pi}$.

Note that (10.11) looks like a discrete Fourier series expansion of the periodic function X . That is, the periodic function is described as a sum of complex exponentials. The only substantial difference, comparing with (10.1), is the sign of the exponent. This sign difference can be easily removed with a change of variables. By doing so, you can discover that $x(-n)$ is the n -th Fourier series coefficient for the function X !

The DTFT (10.11) has similar structure to the DFT (10.9). In fact, the DTFT can be viewed as a generalization of the DFT to signals that are neither periodic nor finite. In other words, as p approaches infinity, ω_0 approaches zero, so instead of a discrete set of frequencies spaced by ω_0 we have a continuum.

The DTFT is a system

$$\text{DTFT}: \text{DiscSignals} \rightarrow \text{ContPeriodic}_{2\pi}$$

and its inverse is

$$\text{InverseDTFT}: \text{ContPeriodic}_{2\pi} \rightarrow \text{DiscSignals}.$$

The inverse is given by

$$\forall n \in \mathbb{Z}, \quad x(n) = \frac{1}{2\pi} \int_0^{2\pi} X(\omega) e^{i\omega n} d\omega. \quad (10.12)$$

Notice that because X is periodic, this can equivalently be written as

$$\forall n \in \mathbb{Z}, \quad x(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X(\omega) e^{i\omega n} d\omega.$$

We integrate over one cycle of the periodic function, so it does not matter where we start. These are depicted graphically in Figure 10.1(e) and (f).

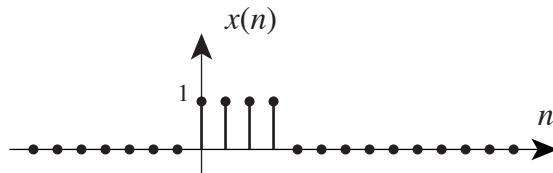


Figure 10.6: A discrete rectangle signal.

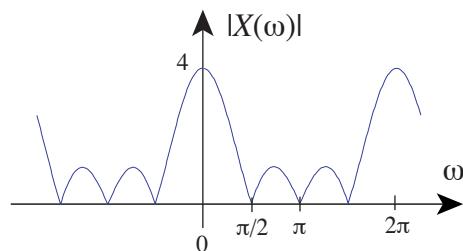


Figure 10.7: Magnitude of the DTFT of a discrete rectangle.

DTFT and *InverseDTFT* are inverses of each other. This follows from the fact that *FourierSeries_p* and *InverseFourierSeries_p* are inverses of each other.

Example 10.3: Consider a **discrete rectangle** $x \in DiscSignals$, shown in Figure 10.6. We can find its DTFT using (10.11) as follows,

$$\begin{aligned} X(\omega) &= \sum_{m=-\infty}^{\infty} x(m)e^{-i\omega m} \\ &= \sum_{m=0}^3 e^{-i\omega m}. \end{aligned}$$

Notice that when $\omega = 0$, this sum is easy to evaluate because $e^0 = 1$, so

$$X(0) = 4.$$

Moreover, when ω is any multiple of 2π , we get $X(\omega) = 4$, as it should, since the DTFT is periodic with period 2π . We can again use the identity (10.10). Letting $N = 3$ and $a = e^{-i\omega}$, we get

$$X(\omega) = \frac{1 - e^{-i4\omega}}{1 - e^{-i\omega}}.$$

The magnitude of this function is plotted in figure 10.5.

Other examples of DTFTs for various signals are given in table 10.3.

10.5 The continuous-time Fourier transform

The frequency response and impulse response of a continuous-time LTI system are related by the **continuous-time Fourier transform (CTFT)**, more commonly called simply the **Fourier transform (FT)**,

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = \int_{-\infty}^{\infty} x(t)e^{-i\omega t} dt.$$

(10.13)

Signal	DTFT	Reference
$\forall n \in \mathbb{Z}, \quad x(n) = \delta(n)$	$\forall \omega \in \mathbb{R}, \quad X(\omega) = 1$	Example 10.8
$\forall n \in \mathbb{Z}, \quad x(n) = \delta(n - N)$	$\forall \omega \in \mathbb{R}, \quad X(\omega) = e^{-i\omega N}$	Example 10.8
$\forall n \in \mathbb{Z}, \quad x(n) = K$	$\forall \omega \in \mathbb{R}, \quad X(\omega) = 2\pi K \sum_{k=-\infty}^{\infty} \delta(\omega - k2\pi)$	Section 10.7.5
$\forall n \in \mathbb{Z}, \quad x(n) = a^n u(n), \quad a < 1$	$\forall \omega \in \mathbb{R}, \quad X(\omega) = \frac{1}{1 - ae^{-i\omega}}$	Exercise 18
$\forall n \in \mathbb{Z}, \quad x(n) = \begin{cases} 1 & \text{if } n \leq M \\ 0 & \text{otherwise} \end{cases}$	$\forall \omega \in \mathbb{R}, \quad X(\omega) = \frac{\sin(\omega(M + 0.5))}{\sin(\omega/2)}$	Exercise 8
$\forall n \in \mathbb{Z}, \quad x(n) = \frac{\sin(Wn)}{\pi n}, \quad 0 < W < \pi$	$\forall \omega \in [-\pi, \pi], \quad X(\omega) = \begin{cases} 1 & \text{if } \omega \leq W \\ 0 & \text{otherwise} \end{cases}$	—

Table 10.3: Discrete time Fourier transforms of key signals. The function u is the unit step, given by (2.16).

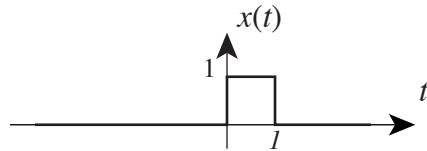


Figure 10.8: A rectangular pulse.

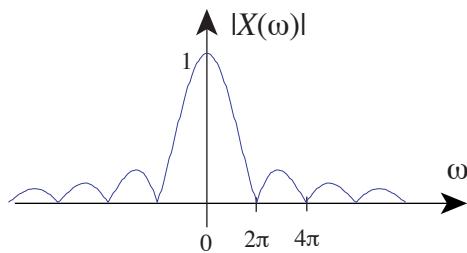


Figure 10.9: Magnitude of the Fourier transform of the rectangular pulse in Figure 10.8.

The CTFT can be defined for any function $x \in \text{ContSignals}$ where the integral exists. It need not be the impulse response of any system, and it need not be periodic or finite. The inverse relation is

$$\forall t \in \mathbb{R}, \quad x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\omega) e^{i\omega t} d\omega. \quad (10.14)$$

It is true but difficult to prove that the CTFT and the inverse CTFT are indeed inverses.

The CTFT can be viewed as a generalization of both the FS and DTFT where neither the frequency domain nor the time domain signal needs to be periodic. Alternatively, it can be viewed as the last remaining Fourier transform, where neither time nor frequency is discrete. Graphically, the CTFT is a system as shown in Figure 10.1(g) and (h).

Example 10.4: Consider a **rectangular pulse** $x \in ContSignals$, shown in Figure 10.8. We can find its continuous-time Fourier transform using (10.13) as follows,

$$\begin{aligned} X(\omega) &= \int_{-\infty}^{\infty} x(t)e^{-i\omega t} dt \\ &= \int_0^1 e^{-i\omega t} dt. \end{aligned}$$

Notice that when $\omega = 0$, this integral is easy to evaluate because $e^0 = 1$, so

$$X(0) = 1.$$

We can use (10.5) to solve the integral in general,

$$X(\omega) = \frac{i}{\omega} [e^{-i\omega} - 1].$$

We can get better intuition about this by manipulating it as follows,

$$\begin{aligned} X(\omega) &= \frac{i}{\omega} e^{-i\omega/2} \left[e^{-i\omega/2} - e^{i\omega/2} \right] \\ &= e^{-i\omega/2} \left[\frac{\sin(\omega/2)}{\omega/2} \right]. \end{aligned}$$

The leading factor has unit magnitude, so we see that the magnitude can be written

$$|X(\omega)| = \left| \frac{\sin(\omega/2)}{\omega/2} \right|.$$

This magnitude is plotted in Figure 10.9. Notice that the magnitude decays rather slowly as ω gets large (as $1/\omega$).

Other examples of Fourier transforms for various signals are given in table 10.4. The four Fourier transforms are summarized in table 10.5.

Signal	CTFT	Reference
$\forall t \in \mathbb{R}, \quad x(t) = \delta(t)$	$\forall \omega \in \mathbb{R}, \quad X(\omega) = 1$	Example 10.7
$\forall t \in \mathbb{R}, \quad x(t) = \delta(t - \tau), \tau \in \mathbb{R}$	$\forall \omega \in \mathbb{R}, \quad X(\omega) = e^{-j\omega\tau}$	Example 10.7
$\forall t \in \mathbb{R}, \quad x(t) = K$	$\forall \omega \in \mathbb{R}, \quad X(\omega) = 2\pi K \delta(\omega)$	Section 10.7.5
$\forall t \in \mathbb{R},$ $x(t) = a^t u(t), \quad 0 < a < 1$	$\forall \omega \in \mathbb{R},$ $X(\omega) = \frac{1}{j\omega - \ln(a)}$	—
$\forall t \in \mathbb{R},$ $x(t) = \begin{cases} \pi/a & \text{if } t \leq a \\ 0 & \text{otherwise} \end{cases}$	$\forall \omega \in \mathbb{R},$ $X(\omega) = \frac{2\pi \sin(a\omega)}{a\omega}$	Exercise 23
$\forall t \in \mathbb{R},$ $x(t) = \frac{\sin(\pi t/T)}{\pi t/T},$	$\forall \omega \in \mathbb{R},$ $X(\omega) = \begin{cases} T & \text{if } \omega \leq \pi/T \\ 0 & \text{otherwise} \end{cases}$	Exercise 21

Table 10.4: Continuous time Fourier transforms of key signals. The function u is the unit step, given by (9.27).

	aperiodic time continuous frequency	periodic time discrete frequency
aperiodic frequency continuous time	<p><i>CTFT:</i> $ContSignals \rightarrow ContSignals$</p> $X(\omega) = \int_{-\infty}^{\infty} x(t)e^{-i\omega t} dt$ <p><i>InverseCTFT:</i> $ContSignals \rightarrow ContSignals$</p> $x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\omega)e^{i\omega t} d\omega$	<p><i>FourierSeries_p:</i> $ContPeriodic_p \rightarrow DiscSignals$</p> $X_m = \frac{1}{p} \int_0^p x(t)e^{-im\omega_0 t} dt$ <p><i>InverseFourierSeries_p:</i> $DiscSignals \rightarrow ContPeriodic_p$</p> $x(t) = \sum_{k=-\infty}^{\infty} X_k e^{ik\omega_0 t}$
periodic frequency discrete time	<p><i>DTFT:</i> $DiscSignals \rightarrow ContPeriodic_{2\pi}$</p> $X(\omega) = \sum_{n=-\infty}^{\infty} x(n)e^{-in\omega}$ <p><i>InverseDTFT:</i> $ContPeriodic_{2\pi} \rightarrow DiscSignals$</p> $x(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X(\omega)e^{i\omega n} d\omega$	<p><i>DFT_p:</i> $DiscPeriodic_p \rightarrow DiscPeriodic_p$</p> $X_k = \sum_{n=0}^{p-1} x(n)e^{-ink\omega_0}$ <p><i>InverseDFT_p:</i> $DiscPeriodic_p \rightarrow DiscPeriodic_p$</p> $x(n) = \frac{1}{p} \sum_{k=0}^{p-1} X_k e^{ik\omega_0 n}$

Table 10.5: The four Fourier transforms summarized. The column and row titles tell you when to use the specified Fourier transform and its inverse. The first row applies to continuous-time signals, and the second column applies to periodic signals. Thus, if you have a continuous-time periodic signal, you should use the Fourier series at the upper right.

10.6 Fourier transforms vs. Fourier series

For each of continuous and discrete-time signals, we have a Fourier transform and a Fourier series (see table 10.5). The Fourier series applies only to periodic signals, while the Fourier transforms apply to any signal. The Fourier transforms, therefore, must also be applicable to periodic signals. Why do we need the Fourier series? Moreover, if we have a finite signal, then we can find its Fourier series by considering it to be a periodic signal, or we can find its Fourier transform by considering it to be zero outside its finite domain. Which should we do?

10.6.1 Fourier transforms of finite signals

Consider a discrete-time signal y that is finite. Suppose it is defined for the domain $[0, p - 1] \subset \mathbb{Z}$. As we did in Section 7.4, we can define a related periodic signal x as

$$\forall n \in \mathbb{Z}, \quad x(n) = \sum_{m=-\infty}^{\infty} y'(n - mp)$$

where

$$\forall n \in \mathbb{Z}, \quad y'(n) = \begin{cases} y(n) & \text{if } n \in [0, p - 1] \\ 0 & \text{otherwise} \end{cases}$$

The signal y' , of course, is an ordinary discrete-time signal, and hence possesses a DTFT. The signal x is a periodic signal, and therefore possesses a DFT. The DTFT and DFT are closely related. The DTFT is given by

$$\begin{aligned} \forall \omega \in \mathbb{R}, \quad Y'(\omega) &= \sum_{n=-\infty}^{\infty} y'(n) e^{-in\omega} \\ &= \sum_{n=0}^{p-1} y(n) e^{-in\omega}. \end{aligned}$$

The DFT is

$$\begin{aligned} \forall k \in \mathbb{Z}, \quad X_k &= \sum_{n=0}^{p-1} x(n) e^{-ink\omega_0} \\ &= \sum_{n=0}^{p-1} y(n) e^{-ink\omega_0}. \end{aligned}$$

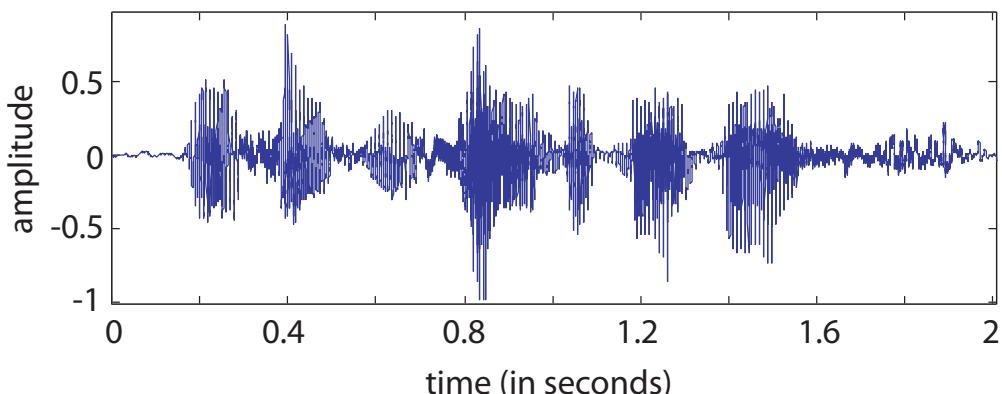


Figure 10.10: Two seconds of speech.

Comparing these, we see that

$$\forall k \in \mathbb{Z}, \quad X_k = Y'(k\omega_0).$$

In words, the DFT of the periodic signal is equal to samples of the DTFT of the finite signal with sampling interval $\omega_0 = 2\pi/p$. This fact proves extremely useful when doing Fourier analysis of real-world signals, as we see in the next subsection.

10.6.2 Fourier analysis of a speech signal

Consider the speech signal shown in Figure 10.10. It is two seconds of sound sampled at 8 kHz, for a total of 16,000 samples. This is a finite signal, so we can find a DFT or DTFT, as explained in the previous section. However, this would not be all that useful. As is evident from the figure, the character of the signal changes several times in the two seconds. The speech sound is one of the authors saying “this is the sound of my voice.” Usually, it is more interesting to perform Fourier analysis on a single **phoneme**, or elemental sound. Such analysis might be, for example, the first stage of a speech recognition system, which attempts to automatically determine what was said.

Consider a much smaller segment of speech shown at the top in Figure 10.11. This is approximately 64 msec of speech, or 512 samples at rate 8,000 samples/second. This

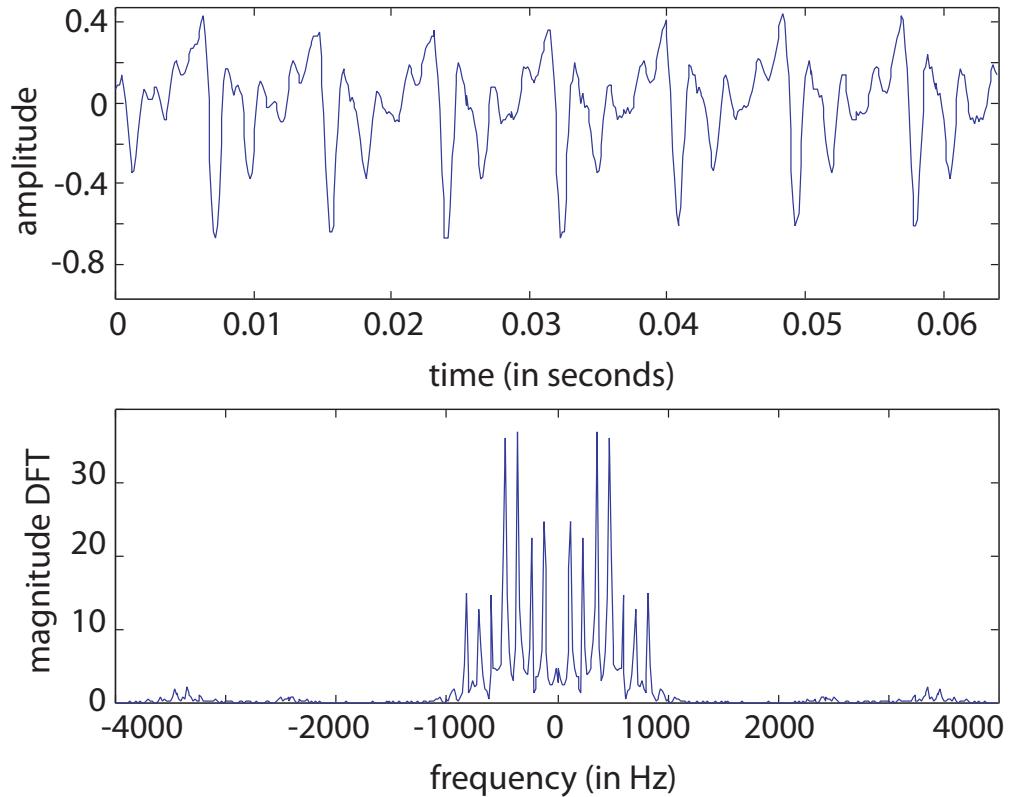


Figure 10.11: A voiced segment of speech (top) and one cycle of the magnitude of its DFT (bottom).

particular segment is the vowel sound in the word “sound.” Notice that the signal has quite a bit of structure. Fourier analysis can reveal a great deal about that structure.

The first issue is to decide which of the four Fourier transforms to apply. This is easy, since there is only one of the four that is computable, the DFT. Since we do not have an analytic expression for the speech signal, we cannot algebraically determine the DTFT. However, we know from the previous section that the DFT yields samples of the DTFT of a finite signal, so calculating the DFT reveals the structure of the DTFT.

The DFT of these 512 samples is shown at the bottom in Figure 10.11, which shows one cycle of the periodic DFT. The horizontal axis is labeled with the frequencies in Hz rather than the index k of the DFT coefficient. Recall that the k -th coefficient of the DFT represents a complex exponential with frequency $k\omega_0 = k2\pi/p$ radians/sample. To convert this to Hertz, we watch the units,

$$(k2\pi/p)[\text{radians/sample}] \times (1/T)[\text{samples/second}] \times (1/2\pi)[\text{cycles/radian}] \\ = k/(pT)[\text{cycles/second}],$$

where $T = 1/8000$ is the sampling interval.

Although this plot shows the DFT, the plot can equally well be interpreted as a plot of the DTFT. It shows 512 values of the DFT (one cycle of the periodic signal), and instead of showing each individual value, it runs them together as a continuous curve. In fact, since the DFT is samples of the DTFT, that continuous curve is a pretty good estimate of the shape of the DTFT. Of course, the samples might not be close together enough to accurately represent the DTFT, but probably they are. The next chapter will examine this issue in considerable detail.

Notice that most of the signal is concentrated below 1 kHz. In Figure 10.12, we have zoomed in to this region of the spectrum. Notice that the DFT is strongly peaked, with the lowest frequency peak occurring at about 120 Hz. Indeed, this is not surprising, because the time-domain signal at the top of Figure 10.11 looks somewhat periodic, with a period of about 80 msec, roughly the inverse of 120 Hz. That is, it looks like a periodic signal with fundamental frequency 120 Hz, and various harmonics. The weights of the harmonics are proportional to the heights of the peaks in Figure 10.12.

The vowel in the word “sound” is created by vibrating the human vocal chords, and then shaping the mouth into an acoustic cavity that alters the sound produced by the vocal chords. A sound that uses the vocal chords is called by linguists a **voiced sound**. By contrast, the “s” in “this” is an **unvoiced sound**. It is created without the help of the vocal chords by forcing air through a narrow passage in the mouth to create turbulence.

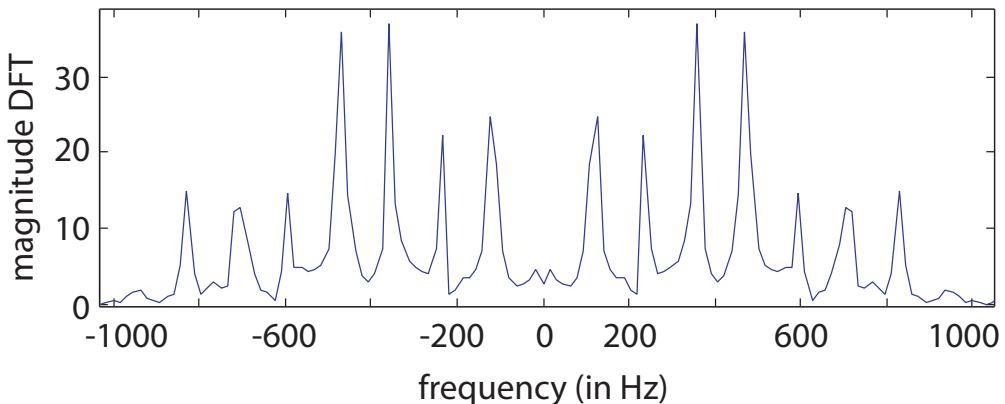


Figure 10.12: DFT of the voiced segment of speech, shown over a narrower frequency range.

The “s” in “this” is shown in Figure 10.13. It is very different from the vowel sound in 10.11. In particular, it looks much less regular. There is no evident periodicity in the signal, so the DFT does not reveal a fundamental frequency and harmonics. It is a noise-like signal, where the DFT reveals that much of the noise is at low frequencies, below 500 Hz, but there are also significant components all the way out to 4 kHz.

The analysis we have done on the segments of speech is a typical use of Fourier analysis. A long (even infinite) signal is divided into short segments, such as the two 512-sample segments that we examined above. These segments are studied by calculating their DFT. Since the DFT is a finite summation, it is easy to realize on a computer. Also, as mentioned before, there is a highly efficient algorithm called the **fast Fourier transform** or **FFT** to calculate the DFT. The `fft` function in Matlab was used to calculate the DFTs in figures 10.11 and 10.13. The DFT yields samples of the DTFT of the finite segment of signal. The spectrogram for the signal in Figure 10.10 is shown in Figure 10.14.

10.6.3 Fourier transforms of periodic signals

In the previous two sections, we have seen the relationship between the DTFT of a finite signal and the DFT of the periodic signal that is constructed by repeating the finite signal.

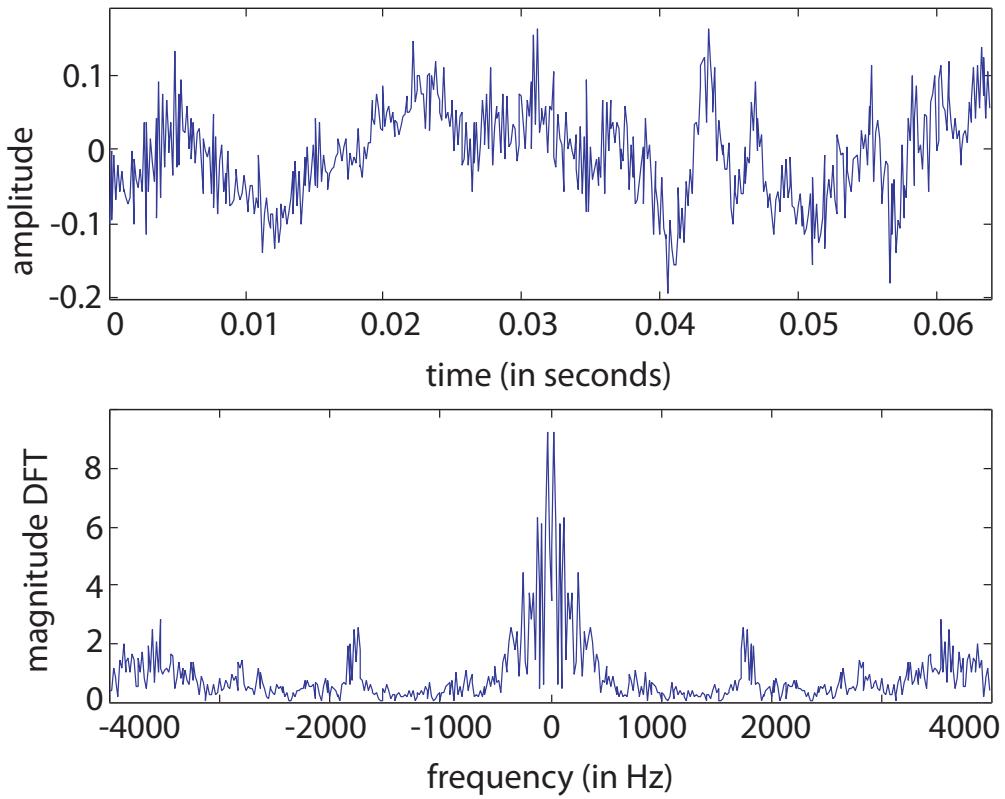


Figure 10.13: An unvoiced segment of speech (top) and one cycle of the magnitude of its DFT (bottom).

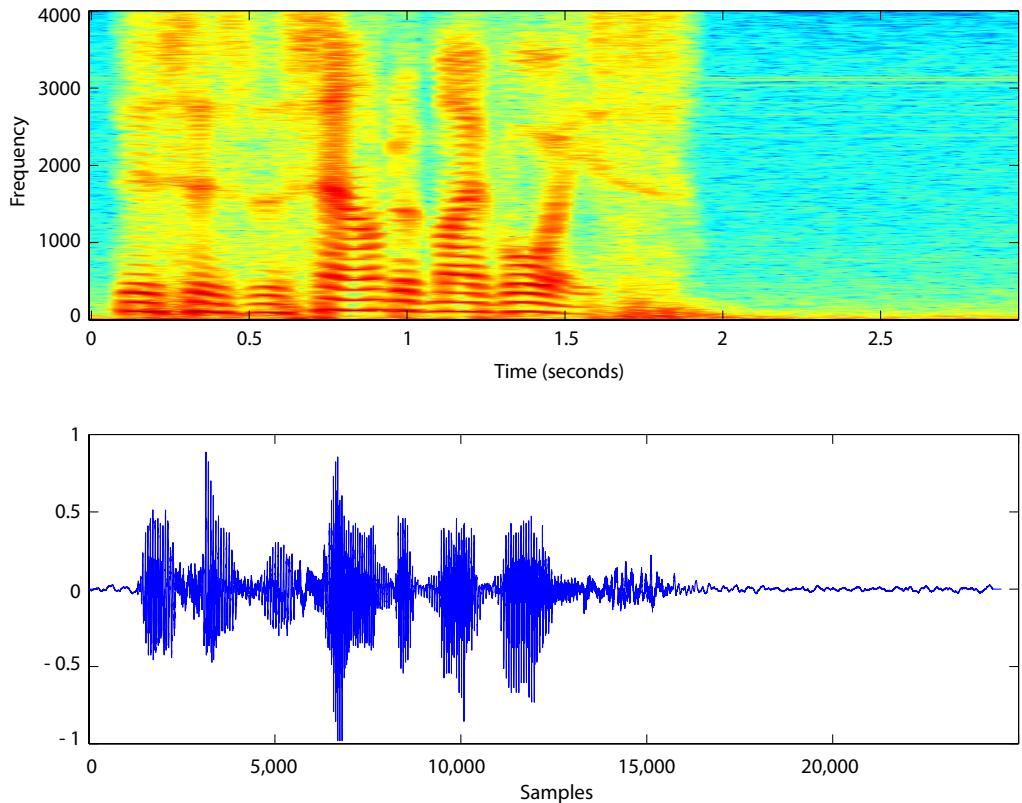


Figure 10.14: Spectrogram of the voice segment in Figure 10.10.

The periodic signal, however, also has a DTFT itself. In the interest of variety, we will explore this concept in continuous time.

A periodic continuous-time signal has a Fourier transform. But, as we will see, that Fourier transform has Dirac delta functions in it, which are mathematically tricky. Recall that a Dirac delta function is an infinitely narrow and infinitely high pulse. The Fourier series permits us to talk about the frequency domain representation of a periodic signal without dealing with Dirac delta functions.

It is useful, certainly, to simplify the mathematics. Using a Fourier series whenever possible allows us to do that. Moreover, when working with signals computationally, everything must be discrete and finite. Computers cannot deal with infinitely narrow and infinitely high pulses numerically. Computation, therefore, must be done with the only transform that is completely discrete and finite, the DFS, or its scaled cousin, the DFT.

To be concrete, suppose a continuous-time signal x has Fourier transform

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = 2\pi\delta(\omega - \omega_0) \quad (10.15)$$

for some real value ω_0 . We can find x using the inverse CTFT (10.14),

$$\forall t \in \mathbb{R}, \quad x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} 2\pi\delta(\omega - \omega_0)e^{i\omega t} d\omega.$$

Using the sifting rule, this evaluates to

$$x(t) = e^{i\omega_0 t}.$$

This is a periodic function with period $p = 2\pi/\omega_0$. From table 10.1, we see that the Fourier series for x is

$$\forall m \in \mathbb{Z}, \quad X_m = \begin{cases} 1 & \text{if } m = 1 \\ 0 & \text{otherwise} \end{cases}$$

There is exactly one non-zero Fourier series coefficient, which corresponds to the exactly one Dirac delta pulse in the Fourier transform (10.15).

More generally, suppose x has multiple Dirac delta pulses in its Fourier transform, each with different weights,

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = 2\pi \sum_{m=-\infty}^{\infty} X_m \delta(\omega - m\omega_0). \quad (10.16)$$

The inverse CTFT (10.14) tells us that

$$\forall t \in \mathbb{R}, \quad x(t) = \sum_{m=-\infty}^{\infty} X_m e^{im\omega_0 t}.$$

This is a periodic function with fundamental frequency ω_0 , and harmonics in various weights. Its Fourier series coefficients, by inspection, are just X_m . Thus, for a periodic signal, (10.16) relates the CTFT and the Fourier series. The Fourier series gives the weights of a set of Dirac delta pulses in the Fourier transform, within a scaling factor of 2π .

Example 10.5: Consider x given by

$$\forall t \in \mathbb{R}, \quad x(t) = \cos(\omega_0 t).$$

From table 10.1, we see that the Fourier series for x is

$$\forall m \in \mathbb{Z}, \quad X_m = \begin{cases} 1/2 & \text{if } |m| = 1 \\ 0 & \text{otherwise} \end{cases}$$

There are only two non-zero Fourier series coefficients. We can use (10.16) to write down its Fourier transform,

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = \pi\delta(\omega + \omega_0) + \pi\delta(\omega - \omega_0).$$

We sketch this as shown in Figure 10.15. See Exercise 9 at the end of the chapter for a similar result for a sin function.

Example 10.6: Consider the square wave of example 10.1. The Fourier series coefficients are

$$X_m = \begin{cases} 1/2 & \text{if } m = 0 \\ 0 & \text{if } m \text{ is even and } m \neq 0 \\ -i/m\pi & \text{if } m \text{ is odd} \end{cases}$$

The Fourier transform, therefore, has Dirac delta pulses with these weights at multiples of ω_0 , scaled by 2π , as shown in Figure 10.16.

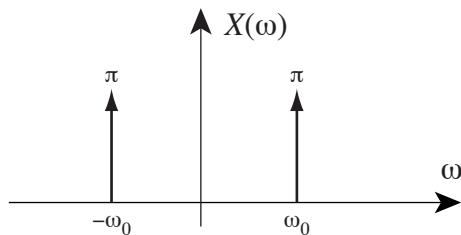


Figure 10.15: Fourier transform of a cosine.

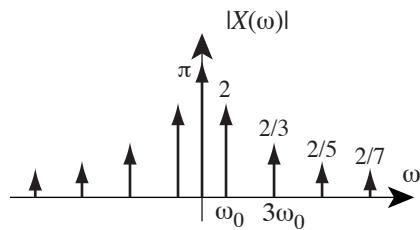


Figure 10.16: Fourier transform of a square wave.

The same concept applies in the discrete-time case, although some care is needed because the DTFT and DFT are both periodic, and not every function of the form $e^{j\omega n}$ is periodic (see Section 7.6.1). In fact, in Figure 10.11, the peaks in the spectrum hint at the Dirac delta functions in the DTFT. The signal appears to be roughly periodic with period 120 Hz, so the DFT shows strong peaks at multiples of 120 Hz. If the signal were perfectly periodic, and if we were plotting the DTFT instead of the DFT, then these peaks would become infinitely narrow and infinitely high.

10.7 Properties of Fourier transforms

In this section, we give a number of useful properties of the various Fourier transforms, together with a number of illustrative examples. These properties are summarized in tables 10.6 through 10.9. The properties and examples can often be used to avoid solving integrals or summations to find the Fourier transform of some signal, or to find an inverse Fourier transform.

10.7.1 Convolution

Suppose a discrete-time LTI system has impulse response h and frequency response H . We have seen that if the input to this system is a complex exponential, $e^{i\omega n}$, then the output is $H(\omega)e^{i\omega n}$. Suppose the input is instead an arbitrary signal x with DTFT X . Using the inverse DTFT relation, we know that

$$\forall n \in \mathbb{Z}, \quad x(n) = \frac{1}{2\pi} \int_0^{2\pi} X(\omega) e^{i\omega n} d\omega.$$

View this as a summation of exponentials, each with weight $X(\omega)$. An integral, after all, is summation over a continuum. Each term in the summation is $X(\omega)e^{i\omega n}$. If this term were an input by itself, then the output would be $H(\omega)X(\omega)e^{i\omega n}$. Thus, by linearity, if the input is x , the output should be

$$\forall n \in \mathbb{Z}, \quad y(n) = \frac{1}{2\pi} \int_0^{2\pi} H(\omega)X(\omega) e^{i\omega n} d\omega$$

Time domain	Frequency domain	Reference
$\forall t \in \mathbb{R}, \quad x(t) \text{ is real}$	$\forall m \in \mathbb{Z}, \quad X_m = X_{-m}^*$	Section 10.7.2
$\forall t \in \mathbb{R}, \quad x(t) = x^*(-t)$	$\forall m \in \mathbb{Z}, \quad X_m \text{ is real}$	Section 10.7.2
$\forall t \in \mathbb{R}, \quad y(t) = x(t - \tau)$	$\forall m \in \mathbb{Z}, \quad Y_m = e^{-im\omega_0\tau}X_m$	Section 13
$\forall t \in \mathbb{R}, \quad y(t) = e^{i\omega_1 t}x(t)$ where $\omega_1 = M\omega_0$, for some $M \in \mathbb{Z}$	$\forall m \in \mathbb{Z}, \quad Y_m = X_{m-M}$	Section 13
$\forall t \in \mathbb{R}, \quad y(t) = \cos(\omega_1 t)x(t)$ where $\omega_1 = M\omega_0$, for some $M \in \mathbb{Z}$	$\forall m \in \mathbb{Z}, \quad Y_m = (X_{m-M} + X_{m+M})/2$	Example 13
$\forall t \in \mathbb{R}, \quad y(t) = \sin(\omega_1 t)x(t)$ where $\omega_1 = M\omega_0$, for some $M \in \mathbb{Z}$	$\forall m \in \mathbb{Z}, \quad Y_m = (X_{m-M} - X_{m+M})/2i$	Exercise 13
$\forall t \in \mathbb{R}, \quad y(t) = ax(t) + bw(t)$	$\forall m \in \mathbb{Z}, \quad Y_m = aX_m + bW_m$	Section 10.7.4
$\forall t \in \mathbb{R}, \quad y(t) = x^*(t)$	$\forall m \in \mathbb{Z}, \quad Y_m = X_{-m}^*$	—

Table 10.6: Properties of the Fourier series. All time-domain signals are assumed to be periodic with period p , and fundamental frequency $\omega_0 = 2\pi/p$.

Time domain	Frequency domain	Reference
$\forall n \in \mathbb{Z}, \quad x(n) \text{ is real}$	$\forall k \in \mathbb{Z}, \quad X'_k = X'^*_{-k}$	Section 10.7.2
$\forall n \in \mathbb{Z}, \quad x(n) = x^*(-n)$	$\forall k \in \mathbb{Z}, \quad X'_k \text{ is real}$	Section 10.7.2
$\forall n \in \mathbb{Z}, \quad y(n) = x(n - N)$	$\forall k \in \mathbb{Z}, \quad Y'_k = e^{-ik\omega_0 N} X'_k$	-
$\forall n \in \mathbb{Z}, \quad y(n) = e^{i\omega_1 n} x(n)$ where $\omega_1 = M\omega_0$, for some $M \in \mathbb{Z}$	$\forall k \in \mathbb{Z}, \quad Y'_k = X'_{k-M}$	-
$\forall n \in \mathbb{Z}, \quad y(n) = \cos(\omega_1 n) x(n)$ where $\omega_1 = M\omega_0$, for some $M \in \mathbb{Z}$	$\forall k \in \mathbb{Z}, \quad Y'_k = (X'_{k-M} + X'_{k+M})/2$	-
$\forall n \in \mathbb{Z}, \quad y(n) = \sin(\omega_1 n) x(n)$ where $\omega_1 = M\omega_0$, for some $M \in \mathbb{Z}$	$\forall k \in \mathbb{Z}, \quad Y'_k = (X'_{k-M} - X'_{k+M})/2i$	-
$\forall n \in \mathbb{Z}, \quad y(n) = ax(n) + bw(n)$	$\forall k \in \mathbb{Z}, \quad Y'_k = aX'_k + bW'_k$	Section 10.7.4
$\forall n \in \mathbb{Z}, \quad y(n) = x^*(n)$	$\forall k \in \mathbb{Z}, \quad Y_k = X^*_{-k}$	-

Table 10.7: Properties of the DFT. All time-domain signals are assumed to be periodic with period p , and fundamental frequency $\omega_0 = 2\pi/p$.

Time domain	Frequency domain	Reference
$\forall n \in \mathbb{Z}, \quad x(n) \text{ is real}$	$\forall \omega \in \mathbb{R}, \quad X(\omega) = X^*(-\omega)$	Section 10.7.2
$\forall n \in \mathbb{Z}, \quad x(n) = x^*(-n)$	$\forall \omega \in \mathbb{R}, \quad X(\omega) \text{ is real}$	Section 10.7.2
$\forall n \in \mathbb{Z}, \quad y(n) = x(n - N)$	$\forall \omega \in \mathbb{R}, \quad Y(\omega) = e^{-i\omega N}X(\omega)$	Section 10.7.3
$\forall n \in \mathbb{Z}, \quad y(n) = e^{i\omega_1 n}x(n)$	$\forall \omega \in \mathbb{R}, \quad Y(\omega) = X(\omega - \omega_1)$	Section 10.7.6
$\forall n \in \mathbb{Z}, \quad y(n) = \cos(\omega_1 n)x(n)$	$\forall \omega \in \mathbb{R}, \quad Y(\omega) = (X(\omega - \omega_1) + X(\omega + \omega_1))/2$	Example 10.11
$\forall n \in \mathbb{Z}, \quad y(n) = \sin(\omega_1 n)x(n)$	$\forall \omega \in \mathbb{R}, \quad Y(\omega) = (X(\omega - \omega_1) - X(\omega + \omega_1))/2i$	Exercise 12
$\forall n \in \mathbb{Z}, \quad x(n) = ax_1(n) + bx_2(n)$	$\forall \omega \in \mathbb{R}, \quad X(\omega) = aX_1(\omega) + bX_2(\omega)$	Section 10.7.4
$\forall n \in \mathbb{Z}, \quad y(n) = (h * x)(n)$	$\forall \omega \in \mathbb{R}, \quad Y(\omega) = H(\omega)X(\omega)$	Section 10.7.1
$\forall n \in \mathbb{Z}, \quad y(n) = x(n)p(n)$	$\forall \omega \in \mathbb{R}, \quad Y(\omega) = \frac{1}{2\pi} \int_0^{2\pi} X(\Omega)P(\omega - \Omega)d\Omega$	Box on page 459
$y(n) = \begin{cases} x(n/N) & n \text{ multiple of } N \\ 0 & \text{otherwise} \end{cases}$	$\forall \omega \in \mathbb{R}, \quad Y(\omega) = X(N\omega)$	Exercise 14

Table 10.8: Properties of the DTFT.

Time domain	Frequency domain	Reference
$\forall t \in \mathbb{R}, \quad x(t) \text{ is real}$	$\forall \omega \in \mathbb{R}, \quad X(\omega) = X^*(-\omega)$	Section 10.7.2
$\forall t \in \mathbb{R}, \quad x(t) = x^*(-t)$	$\forall \omega \in \mathbb{R}, \quad X(\omega) \text{ is real}$	Section 10.7.2
$\forall t \in \mathbb{R}, \quad y(t) = x(t - \tau)$	$\forall \omega \in \mathbb{R}, \quad Y(\omega) = e^{-i\omega\tau}X(\omega)$	Section 10.7.3
$\forall t \in \mathbb{R}, \quad y(t) = e^{i\omega_1 t}x(t)$	$\forall \omega \in \mathbb{R}, \quad Y(\omega) = X(\omega - \omega_1)$	Section 10.7.6
$\forall t \in \mathbb{R}, \quad y(t) = \cos(\omega_1 t)x(t)$	$\forall \omega \in \mathbb{R}, \quad Y(\omega) = (X(\omega - \omega_1) + X(\omega + \omega_1))/2$	Example 10.11
$\forall t \in \mathbb{Z}, \quad y(t) = \sin(\omega_1 t)x(t)$	$\forall \omega \in \mathbb{R}, \quad Y(\omega) = (X(\omega - \omega_1) - X(\omega + \omega_1))/2i$	Exercise 12
$\forall t \in \mathbb{R}, \quad x(t) = ax_1(t) + bx_2(t)$	$\forall \omega \in \mathbb{R}, \quad X(\omega) = aX_1(\omega) + bX_2(\omega)$	Section 10.7.4
$\forall t \in \mathbb{R}, \quad y(t) = (h * x)(t)$	$\forall \omega \in \mathbb{R}, \quad Y(\omega) = H(\omega)X(\omega)$	Section 10.7.1
$\forall t \in \mathbb{R}, \quad y(t) = x(t)p(t)$	$\forall \omega \in \mathbb{R}, \quad Y(\omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\Omega)P(\omega - \Omega)d\Omega$	-
$\forall t \in \mathbb{R}, \quad y(t) = x(at)$	$\forall \omega \in \mathbb{R}, \quad Y(\omega) = \frac{1}{ a } X(\Omega/a)$	Exercise 11

Table 10.9: Properties of the CTFT.

Comparing to the inverse DTFT relation for $y(n)$, we see that

$$\boxed{\forall \omega \in \mathbb{R}, \quad Y(\omega) = H(\omega)X(\omega).} \quad (10.17)$$

This is the frequency-domain version of convolution

$$\forall n \in \mathbb{Z}, \quad y(n) = (h * x)(n).$$

Thus, the frequency response of an LTI system multiplies the DTFT of the input. This is intuitive, since the frequency response gives the weight imposed by the system on each frequency component of the input.

Equation (10.17) applies equally well to continuous-time systems, but in that case, H is the CTFT of the impulse response, and X is the CTFT of the input.

10.7.2 Conjugate symmetry

We have already shown (see (8.29)) that for real-valued signals, the Fourier series coefficients are conjugate symmetric,

$$X_k = X_{-k}^*.$$

In fact, all the Fourier transforms are conjugate symmetric if the time-domain function is real. We illustrate this with the CTFT. Suppose $x: \mathbb{R} \rightarrow \mathbb{R}$ is a real-valued signal, and let $X = CTFT(x)$. In general, $X(\omega)$ will be complex-valued. However, from (10.13), we have

$$\begin{aligned} [X(-\omega)]^* &= \int_{-\infty}^{\infty} [x(t)e^{i\omega t}]^* dt \\ &= \int_{-\infty}^{\infty} x(t)e^{-i\omega t} dt \\ &= X(\omega), \end{aligned}$$

Thus,

$$X(\omega) = X^*(-\omega),$$

i.e. for real-valued signals, $X(\omega)$ and $X(-\omega)$ are complex conjugates of one another.

We can show that, conversely, if the Fourier transform is conjugate symmetric, then the time-domain function is real. To do this, write the inverse CTFT

$$x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\omega)e^{i\omega t} d\omega$$

and then conjugate both sides,

$$x^*(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X^*(\omega) e^{-i\omega t} d\omega.$$

By changing variables (replacing ω with $-\omega$) and using the conjugate symmetry of X , we can show that

$$x^*(t) = x(t),$$

which implies that $x(t)$ is real for all t .

The inverse Fourier transforms can be used to show that if a time-domain function is conjugate symmetric,

$$x(t) = x^*(-t),$$

then its Fourier transform is real. The same property applies to all four Fourier transforms.

In summary, if a function in one domain (time or frequency) is conjugate symmetric, then the function in the other domain (frequency or time) is real.

10.7.3 Time shifting

Given a continuous-time function x and its Fourier transform $X = CTFT(x)$, let y be defined by

$$\forall t \in \mathbb{R}, \quad y(t) = x(t - \tau)$$

for some real constant τ . This is called **time shifting** or **delay**. We can find $Y = CTFT(y)$ in terms of X as follows,

$$\begin{aligned} Y(\omega) &= \int_{-\infty}^{\infty} y(t)e^{-i\omega t} dt \\ &= \int_{-\infty}^{\infty} x(t - \tau)e^{-i\omega t} dt \\ &= \int_{-\infty}^{\infty} x(t)e^{-i\omega(t+\tau)} dt \\ &= e^{-i\omega\tau} \int_{-\infty}^{\infty} x(t)e^{-i\omega t} dt \\ &= e^{-i\omega\tau} X(\omega). \end{aligned}$$

Thus, in summary,

$$y(t) = x(t - \tau) \Leftrightarrow Y(\omega) = e^{-i\omega\tau} X(\omega). \quad (10.18)$$

The bidirectional arrow indicates that this relationship works both ways. If you know that $Y(\omega) = e^{-i\omega\tau} X(\omega)$, then you can conclude that $y(t) = x(t - \tau)$.

Example 10.7: One of the simplest Fourier transforms to compute is that of x when

$$x(t) = \delta(t),$$

where δ is the Dirac delta function. Plugging into the formula,

$$\begin{aligned} X(\omega) &= \int_{-\infty}^{\infty} x(t)e^{-i\omega t} dt \\ &= \int_{-\infty}^{\infty} \delta(t)e^{-i\omega t} dt \\ &= e^{-i\omega 0} \\ &= 1, \end{aligned}$$

where we have used the sifting property of the delta function. To see how the sifting property works, note that the integrand is zero everywhere except where $t = 0$, at which point the complex exponential evaluates to 1. Then the integral of the delta function itself has value one.

The Fourier transform is a constant, 1. This indicates that the Dirac delta function, interestingly, contains all frequencies in equal amounts.

Moreover, this result is intuitive if one considers an LTI system with impulse response $h(t) = \delta(t)$. Such a system responds to an impulse by producing an impulse, which suggests that any input will be simply passed through unchanged. Indeed, its frequency response is $H(\omega) = 1$ for all $\omega \in \mathbb{R}$, so given an input x with Fourier transform X , the output y has Fourier transform

$$Y(\omega) = H(\omega)X(\omega) = X(\omega).$$

Since the output has the same Fourier transform as the input, the output is the same as the input.

Using (10.18), we can now find the Fourier transform of another signal

$$x(t) = \delta(t - \tau),$$

for some constant $\tau \in \mathbb{R}$. It is

$$X(\omega) = e^{-i\omega\tau}.$$

Note that, as required, this is conjugate symmetric. Moreover, it has magnitude 1. Its phase is $-\omega\tau$, a linear function of ω .

Again, we can gain some intuition by considering an LTI system with impulse response

$$h(t) = \delta(t - \tau). \tag{10.19}$$

Such a system introduces a fixed time delay of τ . Its frequency response is

$$H(\omega) = e^{-i\omega\tau}. \tag{10.20}$$

Since this has magnitude 1 for all ω , it tells us that all frequencies get through the delay system unattenuated, as expected. However, each frequency ω will experience a phase shift of $-\omega\tau$, corresponding to a time delay of τ .

Discrete-time signals are similar. Consider a discrete-time signal x with $X = DTFT(x)$, and let y be defined by

$$\forall t \in \mathbb{R}, \quad y(n) = x(n - N)$$

for some integer constant N . By similar methods, we can find that

$$\boxed{y(n) = x(n - N) \Leftrightarrow Y(\omega) = e^{-i\omega N}X(\omega).} \quad (10.21)$$

Example 10.8: Suppose we have a discrete-time signal x given by

$$x(n) = \delta(n),$$

where δ is the Kronecker delta function. It is easy to show from the DTFT definition that

$$X(\omega) = 1.$$

Using (10.21), we can now find the Fourier transform of another signal

$$x(n) = \delta(n - N),$$

for some constant $N \in \mathbb{Z}$. It is

$$X(\omega) = e^{-i\omega N}.$$

Notice that if $N = 0$, this reduces to $X(\omega) = 1$, as expected.

10.7.4 Linearity

Consider three discrete-time signals x, x_1, x_2 , related by

$$\forall n \in \mathbb{Z}, \quad x(n) = ax_1(n) + bx_2(n).$$

Then it is easy to see from the definition of the DTFT that

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = aX_1(\omega) + bX_2(\omega)$$

where $X = DTFT(x)$, $X_1 = DTFT(x_1)$, and $X_2 = DTFT(x_2)$.

The same linearity property applies to the CTFT,

$$x(t) = ax_1(t) + bx_2(t) \Leftrightarrow X(\omega) = aX_1(\omega) + bX_2(\omega)$$

Linearity of the Fourier transform is one of the most useful properties for avoiding evaluation of integrals and summations.

Example 10.9: Consider for example the discrete-time signal x given by

$$x(n) = \delta(n+1) + \delta(n-1),$$

where δ is the Kronecker delta function. Using linearity, we know that the DTFT of x is the sum of the DTFT of $\delta(n+1)$ and the DTFT of $\delta(n-1)$. From the previous example, we know those two DTFTs, so

$$X(\omega) = e^{i\omega} + e^{-i\omega}$$

because N is -1 and 1 , respectively. Using Euler's relation, we can simplify this to get

$$X(\omega) = 2 \cos(\omega).$$

Interestingly, the DTFT of this example turns out to be real. This is because the time-domain function is conjugate symmetric (the conjugate of something real is itself). Moreover, since it is real in the time domain, the DTFT turns out to be conjugate symmetric.

Linearity can also be used to find inverse Fourier transforms.

Example 10.10: Suppose you are told that a continuous-time signal has Fourier transform

$$X(\omega) = \cos(\omega).$$

How would you find the time-domain function? You could evaluate the inverse CTFT, but the integration that you would have to perform is quite difficult. Instead, use Euler's relation to write

$$X(\omega) = (e^{i\omega} + e^{-i\omega})/2.$$

Then use linearity. The inverse Fourier transform of this sum will be the sum of the inverse Fourier transforms of the terms. These we can recognize from (10.19) and (10.20), so

$$x(t) = (\delta(t+1) + \delta(t-1))/2,$$

where δ is the Dirac delta function.

10.7.5 Constant signals

We have seen that the Fourier transform of a delta function is a constant. With the symmetries that we have observed between time and frequency, it should come as no surprise that the Fourier transform of a constant is a delta function.

Consider first a continuous-time signal x given by

$$\forall t \in \mathbb{R}, \quad x(t) = K$$

for some real constant K . Its CTFT is

$$X(\omega) = K \int_{-\infty}^{\infty} e^{-i\omega t} dt,$$

which is not easy to evaluate. This integral is mathematically subtle. The answer is

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = 2\pi K \delta(\omega),$$

where δ is the Dirac delta function. What this says is that a constant in the time domain is concentrated at zero frequency in the frequency domain (which should not be surprising). Except for the multiplying constant of 2π , we probably could have guessed this answer. We can verify this answer by evaluating the inverse CTFT,

$$\begin{aligned} x(t) &= \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\omega) e^{i\omega t} d\omega \\ &= K \int_{-\infty}^{\infty} \delta(\omega) e^{i\omega t} d\omega \\ &= K, \end{aligned}$$

where the final step follows from the sifting property of the Dirac delta function. Thus, in summary,

$$x(t) = K \Leftrightarrow X(\omega) = 2\pi K \delta(\omega) \quad (10.22)$$

The discrete-time case is similar, but there is one subtlety because the DTFT is periodic. Let x be a discrete time signal where

$$\forall n \in \mathbb{Z}, \quad x(n) = K$$

for some real constant K . Its DTFT is

$$\forall \omega \in [-\pi, \pi], \quad X(\omega) = 2\pi K \delta(\omega),$$

where δ is the Dirac delta function. This is easy to verify using the inverse DTFT. Again, what this says is that a constant in the time domain is concentrated at zero frequency in the frequency domain (which should not be surprising). However, recall that a DTFT is periodic with period 2π , meaning that for all integers N ,

$$X(\omega) = X(\omega + N2\pi).$$

Thus, in addition to a delta function at $\omega = 0$, there must be one at $\omega = 2\pi$, $\omega = -2\pi$, $\omega = 4\pi$, etc. This can be written using a shift-and-add summation,

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = 2\pi K \sum_{k=-\infty}^{\infty} \delta(\omega - k2\pi).$$

Thus, in summary,

$$x(n) = K \Leftrightarrow X(\omega) = 2\pi K \sum_{k=-\infty}^{\infty} \delta(\omega - k2\pi). \quad (10.23)$$

10.7.6 Frequency shifting and modulation

Suppose that x is a continuous-time signal with CTFT X . Let y be another continuous-time signal defined by

$$y(t) = x(t)e^{i\omega_0 t}$$

for some real constant ω_0 . The CTFT of y is easy to compute,

$$\begin{aligned} Y(\omega) &= \int_{-\infty}^{\infty} y(t)e^{-i\omega t} dt \\ &= \int_{-\infty}^{\infty} x(t)e^{i\omega_0 t} e^{-i\omega t} dt \\ &= \int_{-\infty}^{\infty} x(t)e^{-i(\omega - \omega_0)t} dt \\ &= X(\omega - \omega_0). \end{aligned}$$

Thus, the Fourier transform of y is the same as that of x , but shifted to the right by ω_0 . In summary,

$$y(t) = x(t)e^{i\omega_0 t} \Leftrightarrow Y(\omega) = X(\omega - \omega_0). \quad (10.24)$$

This result can be used to determine the effect of multiplying a signal by a sinusoid, a process called **modulation** (see Exercise 16).

Example 10.11: Suppose

$$y(t) = x(t)\cos(\omega_0 t).$$

Use Euler's relation to rewrite this

$$y(t) = x(t)(e^{i\omega_0 t} + e^{-i\omega_0 t})/2.$$

Then use (10.24) to get the CTFT,

$$Y(\omega) = (X(\omega - \omega_0) + X(\omega + \omega_0))/2.$$

We can combine (10.24) with (10.22) to get the following facts:

$$x(t) = e^{i\omega_0 t} \Leftrightarrow X(\omega) = 2\pi\delta(\omega - \omega_0). \quad (10.25)$$

This says that a complex exponential signal with frequency ω_0 is concentrated in the frequency domain at frequency ω_0 , which should not be surprising. Similarly,

$$x(t) = \cos(\omega_0 t) \Leftrightarrow X(\omega) = \pi(\delta(\omega - \omega_0) + \delta(\omega + \omega_0)). \quad (10.26)$$

We can get a similar set of results for discrete-time signals. We summarize the results here, and leave their verification to the reader (see Exercise 14):

$$y(n) = x(n)e^{i\omega_0 n} \Leftrightarrow Y(\omega) = X(\omega - \omega_0). \quad (10.27)$$

$$y(n) = x(n) \cos(\omega_0 n) \Leftrightarrow Y(\omega) = (X(\omega - \omega_0) + X(\omega + \omega_0))/2. \quad (10.28)$$

$$x(n) = e^{i\omega_0 n} \Leftrightarrow X(\omega) = 2\pi \sum_{k=-\infty}^{\infty} \delta(\omega - \omega_0 - k2\pi). \quad (10.29)$$

$$x(n) = \cos(\omega_0 n) \Leftrightarrow X(\omega) = \pi \sum_{k=-\infty}^{\infty} (\delta(\omega - \omega_0 - k2\pi) + \delta(\omega + \omega_0 - k2\pi)). \quad (10.30)$$

Additional properties of Fourier transforms are explored in the exercises.

10.8 Summary

In previous chapters, we developed the result that signals can be represented as sums of sinusoids. We used this representation to analyze the effect that a linear time invariant system has on signals. We variously considered periodic and non-periodic signals and impulse and frequency responses of LTI systems.

In this chapter, we unified all frequency domain discussion by showing that there are four closely interrelated Fourier transforms. Two of these apply to discrete-time signals, and two apply to continuous-time signals. Two of them apply to periodic signals, and two of them apply to non-periodic signals.

The four Fourier transforms can be viewed as generalizations of the Fourier series. Consequently, they share many properties that are rooted in the Fourier series. These properties can be leveraged to analyze more complicated signals by using an analysis of simpler signals.

Probing Further: Multiplying signals

We have seen that convolution in the time domain corresponds to multiplication in the frequency domain. It turns out that this relationship is symmetric, in that multiplication in the time domain corresponds to a peculiar form of convolution in the frequency domain. That is, given two discrete-time signals x and p with DTFTs X and P , if we multiply them in the time domain,

$$\forall n \in \mathbb{Z}, \quad y(n) = x(n)p(n)$$

then in the frequency domain, $Y(\omega) = (X \circledast P)(\omega)$, where the symbol “ \circledast ” indicates **circular convolution**, defined by

$$\forall \omega \in \mathbb{R}, \quad (X \circledast P)(\omega) = \frac{1}{2\pi} \int_0^{2\pi} X(\Omega)P(\omega - \Omega)d\Omega.$$

To verify this, we can substitute into the above integral the definitions for the DTFTs $X(\omega)$ and $P(\omega)$ to get

$$\begin{aligned} (X \circledast P)(\omega) &= \frac{1}{2\pi} \int_0^{2\pi} \left(\sum_{m=-\infty}^{\infty} x(m)e^{-i\Omega m} \right) \left(\sum_{k=-\infty}^{\infty} p(k)e^{-i(\omega-\Omega)k} \right) d\Omega \\ &= \sum_{k=-\infty}^{\infty} p(k)e^{-i\omega k} \sum_{m=-\infty}^{\infty} x(m) \frac{1}{2\pi} \int_0^{2\pi} e^{-i\Omega(m-k)} d\Omega \\ &= \sum_{k=-\infty}^{\infty} p(k)x(k)e^{-i\omega k}, \end{aligned}$$

where the last equality follows from the observation that the integral in the middle expression is zero except when $m = k$, when it has value one. Thus, $(X \circledast P)(\omega)$ is the DTFT of $y = xp$, as we claimed. The continuous-time case is somewhat simpler. If we have $\forall t \in \mathbb{R}, \quad y(t) = x(t)p(t)$ then in the frequency domain,

$$\forall \omega \in \mathbb{R}, \quad Y(\omega) = \frac{1}{2\pi} (X * P)(\omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\Omega)P(\omega - \Omega)d\Omega.$$

The “ $*$ ” indicates ordinary convolution.

Exercises

Each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **E** Show that if two discrete-time systems with frequency responses $H_1(\omega)$ and $H_2(\omega)$ are connected in cascade, that the DTFT of the output is given by $Y(\omega) = H_1(\omega)H_2(\omega)X(\omega)$, where $X(\omega)$ is the DTFT of the input.
2. **E** This exercise verifies some of the relations in table 10.1.

- (a) Let x be given by

$$\forall t \in \mathbb{R}, \quad x(t) = e^{i\omega_0 t},$$

where $\omega_0 \neq 0$. Use (10.2) to verify that its Fourier series coefficients are

$$\forall m \in \mathbb{Z}, \quad X_m = \begin{cases} 1 & \text{if } m = 1 \\ 0 & \text{otherwise} \end{cases}$$

- (b) Let x be given by

$$\forall t \in \mathbb{R}, \quad x(t) = \cos(\omega_0 t),$$

where $\omega_0 \neq 0$. Use part (a) and properties of the Fourier series to verify that its Fourier series coefficients are

$$\forall m \in \mathbb{Z}, \quad X_m = \begin{cases} 1/2 & \text{if } |m| = 1 \\ 0 & \text{otherwise} \end{cases}$$

- (c) Let x be given by

$$\forall t \in \mathbb{R}, \quad x(t) = \sin(\omega_0 t),$$

where $\omega_0 \neq 0$. Use part (a) and properties of the Fourier series to verify that its Fourier series coefficients are

$$\forall m \in \mathbb{Z}, \quad X_m = \begin{cases} 1/2i & \text{if } m = 1 \\ -1/2i & \text{if } m = -1 \\ 0 & \text{otherwise} \end{cases}$$

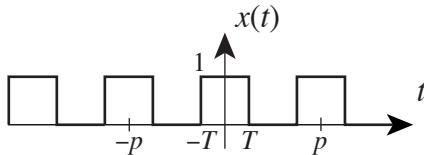


Figure 10.17: A symmetric square wave.

(d) Let x be given by

$$\forall t \in \mathbb{R}, \quad x(t) = 1.$$

Use (10.2) to verify that its Fourier series coefficients are

$$\forall m \in \mathbb{Z}, \quad X_m = \begin{cases} 1 & \text{if } m = 0 \\ 0 & \text{otherwise} \end{cases}$$

Notice that the answer does not depend on your choice for p .

3. T Consider a symmetric square wave $x \in ContPeriodic_p$, shown in Figure 10.17. It is periodic with period p , and its fundamental frequency is $\omega_0 = 2\pi/p$ radians/second. Over one period, this is given by

$$\forall t \in [0, p], \quad x(t) = \begin{cases} 1 & \text{if } t < T \text{ or } t > p - T \\ 0 & \text{otherwise} \end{cases}$$

(a) Show that its Fourier series coefficients are given by

$$\forall m \in \mathbb{Z}, \quad X_m = \begin{cases} 2T/p & \text{if } m = 0 \\ \sin(m\omega_0 T)/(m\pi) & \text{otherwise} \end{cases}$$

You can use l'Hôpital's rule (see page 65) to verify that $\sin(x)/x = 1$ when $x = 0$, so this can be written more simply as

$$\forall m \in \mathbb{Z}, \quad X_m = \frac{\sin(m\omega_0 T)}{m\pi} \tag{10.31}$$

Note that this is real, as expected, since x is symmetric. **Hint:** The integration formula (10.5) may be helpful.

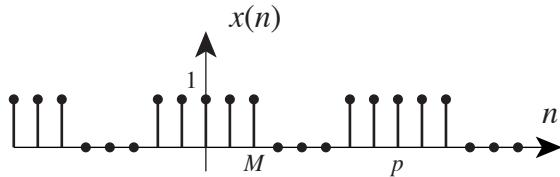


Figure 10.18: A symmetric discrete square wave.

- (b) Let $T = 0.5$, and use Matlab to plot the Fourier series coefficients as a stem plot (using the `stem` command) for m ranging from -20 to 20. Note that you will have to be careful to avoid a divide by zero error at $m = 0$. Construct plots for $p = 2$, $p = 4$, and $p = 8$.
4. E Let x be a periodic **impulse train**, given by

$$\forall t \in \mathbb{R}, \quad x(t) = \sum_{n=-\infty}^{\infty} \delta(t-np)$$

where $p > 0$ is the period. This signal has a Dirac delta function at all multiples of p . Use (10.2) to verify that its Fourier series coefficients are

$$\forall m \in \mathbb{Z}, \quad X_m = 1/p.$$

Note that there is a subtlety in using (10.2) here. There are impulses at each end of the integration interval. This subtlety can be avoided by observing that (10.2) can, in fact, integrate over any interval that covers one period. Thus, it can equally well be written

$$\forall m \in \mathbb{Z}, \quad X_m = \frac{1}{p} \int_{-p/2}^{p/2} x(t) e^{-im\omega_0 t} dt.$$

This simplifies the problem considerably.

5. E This exercise verifies some of the relations in table 10.2. In all cases, assume that the frequency f is rational, and that it is related to the period p by $f = m/p$ for some integer m (see Section 7.6.1).

- (a) Let x be given by

$$\forall n \in \mathbb{Z}, \quad x(n) = e^{j2\pi f n},$$

where $f \neq 0$. Use (10.9) to verify that its Fourier series coefficients are

$$\forall k \in \mathbb{Z}, \quad X'_k = \begin{cases} p & \text{if } k \in \{\dots, m-2p, m-p, m, m+p, m+2p, \dots\} \\ 0 & \text{otherwise} \end{cases}$$

(b) Let x be given by

$$\forall n \in \mathbb{Z}, \quad x(n) = \cos(2\pi fn),$$

where $f \neq 0$. Use part (a) and properties of the DFT to verify that its Fourier series coefficients are

$$X'_k = \begin{cases} p/2 & \text{if } k \in \{\dots, m-2p, m-p, m, m+p, m+2p, \dots\} \\ p/2 & \text{if } k \in \{\dots, -m-2p, -m-p, -m, -m+p, -m+2p, \dots\} \\ 0 & \text{otherwise} \end{cases}$$

(c) Let x be given by

$$\forall n \in \mathbb{Z}, \quad x(n) = \sin(i2\pi fn),$$

where $f \neq 0$. Use part (a) and properties of the DFT to verify that its Fourier series coefficients are

$$X'_k = \begin{cases} p/2i & \text{if } k \in \{\dots, m-2p, m-p, m, m+p, m+2p, \dots\} \\ -p/2i & \text{if } k \in \{\dots, -m-2p, -m-p, -m, -m+p, -m+2p, \dots\} \\ 0 & \text{otherwise} \end{cases}$$

(d) Let x be given by

$$\forall n \in \mathbb{Z}, \quad x(n) = 1.$$

Use (10.9) to verify that its Fourier series coefficients are

$$X_m = \begin{cases} p & \text{if } k \in \{\dots, -2p, -p, 0, p, 2p, \dots\} \\ 0 & \text{otherwise} \end{cases}$$

Notice that this result depends on your choice for p . This is a consequence of the unfortunate scaling that is used for the DFT, vs. the discrete Fourier series (DFS).

6. T Consider a symmetric discrete square wave $x \in DiscPeriodic_p$, shown in Figure 10.18. It is periodic with period p , and its fundamental frequency is $\omega_0 = 2\pi/p$ radians/sample. Over one period, this is given by

$$\forall n \in \{0, 1, \dots, p-1\}, \quad x(n) = \begin{cases} 1 & \text{if } n \leq M \text{ or } n \geq p-M \\ 0 & \text{otherwise} \end{cases}$$

where, in the figure, $M = 2$ and $p = 8$. For this problem, however, assume that M and p can be any positive integers where $p > 2M$.

- (a) Show that the DFT is given by

$$\forall k \in \mathbb{Z}, \quad X'_k = \begin{cases} 2M+1, & \text{if } k \text{ is a multiple of } p \\ \sin(k(M+0.5)\omega_0)/\sin(k\omega_0/2), & \text{otherwise} \end{cases}$$

You can use l'Hôpital's rule (see page 65) to verify that

$$\sin(Kx)/\sin(x) = K$$

when $x = 0$, so this can be written more simply as

$$\forall k \in \mathbb{Z}, \quad X'_k = \frac{\sin(k(M+0.5)\omega_0)}{\sin(k\omega_0/2)} \quad (10.32)$$

Note that this is real, as expected, since x is symmetric. **Hint:** The summation identity formula (10.10) may be helpful.

- (b) Let $M = 2$ and use Matlab to plot the Fourier series coefficients as a stem plot (using the `stem` command) for m ranging from $-p + 1$ to $p - 1$. Note that you will have to be careful to avoid a divide by zero error at $k = 0$. Construct plots for $p = 8$, $p = 16$, and $p = 32$.

7. E Let x be a discrete periodic impulse train, given by

$$\forall n \in \mathbb{Z}, \quad x(n) = \sum_{m=-\infty}^{\infty} \delta(n - mp)$$

where $p > 0$ is the integer period. This signal has a Kronecker delta function at all multiples of p . Use (10.9) to verify that its DFT coefficients are

$$\forall k \in \mathbb{Z}, \quad X'_k = 1.$$

8. T Consider a symmetric discrete rectangle $x \in DiscSignals$, shown in Figure 10.19. This is given by

$$\forall n \in \mathbb{Z}, \quad x(n) = \begin{cases} 1 & \text{if } |n| \leq M \\ 0 & \text{otherwise} \end{cases}$$

- (a) Show that its DTFT is given by

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = \frac{\sin(\omega(M+0.5))}{\sin(\omega/2)}$$

Hint: The summation identity formula (10.10) may be helpful.

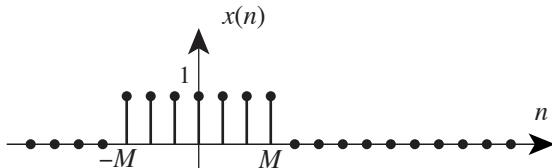


Figure 10.19: A symmetric discrete rectangle signal.

- (b) Let $M = 3$ and use Matlab to plot the DTFT with ω ranging from $-\pi$ to π .

9. E Consider x given by

$$\forall t \in \mathbb{R}, \quad x(t) = \sin(\omega_0 t).$$

Show that the CTFT is given by

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = (\pi/i)\delta(\omega - \omega_0) - (\pi/i)\delta(\omega + \omega_0).$$

10. C In Section 10.6 we explored the relationship between the CTFT of a periodic continuous-time signal and its Fourier series. In this problem we do the same for discrete-time signals.

- (a) Consider a discrete-time signal x with DTFT given by

$$\forall \omega \in [-\pi, \pi], \quad X(\omega) = 2\pi\delta(\omega - \omega_0)$$

where $\omega_0 = 2\pi/p$ for some integer p . The DTFT above is given over one cycle only, but note that since it is a DTFT, it is periodic. Use the inverse DTFT to determine x .

- (b) Is x in part (a) periodic? If so, what is the period, and what is its DFT?
(c) More generally, consider a discrete-time signal x with DTFT given by

$$\forall \omega \in [-\pi, \pi], \quad X(\omega) = 2\pi \sum_{k=-\lfloor p/2 \rfloor}^{\lfloor p/2 \rfloor} X_k \delta(\omega - k\omega_0)$$

where $\omega_0 = 2\pi/p$ for some integer p . For simplicity, assume that p is odd, and let $\lfloor p/2 \rfloor$ be the largest integer less than p . Use the inverse DTFT to determine x .

- (d) Is x in part (c) periodic? If so, what is the period, and what is its DFT? Give the DTFT in terms of the DFT coefficients.

11. **T** Consider a continuous-time signal x with Fourier transform X . Let y be such that

$$\forall t \in \mathbb{R}, \quad y(t) = x(at),$$

for some real number a . Show that its Fourier transform Y is such that

$$\forall \omega \in \mathbb{R}, \quad Y(\omega) = \frac{1}{|a|} X(\omega/a).$$

12. **E** Consider the discrete-time signal y given by

$$\forall n \in \mathbb{Z}, \quad y(n) = \sin(\omega_1 n)x(n).$$

Show that the DTFT is

$$\forall \omega \in \mathbb{R}, \quad Y(\omega) = (X(\omega - \omega_1) - X(\omega + \omega_1))/2i,$$

where $X = DTFT(x)$.

13. **E** In this exercise, you verify various properties of the Fourier series in table 10.6. In all parts below, x is a periodic continuous-time signal with period p and fundamental frequency $\omega_0 = 2\pi/p$.

- (a) Let y be given by

$$\forall t \in \mathbb{R}, \quad y(t) = x(t - \tau)$$

for some real number τ . Show that the Fourier series coefficients of y are given by

$$\forall m \in \mathbb{R}, \quad Y_m = e^{-im\omega_0\tau} X_m,$$

where X_m are the Fourier series coefficients of x .

- (b) Let y be given by

$$\forall t \in \mathbb{R}, \quad y(t) = e^{i\omega_1 t} x(t)$$

where $\omega_1 = M\omega_0$, for some $M \in \mathbb{Z}$. Show that the Fourier series coefficients of y are given by

$$\forall m \in \mathbb{Z}, \quad Y_m = X_{m-M},$$

where X_m are the Fourier series coefficients of x .

- (c) Let y be given by

$$\forall t \in \mathbb{R}, \quad y(t) = \cos(\omega_1 t)x(t)$$

where $\omega_1 = M\omega_0$, for some $M \in \mathbb{Z}$. Show that the Fourier series coefficients of y are given by

$$\forall m \in \mathbb{Z}, \quad Y_m = (X_{m-M} + X_{m+M})/2,$$

where X_m are the Fourier series coefficients of x .

- (d) Let y be given by

$$\forall t \in \mathbb{R}, \quad y(t) = \sin(\omega_1 t)x(t)$$

where $\omega_1 = M\omega_0$, for some $M \in \mathbb{Z}$. Show that the Fourier series coefficients of y are given by

$$\forall m \in \mathbb{Z}, \quad Y_m = (X_{m-M} - X_{m+M})/2i,$$

where X_m are the Fourier series coefficients of x .

14. T Consider a discrete-time signal x with Fourier transform X . For each of the new signals defined below, show that its Fourier transform is as shown.

- (a) If y is such that

$$\forall n \in \mathbb{Z}, \quad y(n) = \begin{cases} x(n/N) & \text{if } n \text{ is an integer multiple of } N \\ 0 & \text{otherwise} \end{cases}$$

for some integer N , then its Fourier transform Y is such that

$$\forall \omega \in \mathbb{R}, \quad Y(\omega) = X(\omega N).$$

- (b) If w is such that

$$\forall n \in \mathbb{Z}, \quad w(n) = x(n)e^{j\alpha n},$$

for some real number α , then its Fourier transform W is such that

$$\forall \omega \in \mathbb{R}, \quad W(\omega) = X(\omega - \alpha).$$

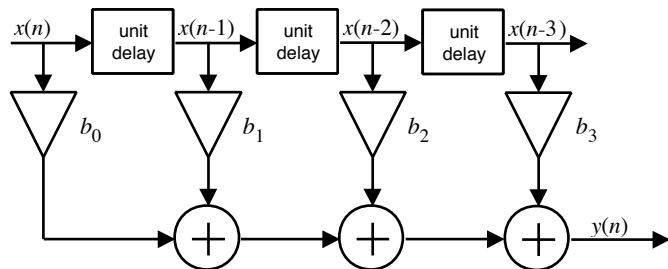
- (c) If z is such that

$$\forall n \in \mathbb{Z}, \quad z(n) = x(n)\cos(\alpha n),$$

for some real number α , then its Fourier transform Z is such that

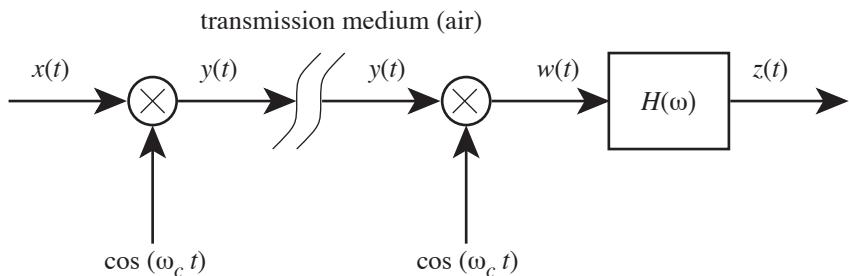
$$Z(\omega) = (X(\omega - \alpha) + X(\omega + \alpha))/2.$$

15. T Consider the FIR system described by the following block diagram:



The notation here is the same as in Figure 9.15. Suppose that this system has frequency response H . Define a new system with the identical structure as above, except that each unit delay is replaced by a double delay (two cascaded unit delays). Find the frequency response of that system in terms of H .

16. T This exercise discusses **amplitude modulation** or **AM**. AM is a technique that is used to convert low frequency signals into high frequency signals for transmission over a radio channel. Conversion of the high frequency signal back to a low frequency signal is called **demodulation**. The system structure is depicted below:

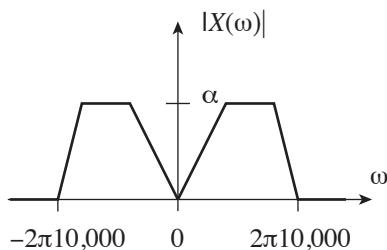


The circular components multiply their input signals. The transmission medium (air, for radio signals) is approximated here as a medium that passes the signal y unaltered.

Suppose your AM radio station is allowed to transmit signals at a carrier frequency of 740 kHz (this is the frequency of KCBS in San Francisco). Suppose you want to send the audio signal $x : \mathbb{R} \rightarrow \mathbb{R}$. The AM signal that you would transmit is given by, for all $t \in \mathbb{R}$,

$$y(t) = x(t) \cos(\omega_c t),$$

where $\omega_c = 2\pi \times 740,000$ is the **carrier frequency** (in radians per second). Suppose $X(\omega)$ is the Fourier transform of an audio signal with magnitude as shown below:



- (a) Show that the Fourier transform Y of y in terms of X is

$$Y(\omega) = (X(\omega - \omega_c) + X(\omega + \omega_c))/2.$$

- (b) Carefully sketch $|Y(\omega)|$ and note the important magnitudes and frequencies on your sketch.

Note that if $X(\omega) = 0$ for $|\omega| > 2\pi \times 10,000$, then $Y(\omega) = 0$ for $||\omega| - |\omega_c|| > 2\pi \times 10,000$. In words, if the signal x being modulated is bandlimited to less than 10 kHz, then the modulated signal is bandlimited to frequencies that are within 10 kHz of the carrier frequency. Thus, an AM radio station only needs to occupy 20 kHz of the radio spectrum in order to transmit audio signals up to 10 kHz.

- (c) At the receiver, the problem is to recover the audio signal x from y . One way is to demodulate by multiplying y by a sinewave at the carrier frequency to obtain the signal w , where

$$w(t) = y(t) \cos(\omega_c t).$$

What is the Fourier transform W of w in terms of X ? Sketch $|W(\omega)|$ and note the important magnitudes and frequencies.

- (d) After performing the demodulation of part (c), an AM receiver will filter the received signal through a low-pass filter with frequency response $H(\omega)$ such that $H(\omega) = 1$ for $|\omega| \leq 2\pi \times 10,000$ and $|H(\omega)| = 0$ for $|\omega| > 2\pi \times 20,000$. Let z be the filtered signal, as shown in the figure above. What is the Fourier transform Z of z ? What is the relationship between z and x ?

17. T In the following parts, assume that x is a discrete-time signal given by

$$\forall n \in \mathbb{Z}, \quad x(n) = \delta(n+1) + \delta(n) + \delta(n-1),$$

and that S is an LTI system with frequency response H given by

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = e^{-i\omega}.$$

- Find $X = DTFT(x)$ and make a well-labeled sketch for $\omega \in [-\pi, \pi]$ in radians/sample. Check that X is periodic with period 2π .
- Let $y = S(x)$. Find $Y = DTFT(y)$.
- Find $y = S(x)$.
- Sketch x and y and comment on what the system S does.

18. T Consider a causal discrete-time LTI system S with input x and output y such that

$$\forall n \in \mathbb{Z}, \quad y(n) = x(n) + ay(n-1)$$

where $a \in \mathbb{R}$ is a given constant such that $|a| < 1$.

- Find the impulse response h of S .
- Find the frequency response of S by letting the input be $e^{i\omega n}$ and the output be $H(\omega)e^{i\omega n}$, and solving for $H(\omega)$.
- Use your results in parts (a) and (b) and the fact that the DTFT of an impulse response is the frequency response to show that h given by

$$\forall n \in \mathbb{Z}, \quad h(n) = a^n u(n)$$

has the discrete-time Fourier transform $H = DTFT(h)$ given by

$$H(\omega) = \frac{1}{1 - ae^{-i\omega}},$$

where $u(n)$ is the unit step, given by (2.16).

- Use Matlab to plot $h(n)$ and $|H(\omega)|$ for $a = -0.9$ and $a = 0.9$. You may choose the interval of n for your plot of h , but you should plot $|H(\omega)|$ in the interval $\omega \in [-\pi, \pi]$. Discuss the differences between these plots for the two different values of a .

19. T Suppose a discrete-time signal x has DTFT given by

$$X(\omega) = i \sin(K\omega)$$

for some positive integer K . Note that $X(\omega)$ is periodic with period 2π , as it must be to be a DTFT.

- (a) Determine from the symmetry properties of X whether the time-domain signal x is real.
 - (b) Find x . **Hint:** Use Euler's relation and the linearity of the DTFT.
20. T Consider a periodic continuous-time signal x with period p and Fourier series $X : \mathbb{Z} \rightarrow \mathbb{C}$. Let y be another signal given by

$$y(t) = x(t - \tau)$$

for some real constant τ . Find the Fourier series coefficients of y in terms of those of X .

21. T Consider the continuous-time signal given by

$$x(t) = \frac{\sin(\pi t/T)}{(\pi t/T)}.$$

Show that its CTFT is given by

$$X(\omega) = \begin{cases} T, & \text{if } |\omega| \leq \pi/T \\ 0, & \text{if } |\omega| > \pi/T \end{cases}$$

The fact from calculus (10.5) may be useful.

22. T If x is a continuous-time signal with CTFT X , then we can define a new time-domain function y such that

$$\forall t \in \mathbb{R}, \quad y(t) = X(t).$$

That is, the new time domain function has the same shape as the frequency domain function X . Then the CTFT Y of y is given by

$$\forall \omega \in \mathbb{R}, \quad Y(\omega) = 2\pi x(-\omega).$$

That is, the frequency domain of the new function has the shape of the time domain of the old, but reversed and scaled by 2π . This property is called **duality** because it shows that time and frequency are interchangeable. Show that the property is true.

23. T Use the results of exercises 21 and 22 to show that a continuous time signal x given by

$$x(t) = \begin{cases} \pi/a, & \text{if } |t| \leq a \\ 0, & \text{if } |t| > a \end{cases}$$

where a is a positive real number, has CTFT X given by

$$X(\omega) = 2\pi \frac{\sin(a\omega)}{(a\omega)}.$$

11

Sampling and Reconstruction

Contents

11.1 Sampling	474
11.1.1 Sampling a sinusoid	474
<i>Basics: Units</i>	475
11.1.2 Aliasing	476
11.1.3 Perceived pitch experiment	477
11.1.4 Avoiding aliasing ambiguities	481
11.2 Reconstruction	482
<i>Probing Further: Anti-Aliasing for Fonts</i>	482
11.2.1 A model for reconstruction	483
11.3 The Nyquist-Shannon sampling theorem	488
<i>Probing Further: Sampling</i>	492
<i>Probing Further: Impulse Trains</i>	493
11.4 Summary	494
Exercises	495

Digital hardware, including computers, take actions in discrete steps. So they can deal with discrete-time signals, but they cannot directly handle the continuous-time signals that are prevalent in the physical world. This chapter is about the interface between these two worlds, one continuous, the other discrete. A discrete-time signal is constructed by **sampling** a continuous-time signal, and a continuous-time signal is **reconstructed** by **interpolating** a discrete-time signal.



Figure 11.1: Sampler.

11.1 Sampling

A sampler for complex-valued signals is a system

$$\text{Sampler}_T: [\mathbb{R} \rightarrow \mathbb{C}] \rightarrow [\mathbb{Z} \rightarrow \mathbb{C}], \quad (11.1)$$

where T is the **sampling interval** (it has units of seconds/sample). The system is depicted in Figure 11.1. The **sampling frequency** or **sample rate** is $f_s = 1/T$, in units of samples/second (or sometimes, Hertz), or $\omega_s = 2\pi/T$, in units radians/second. If $y = \text{Sampler}_T(x)$ then y is defined by

$$\forall n \in \mathbb{Z}, \quad y(n) = x(nT). \quad (11.2)$$

11.1.1 Sampling a sinusoid

Let $x: \mathbb{R} \rightarrow \mathbb{R}$ be the sinusoidal signal

$$\forall t \in \mathbb{R}, \quad x(t) = \cos(2\pi ft), \quad (11.3)$$

where f is the frequency of the sinewave in Hertz. Let $y = \text{Sampler}_T(x)$. Then

$$\forall n \in \mathbb{Z}, \quad y(n) = \cos(2\pi f n T). \quad (11.4)$$

Although this looks similar to the continuous-time sinusoid, there is a fundamental difference. Because the index n is discrete, it turns out that the frequency f is indistinguishable from frequency $f + f_s$ when looking at the discrete-time signal. This phenomenon is called **aliasing**.

Basics: Units

Recall that frequency can be given with any of various units. The units of the f in (11.3) and (11.4) are Hertz, or cycles/second. In (11.3), it is sensible to give the frequency as $\omega = 2\pi f$, which has units of radians/second. The constant 2π has units of radians/cycle, so the units work out. Moreover, the time argument t has units of seconds, so the argument to the cosine function, $2\pi ft$, has units of radians, as expected.

In the discrete time case (11.4), it is sensible to give the frequency as $2\pi fT$, which has units of radians/sample. The sampling interval T has units of seconds/sample, so again the units work out. Moreover, the integer n has units of samples, so again the argument to the cosine function, $2\pi fnT$, has units of radians, as expected.

In general, when discussing continuous-time signals and their sampled discrete-time signals, it is important to be careful and consistent in the units used, or considerable confusion can result. Many texts talk about **normalized frequency** when discussing discrete-time signals, by which they simply mean frequency in units of radians/sample. This is **normalized** in the sense that it does not depend on the sampling interval.

11.1.2 Aliasing

Consider another sinusoidal signal u given by

$$\forall t \in \mathbb{R}, \quad u(t) = \cos(2\pi(f + Nf_s)t),$$

where N is some integer and $f_s = 1/T$. If $N \neq 0$, then this signal is clearly different from x in (11.3). Let

$$w = \text{Sampler}_T(u).$$

Then for all $n \in \mathbb{Z}$,

$$w(n) = \cos(2\pi(f + Nf_s)nT) = \cos(2\pi fnT + 2\pi Nn) = \cos(2\pi fnT) = y(n),$$

because Nn is an integer. Thus, even though $u \neq x$, $\text{Sampler}_T(u) = \text{Sampler}_T(x)$. Thus, after being sampled, the signals x and u are indistinguishable. This phenomenon is called **aliasing**, presumably because it implies that any discrete-time sinusoidal signal has many continuous-time identities (its “identity” is presumably its frequency).

Example 11.1: A typical sample rate for voice signals is $f_s = 8000$ samples/second, so the sampling interval is $T = 0.125$ msec/sample. A continuous-time sinusoid with frequency 440 Hz, when sampled at this rate, is indistinguishable from a continuous-time sinusoid with frequency 8,440 Hz, when sampled at this same rate.

Example 11.2: Compact discs are created by sampling audio signals at $f_s = 44,100$ Hz, so the sampling interval is about $T = 22.7$ μ sec/sample. A continuous-time sinusoid with frequency 440 Hz, when sampled at this rate, is indistinguishable from a continuous-time sinusoid with frequency 44,540 Hz, when sampled at this same rate.

The frequency domain analysis of the previous chapters relied heavily on complex exponential signals. Recall that a cosine can be given as a sum of two complex exponentials, using Euler’s relation,

$$\cos(2\pi ft) = 0.5(e^{i2\pi ft} + e^{-i2\pi ft}).$$

One of the complex exponentials is at frequency f , and the other is at frequency $-f$. Complex exponentials exhibit the same aliasing behavior that we have illustrated for sinusoids.

Let $x: \mathbb{R} \rightarrow \mathbb{C}$ be

$$\forall t \in \mathbb{R}, \quad x(t) = e^{i2\pi ft}$$

where f is the frequency in Hertz. Let $y = \text{Sampler}_T(x)$. Then for all n in \mathbb{Z} ,

$$y(n) = e^{i2\pi fnT}$$

Consider another complex exponential signal u ,

$$u(t) = e^{i2\pi(f+Nf_s)t}$$

where N is some integer. Let

$$w = \text{Sampler}_T(u).$$

Then for all $n \in \mathbb{Z}$,

$$w(n) = e^{i2\pi(f+Nf_s)nT} = e^{i2\pi fnT} e^{i2\pi Nf_snT} = e^{i2\pi fnT} = y(n),$$

because $e^{i2\pi Nf_snT} = 1$. Thus, as with sinusoids, when we sample a complex exponential signal with frequency f at sample rate f_s , it is indistinguishable from one at frequency $f + f_s$ (or $f + Nf_s$ for any integer N).

There is considerably more to this story. Mathematically, aliasing relates to the periodicity of the frequency domain representation (the DTFT) of a discrete-time signal. We will also see that the effects of aliasing on real-valued signals (like the cosine, but unlike the complex exponential) depend strongly on the conjugate symmetry of the DTFT as well.

11.1.3 Perceived pitch experiment

Consider the following experiment.¹ Generate a discrete-time audio signal with an 8,000 samples/second sample rate according to the formula (11.4). Let the frequency f begin at 0 Hz and sweep upwards through 4 kHz to (at least) 8 kHz. Use the audio output of a computer to listen to the resulting sound. The result is illustrated in Figure 11.2. As the frequency of the continuous-time sinusoid rises, so does the perceived pitch, until the frequency reaches 4 kHz. At that point, the perceived pitch begins to fall rather than rise, even as the frequency of the continuous-time sinusoid continues to rise. It will fall until

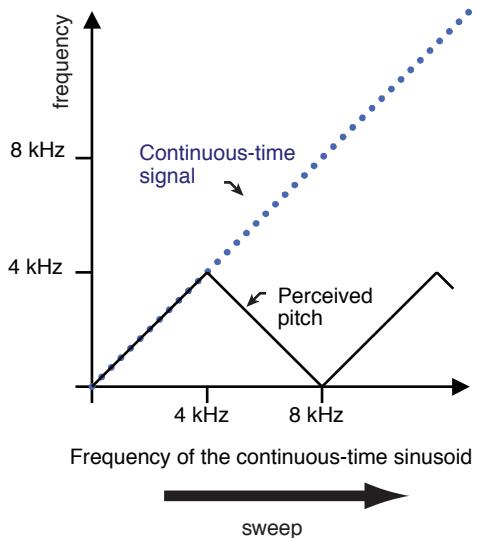


Figure 11.2: As the frequency of a continuous signal increases beyond the Nyquist frequency, the perceived pitch starts to drop.

the frequency reaches 8 kHz, at which point no sound is heard at all (the perceived pitch is 0 Hz). Then the perceived pitch begins to rise again.

That the perceived pitch rises from 0 after the frequency f rises above 8000 Hz is not surprising. We have already determined that in a discrete-time signal, a frequency of f is indistinguishable from a frequency $f + 8000$, assuming the sample rate is 8,000 samples/second. But why does the perceived pitch drop when f rises above 4 kHz?

The frequency 4 kHz, $f_s/2$, is called the **Nyquist frequency**, after Harry Nyquist, an engineer at Bell Labs who, in the 1920s and 1930s, laid much of the groundwork for digital transmission of information. The Nyquist frequency turns out to be a key threshold in the relationship between discrete-time and continuous-time signals, more important even than the sampling frequency. Intuitively, this is because if we sample a sinusoid with a frequency below the Nyquist frequency (below half the sampling frequency), then we take at least two samples per cycle of the sinusoid. It should be intuitively appealing that taking at least two samples per cycle of a sinusoid has some key significance. The two sample minimum allows the samples to capture the oscillatory nature of the sinusoid.

¹This experiment can be performed at <http://www.eecs.berkeley.edu/~al/eecs20/week13/aliasing.html>.

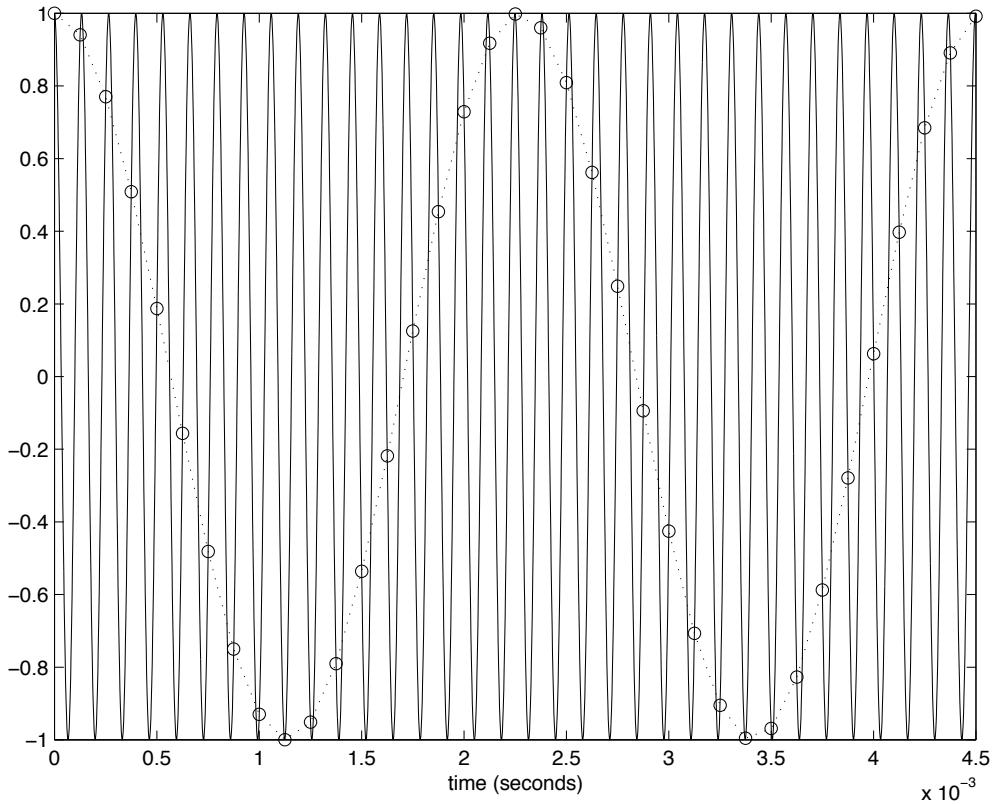


Figure 11.3: A sinusoid at 7.56 kHz and samples taken at 8 kHz.

Fewer than two samples would not do this. However, what happens when fewer than two samples are taken per cycle is not necessarily intuitive. It turns out that the sinusoid masquerades as one of another frequency.

Consider the situation when the frequency f of a continuous-time sinusoid is 7,560 Hz. Figure 11.3 shows 4.5 msec of the continuous-time waveform, together with samples taken at 8 kHz. Notice that the samples trace out another sinusoid. We can determine the frequency of that sinusoid with the help of Figure 11.2, which suggests that the perceived pitch will be $8000 - 7560 = 440$ Hz (the slope of the perceived pitch line is -1 in this region). Indeed, if we listen to the sampled sinusoid, it will be an A-440.

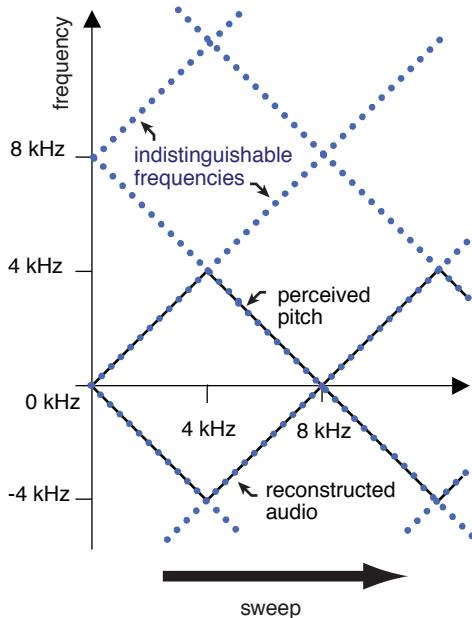


Figure 11.4: As the frequency of a continuous signal increases beyond the Nyquist frequency, the perceived pitch starts to drop because the frequency of the reconstructed continuous-time audio signal stays in the range $-f_s/2$ to $f_s/2$.

Recall that a cosine can be given as a sum of complex exponentials with frequencies that are negatives of one another. Recall further that a complex exponential with frequency f is indistinguishable from one with frequency $f + Nf_s$, for any integer N . A variant of Figure 11.2 that leverages this representation is given in Figure 11.4.

In Figure 11.4, as we sweep the frequency of the continuous-time signal from 0 to 8 kHz, we move from left to right in the figure. The sinusoid consists not only of the rising frequency shown by the dotted line in Figure 11.2, but also of a corresponding falling (negative) frequency as shown in Figure 11.4. Moreover, these two frequencies are indistinguishable, after sampling, from frequencies that are 8 kHz higher or lower, also shown by dotted lines in Figure 11.4.

When the discrete-time signal is converted to a continuous-time audio signal, the hardware performing this conversion can choose any matching pair of positive and negative frequencies. By far the most common choice is to select the matching pair with lowest

frequency, shown in Figure 11.4 by the solid lines behind dotted lines. These result in a sinusoid with frequency between 0 and the Nyquist frequency, $f_s/2$. This is why the perceived pitch falls after sweeping past $f_s/2 = 4$ kHz.

Recall that the frequency-domain representation (i.e. the DTFT) of a discrete-time signal is periodic with period 2π radians/sample. That is, if X is a DTFT, then

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = X(\omega + 2\pi).$$

In radians per second, it is periodic with period $2\pi f_s$. In Hertz, it is periodic with period f_s , the sampling frequency. Thus, in Figure 11.4, the dotted lines represent this periodicity. This periodicity is another way of stating that frequencies separated by f_s are indistinguishable.

11.1.4 Avoiding aliasing ambiguities

Figure 11.4 suggests that even though a discrete-time signal has ambiguous frequency content, it is possible to construct a uniquely defined continuous-time signal from the discrete-time waveform by choosing the one unique frequency for each component that is closest to zero. This will always result in a reconstructed signal that contains only frequencies between zero and the Nyquist frequency.

Correspondingly, this suggests that when sampling a continuous-time signal, if that signal contains only frequencies below the Nyquist frequency, then this reconstruction strategy will perfectly recover the signal. This is an intuitive statement of the [Nyquist-Shannon sampling theorem](#).

If a continuous-time signal contains only frequencies below the Nyquist frequency $f_s/2$, then it can be perfectly reconstructed from samples taken at sampling frequency f_s . This suggests that prior to sampling, it is reasonable to filter a signal to remove components with frequencies above $f_s/2$. A filter that realizes this is called an **anti-aliasing filter**.

Example 11.3: In the telephone network, speech is sampled at 8000 samples per second before being digitized. Prior to this sampling, the speech signal is lowpass filtered to remove frequency components above 4000 Hz. This lowpass filtered speech can then be perfectly reconstructed at the far end of the telephone connection, which receives a stream of samples at 8000 sample per second.

Before probing this further, let us examine in more detail what we mean by reconstruction.

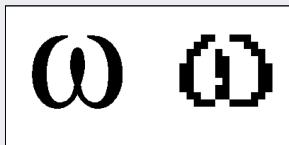
11.2 Reconstruction

Consider a system that constructs a continuous-time signal x from a discrete-time signal y ,

$$\text{DiscToCont}_T : \text{DiscSignals} \rightarrow \text{ContSignals}.$$

Probing Further: Anti-Aliasing for Fonts

When rendering characters on a computer screen, it is common to use **anti-aliasing** to make the characters look better. Consider the two figures below:



At the left is an image of the Greek letter omega. At the right is the result of sampling that rendition by taking only one pixel out of every 100 pixels in the original (every 10-th pixel horizontally and vertically), and then rescaling the image so it has the same size as the one on the left. The original image is discrete, and the resulting image is a smaller discrete image (this process is known as **subsampling**). To the discerning eye, the rendering can be improved considerably. The problem is that the character at the upper left above has hard edges, and hence high (spatial) frequencies. Those high frequencies result in aliasing distortion when subsampling. To improve the result, we first lowpass filter the character (blurring it), and then subsample, as shown below:



The result looks better.



Figure 11.5: Discrete to continuous converter.

This is illustrated in Figure 11.5. Systems that carry out such ‘discrete-to-continuous’ conversion can be realized in any number of ways. Some common examples are illustrated in Figure 11.6, and defined below:

- **zero-order hold:** This means simply that the value of each sample $y(n)$ is held constant for duration T , so that $x(t) = y(n)$ for the time interval from $t = nT$ to $t = (n + 1)T$, as illustrated in figure 11.6(b). Let this system be denoted

$$\text{ZeroOrderHold}_T : \text{DiscSignals} \rightarrow \text{ContSignals}.$$

- **linear interpolation:** Intuitively, this means simply that we connect the dots with straight lines. Specifically, in the time interval from $t = nT$ to $t = (n + 1)T$, $x(t)$ has values that vary along a straight line from $y(n)$ to $y(n + 1)$, as illustrated in figure 11.6(c). Linear interpolation is sometimes called **first-order hold**. Let this system be denoted

$$\text{LinearInterpolator}_T : \text{DiscSignals} \rightarrow \text{ContSignals}.$$

- **ideal interpolation:** It is not yet clear what this should mean, but intuitively, it should result in a smooth curve that passes through the samples, as illustrated in Figure 11.6(d). We will give a precise meaning below. Let this system be denoted

$$\text{IdealInterpolator}_T : \text{DiscSignals} \rightarrow \text{ContSignals}.$$

11.2.1 A model for reconstruction

A convenient mathematical model for reconstruction divides the reconstruction process into a cascade of two systems, as shown in Figure 11.7. Thus

$$x = S(\text{ImpulseGen}_T(y)),$$

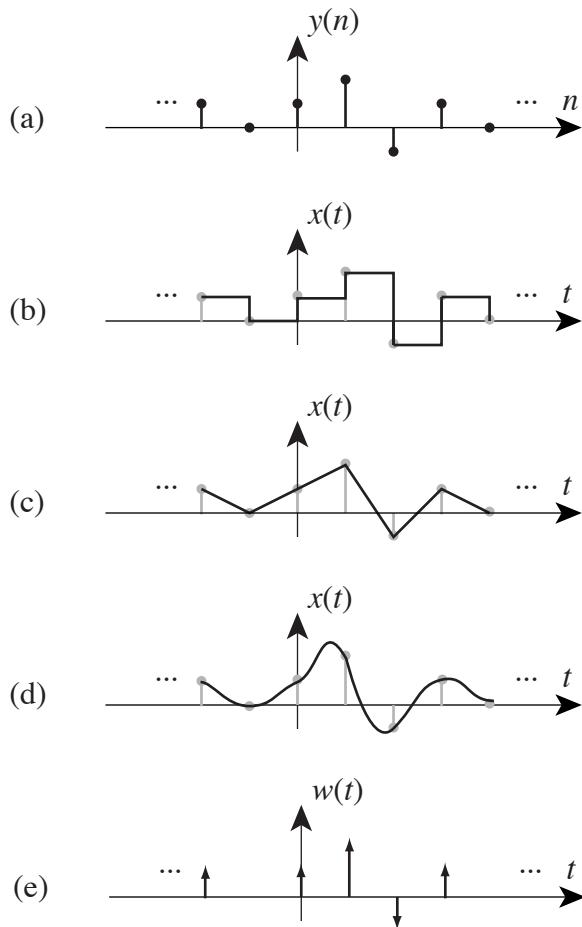


Figure 11.6: A discrete-time signal (a), a continuous-time reconstruction using zero-order hold (b), a reconstruction using linear interpolation (c), a reconstruction using ideal interpolation (d), and a reconstruction using weighted Dirac delta functions (e).

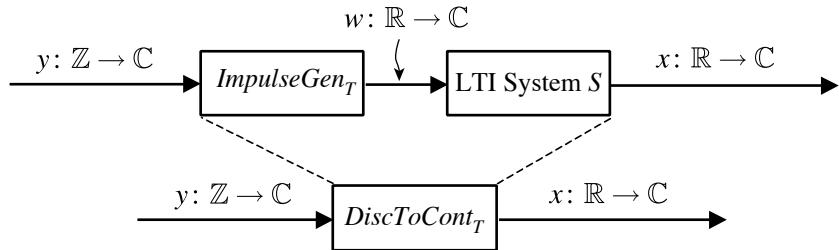


Figure 11.7: A model for reconstruction divides it into two stages.

where S is an LTI system to be determined. The first of these two subsystems,

$$\text{ImpulseGen}_T : \text{DiscSignals} \rightarrow \text{ContSignals},$$

constructs a continuous-time signal, where for all $t \in \mathbb{R}$,

$$w(t) = \sum_{k=-\infty}^{\infty} y(k)\delta(t - kT).$$

This is a continuous-time signal that at each sampling instant kT produces a Dirac delta function with weight equal to the sample value, $y(k)$. This signal is illustrated in Figure 11.6(e). It is a mathematical abstraction, since everyday engineering systems do not exhibit the singularity-like behavior of the Dirac delta function. Nonetheless, it is a useful mathematical abstraction.

The second system in Figure 11.7, S , is a continuous-time LTI filter with an impulse response that determines the interpolation method. The impulse responses that yield the interpolation methods in figure 11.6(b-e) are shown in figure 11.8(b-e). If

$$\forall t \in \mathbb{R}, \quad h(t) = \begin{cases} 1 & 0 \leq t < T \\ 0 & \text{otherwise} \end{cases}$$

then the interpolation method is zero-order hold. If

$$\forall t \in \mathbb{R}, \quad h(t) = \begin{cases} 1 + t/T & -T < t < 0 \\ 1 - t/T & 0 \leq t < T \\ 0 & \text{otherwise} \end{cases}$$

then the interpolation method is linear. If the impulse response is

$$\forall t \in \mathbb{R}, \quad h(t) = \frac{\sin(\pi t/T)}{\pi t/T}$$

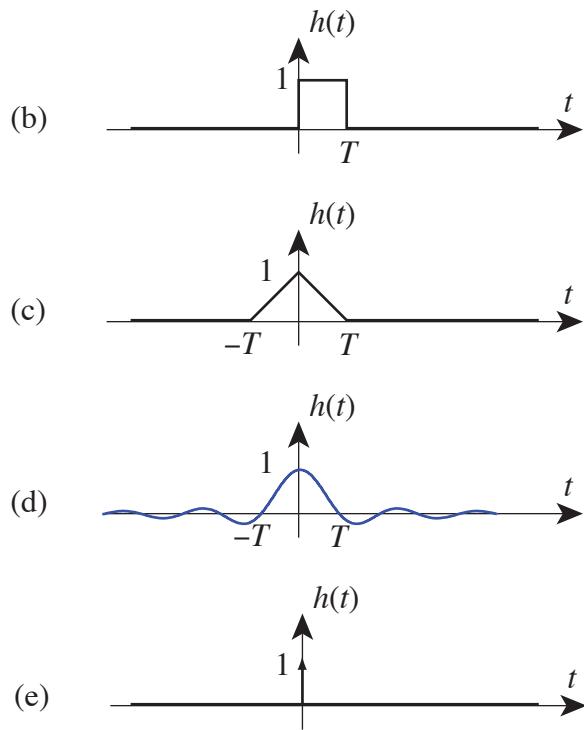


Figure 11.8: The impulse responses for the LTI system S in figure 11.7 that yield the interpolation methods in figure 11.6(b-e).

then the interpolation method is ideal. The above impulse response is called a **sinc function**, and its Fourier transform, from table 10.4, is given by

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = \begin{cases} T & \text{if } |\omega| \leq \pi/T \\ 0 & \text{otherwise} \end{cases}$$

Notice that the Fourier transform is zero at all frequencies above π/T radians/second, or $f_s/2$ Hz, the Nyquist frequency. It is this characteristic that makes it ideal. It precisely performs the strategy illustrated in Figure 11.4, where among all indistinguishable frequencies we select the ones between $-f_s/2$ and $f_s/2$.

If we let $Sinc_T$ denote the LTI system S when the impulse response is a sinc function, then

$$IdealInterpolator_T = Sinc_T \circ ImpulseGen_T.$$

In practice, ideal interpolation is difficult to accomplish. From the expression for the sinc function we can understand why. First, this impulse response is not causal. Second, it is infinite in extent. More importantly, its magnitude decreases rather slowly as t increases or decreases (proportional to $1/t$ only). Thus, truncating it at finite length leads to substantial errors.

If the impulse response of S is

$$h(t) = \delta(t),$$

where δ is the Dirac delta function, then the system S is a pass-through system, and the reconstruction consists of weighted delta functions.

11.3 The Nyquist-Shannon sampling theorem

We can now give a precise statement of the **Nyquist-Shannon sampling theorem**:

If x is a continuous-time signal with Fourier transform X and if $X(\omega)$ is zero outside the range $-\pi/T < \omega < \pi/T$ radians/second, then

$$x = \text{IdealInterpolator}_T(\text{Sampler}_T(x)).$$

We can state this theorem slightly differently. Suppose x is a continuous-time signal with no frequency larger than some f_0 Hertz. Then x can be recovered from its samples if $f_0 < f_s/2$, the Nyquist frequency.

A formal proof of this theorem involves some technical difficulties (it was first given by Claude Shannon of Bell Labs in the late 1940s). But we can get the idea from the following three-step argument (see figure 11.9).

Step 1. Let x be a continuous-time signal with Fourier transform X . At this point we do not require that $X(\omega)$ be zero outside the range $-\pi/T < \omega < \pi/T$. We sample x with sampling interval T to get the discrete-time signal

$$y = \text{Sampler}_T(x).$$

It can be shown (see box on page 492) that the DTFT of y is related to the CTFT of x by

$$Y(\omega) = \frac{1}{T} \sum_{k=-\infty}^{\infty} X\left(\frac{\omega - 2\pi k}{T}\right).$$

This important relation says that the DTFT Y of y is the sum of the CTFT X with copies of it shifted by multiples of $2\pi/T$. Also, the frequency axis is normalized by dividing ω by T . There are two cases to consider, depending on whether the shifted copies overlap.

First, if $X(\omega) = 0$ outside the range $-\pi/T < \omega < \pi/T$, then the copies will not overlap, and in the range $-\pi < \omega < \pi$,

$$Y(\omega) = \frac{1}{T} X\left(\frac{\omega}{T}\right). \quad (11.5)$$

In this range of frequencies, Y has the same shape as X , scaled by $1/T$. This relationship between X and Y is illustrated in figure 11.10, where X is drawn with a triangular shape.

In the second case, illustrated in figure 11.11, X does have non-zero frequency components higher than π/T . Notice that in the sampled signal, the frequencies in the vicinity

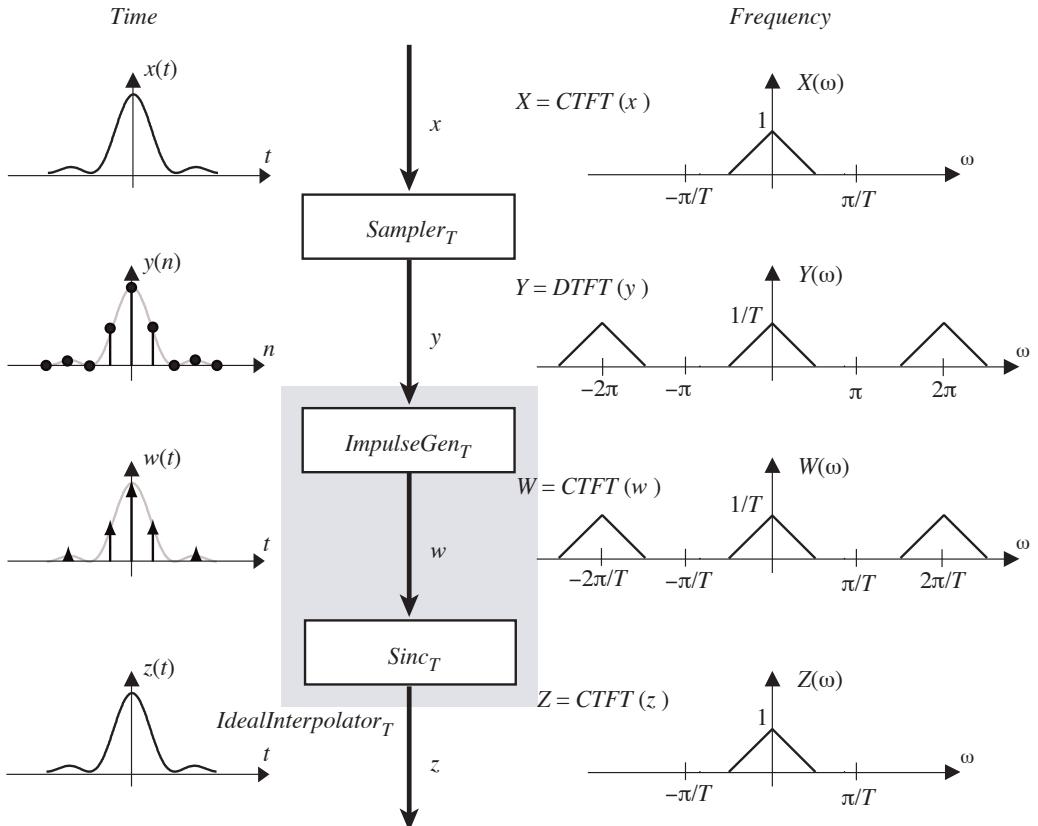


Figure 11.9: Steps in the justification of the Nyquist-Shannon sampling theorem.

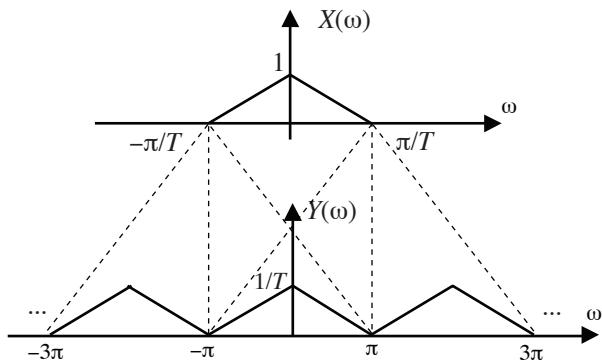


Figure 11.10: Relationship between the CTFT of a continuous-time signal and the DTFT of its discrete-time samples. The DTFT is the sum of the CTFT and its copies shifted by multiples of $2\pi/T$, the sampling frequency in radians per second. The frequency axis is also normalized.

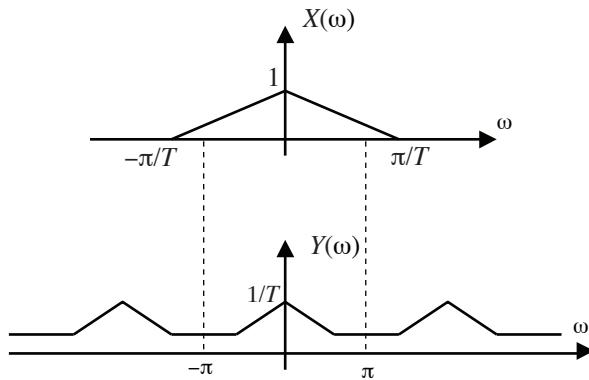


Figure 11.11: Relationship between the CTFT of a continuous-time signal and the DTFT of its discrete-time samples when the continuous-time signal has a broad enough bandwidth to introduce aliasing distortion.

of π are distorted by the overlapping of frequency components above and below π/T in the original signal. This distortion is called **aliasing distortion**.

We continue with the remaining steps, following the signals in figure 11.9.

Step 2. Let w be the signal produced by the impulse generator,

$$\forall t \in \mathbb{R}, \quad w(t) = \sum_{n=-\infty}^{\infty} y(n)\delta(t - nT).$$

The Fourier Transform of w is $W(\omega) = Y(\omega T)$ (see box on page 492).

Step 3. Let z be the output of the $IdealInterpolator_T$. Its Fourier transform is simply

$$\begin{aligned} Z(\omega) &= W(\omega)S(\omega) \\ &= Y(\omega T)S(\omega), \end{aligned}$$

where $S(\omega)$ is the frequency response of the $IdealInterpolator_T$ reconstruction filter. As seen in exercise 21 of Chapter 10,

$$S(\omega) = \begin{cases} T & -\pi/T < \omega < \pi/T \\ 0 & \text{otherwise} \end{cases} \quad (11.6)$$

Substituting for S and Y , we get

$$\begin{aligned} Z(\omega) &= \begin{cases} TY(\omega T) & -\pi/T < \omega < \pi/T \\ 0 & \text{otherwise} \end{cases} \\ &= \begin{cases} \sum_{k=-\infty}^{\infty} X(\omega - 2\pi k/T) & -\pi/T < \omega < \pi/T \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

If $X(\omega)$ is zero for $|\omega|$ larger than the Nyquist frequency π/T , then we conclude that

$$\forall \omega \in \mathbb{R}, \quad Z(\omega) = X(\omega).$$

That is, w is identical to x . This proves the Nyquist-Shannon result.

However, if $X(\omega)$ does have non-zero values for some $|\omega|$ larger than the Nyquist frequency, then z will be different from x , as illustrated in figure 11.11.

Probing Further: Sampling

We construct a mathematical model for sampling a pulse stream given by

$$\forall t \in \mathbb{R}, \quad p(t) = \sum_{k=-\infty}^{\infty} \delta(t - kT),$$

where δ is the [Dirac delta function](#). Let $y(n) = x(nT)$ be a sampling of the continuous-time signal x with sampling period T . Construct first an intermediate continuous-time signal $w(t) = x(t)p(t)$. We can show that the CTFT of w is equal to the DTFT of y . This gives us a way to relate the CTFT of x to the DTFT of its samples y . Recall that multiplication in the time domain results in convolution in the frequency domain (see table 10.9), so

$$W(\omega) = \frac{1}{2\pi} X(\omega) * P(\omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\Omega) P(\omega - \Omega) d\Omega.$$

It can be shown (see box on page 493) that the CTFT of $p(t)$ is

$$P(\omega) = \frac{2\pi}{T} \sum_{k=-\infty}^{\infty} \delta(\omega - k \frac{2\pi}{T}), \quad \text{so}$$

$$\begin{aligned} W(\omega) &= \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\Omega) \frac{2\pi}{T} \sum_{k=-\infty}^{\infty} \delta(\omega - \Omega - k \frac{2\pi}{T}) d\Omega \\ &= \frac{1}{T} \sum_{k=-\infty}^{\infty} \int_{-\infty}^{\infty} X(\Omega) \delta(\omega - \Omega - k \frac{2\pi}{T}) d\Omega \\ &= \frac{1}{T} \sum_{k=-\infty}^{\infty} X(\omega - k \frac{2\pi}{T}) \end{aligned}$$

where the last equality follows from the sifting property (9.11). The next step is to show that $Y(\omega) = W(\omega/T)$. We leave this as an exercise. From this, the basic Nyquist-Shannon result follows,

$$Y(\omega) = \frac{1}{T} \sum_{k=-\infty}^{\infty} X\left(\frac{\omega - 2\pi k}{T}\right).$$

This relates the CTFT X of the signal being sampled x to the DTFT Y of the discrete-time result y .

Probing Further: Impulse Trains

Consider a signal p consisting of periodically repeated Dirac delta functions with period T ,

$$\forall t \in \mathbb{R}, \quad p(t) = \sum_{k=-\infty}^{\infty} \delta(t - kT).$$

This signal has the Fourier series expansion

$$\forall t \in \mathbb{R}, \quad p(t) = \sum_{m=-\infty}^{\infty} \frac{1}{T} e^{i\omega_0 m t},$$

where the fundamental frequency is $\omega_0 = 2\pi/T$. This can be verified by applying the formula from table 10.5. That formula, however, gives an integration range of 0 to the period, which in this case is T . This integral covers one period of the periodic signal, but starts and ends on a delta function in p . To avoid the resultant mathematical subtleties, we can integrate from $-T/2$ to $T/2$, getting Fourier series coefficients

$$\forall m \in \mathbb{Z}, \quad P_m = \frac{1}{T} \int_{-T/2}^{T/2} \left[\sum_{k=-\infty}^{\infty} \delta(t - kT) \right] e^{i\omega_0 m t} dt.$$

The integral is now over a range that includes only one of the delta functions. The kernel of the integral is zero except when $t = 0$, so by the sifting rule, the integral evaluates to 1. Thus, all Fourier series coefficients are $P_m = 1/T$. Using the relationship between the Fourier series and the Fourier Transform of a periodic signal (from Section 10.6.3), we can write the continuous-time Fourier transform of p as

$$\forall \omega \in \mathbb{R}, \quad P(\omega) = \frac{2\pi}{T} \sum_{k=-\infty}^{\infty} \delta\left(\omega - \frac{2\pi}{T} k\right).$$

11.4 Summary

The acts of sampling and reconstructing signals bridge the world of continuous-time physical signals with the discrete computational world. The periodicity of frequencies in the discrete world implies that for each discrete-time sinusoidal signal, there are multiple corresponding discrete-time frequencies. These frequencies are aliases of one another. When a signal is sampled, these frequencies become indistinguishable, and aliasing distortion may result. The Nyquist-Shannon sampling theorem gives a simple condition under which aliasing distortion is avoided. Specifically, if the signal contains no sinusoidal components with frequencies higher than half the sampling frequency, then there will be no aliasing distortion. Half the sampling frequency is called the Nyquist frequency because of this key result.

Exercises

Each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **E** Consider the continuous-time signal

$$x(t) = \cos(10\pi t) + \cos(20\pi t) + \cos(30\pi t).$$

- (a) Find the fundamental frequency. Give the units.
- (b) Find the Fourier series coefficients A_0, A_1, \dots and ϕ_1, ϕ_2, \dots
- (c) Let y be the result of sampling this signal with sampling frequency 10 Hz.
Find the fundamental frequency for y , and give the units.
- (d) For the same y , find the discrete-time Fourier series coefficients, A_0, A_1, \dots and ϕ_1, \dots .
- (e) Find

$$w = \text{IdealInterpolator}_T(\text{Sampler}_T(x))$$

for $T = 0.1$ seconds.

- (f) Is there any aliasing distortion caused by sampling at 10 Hz? If there is, describe the aliasing distortion in words.
 - (g) Give the smallest sampling frequency that avoids aliasing distortion.
2. **E** Verify that Sampler_T defined by (11.1) and (11.2) is linear but not time invariant.
 3. **E** A real-valued sinusoidal signal with a negative frequency is always exactly equal to another sinusoid with positive frequency. Consider a real-valued sinusoid with a negative frequency -440 Hz,

$$y(n) = \cos(-2\pi 440nT + \phi).$$

Find a positive frequency f and phase θ such that

$$y(n) = \cos(2\pi fnT + \theta).$$

4. T Consider a continuous-time signal x where for all $t \in \mathbb{R}$,

$$x(t) = \sum_{k=-\infty}^{\infty} r(t-k).$$

where

$$r(t) = \begin{cases} 1 & 0 \leq t < 0.5 \\ 0 & \text{otherwise} \end{cases}.$$

- (a) Is $x(t)$ periodic? If so, what is the period?
- (b) Suppose that $T = 1$. Give a simple expression for $y = \text{Sampler}_T(x)$.
- (c) Suppose that $T = 0.5$. Give a simple expression for $y = \text{Sampler}_T(x)$ and $z = \text{IdealInterpolator}_T(\text{Sampler}_T(x))$.
- (d) Find an upper bound for T (in seconds) such that

$$x = \text{IdealInterpolator}_T(\text{Sampler}_T(x)),$$

or argue that no value of T makes this assertion true.

5. T Consider a continuous-time signal x with the following finite Fourier series expansion,

$$\forall t \in \mathbb{R}, \quad x(t) = \sum_{k=0}^4 \cos(k\omega_0 t)$$

where $\omega_0 = \pi/4$ radians/second.

- (a) Give an upper bound on T (in seconds) such that

$$x = \text{IdealInterpolator}_T(\text{Sampler}_T(x)).$$

- (b) Suppose that $T = 4$ seconds. Give a simple expression for $y = \text{Sampler}_T(x)$.
- (c) For the same $T = 4$ seconds, give a simple expression for

$$w = \text{IdealInterpolator}_T(\text{Sampler}_T(x)).$$

6. T Consider a continuous-time audio signal x with CTFT shown in Figure 11.12. Note that it contains no frequencies beyond 10 kHz. Suppose it is sampled at 40 kHz to yield a signal that we will call x_{40} . Let X_{40} be the DTFT of x_{40} .

- (a) Sketch $|X_{40}(\omega)|$ and carefully mark the magnitudes and frequencies.

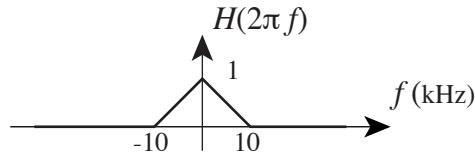


Figure 11.12: CTFT of an audio signal considered in exercise 6.

- (b) Suppose x is sampled at 20,000 samples/second. Let x_{20} be the resulting sampled signal and X_{20} its DTFT. Sketch and compare x_{20} and x_{40} .
- (c) Now suppose x is sampled at 15,000 samples/second. Let x_{15} be the resulting sampled signal and X_{15} its DTFT. Sketch and compare X_{20} and X_{15} . Make sure that your sketch shows aliasing distortion.
7. C Consider two continuous-time sinusoidal signals given by

$$x_1(t) = \cos(\omega_1 t)$$

$$x_2(t) = \cos(\omega_2 t),$$

with frequencies ω_1 and ω_2 radians/second such that

$$0 \leq \omega_1 \leq \pi/T \quad \text{and} \quad 0 \leq \omega_2 \leq \pi/T.$$

Show that if $\omega_1 \neq \omega_2$ then

$$\text{Sampler}_T(x_1) \neq \text{Sampler}_T(x_2).$$

I.e., the two distinct sinusoids cannot be aliases of one another if they both have frequencies below the Nyquist frequency. **Hint:** Try evaluating the sampled signals at $n = 1$.

12

Stability

Contents

12.1 Boundedness and stability	503
12.1.1 Absolutely summable and absolutely integrable	503
12.1.2 Stability	505
<i>Probing Further: Stable systems and their impulse response</i>	507
12.2 The Z transform	509
12.2.1 Structure of the region of convergence	511
12.2.2 Stability and the Z transform	516
12.2.3 Rational Z transforms and poles and zeros	517
12.3 The Laplace transform	521
12.3.1 Structure of the region of convergence	523
12.3.2 Stability and the Laplace transform	527
12.3.3 Rational Laplace transforms and poles and zeros	528
12.4 Summary	530
Exercises	532

The four Fourier transforms prove to be useful tools for analyzing signals and systems. When a system is LTI, it is characterized by its frequency response H , and its input x and output y are related simply by

$$\forall \omega \in \mathbb{R}, \quad Y(\omega) = H(\omega)X(\omega),$$

where Y is the Fourier transform of y , and X is the Fourier transform of x .

However, we ignored a lurking problem. Any of the three Fourier transforms, X , Y , or H , may not exist. Suppose for example that x is a discrete-time signal. Then its Fourier transform (the DTFT) is given by

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = \sum_{n=-\infty}^{\infty} x(n)e^{-i\omega n}. \quad (12.1)$$

This is an infinite sum, properly viewed as the limit

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = \lim_{N \rightarrow \infty} \sum_{n=-N}^{N} x(n)e^{-i\omega n}. \quad (12.2)$$

As with all such limits, there is a risk that it does not exist. If the limit does not exist for any $\omega \in \mathbb{R}$, then the Fourier transform becomes mathematically treacherous at best (involving, for example, Dirac delta functions), and mathematical nonsense at worst.

Example 12.1: Consider the sequence

$$x(n) = \begin{cases} 0, & n \leq 0 \\ a^{n-1}, & n > 0 \end{cases},$$

where $a > 1$ is a constant. Plugging into (12.1), the Fourier transform should be

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = \sum_{n=0}^{\infty} a^{n-1} e^{-i\omega n}.$$

At $\omega = 0$, it is easy to see that this sum is infinite (every term in the sum is greater than or equal to one). At other values of ω , there are also problems. For example, at $\omega = \pi$, the terms of the sum alternate in sign and increase in magnitude as n gets larger. The limit (12.2) clearly will not exist.

A similar problem arises with continuous-time signals. If x is a continuous-time signal, then its Fourier transform (the CTFT) is given by

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = \int_{-\infty}^{\infty} x(t)e^{-i\omega t} dt. \quad (12.3)$$

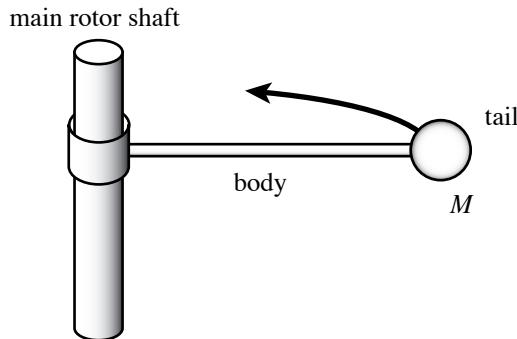


Figure 12.1: A highly simplified helicopter.

Again, there is a risk that this integral does not exist.

This chapter studies signals for which the Fourier transform does not exist. Such signals prove to be both common and useful. The signal in example 12.1 gives the bank balance of example 5.12 when an initial deposit of one dollar is made, and no further deposits or withdrawals are made (thus, it is the impulse response of the bank account). This signal grows without bound, and any signal that grows without bound will cause difficulties when using the Fourier transform.

The bank account is said to be an **unstable system**, because its output can grow without bound even when the input is always bounded. Such unstable systems are common, so it is unfortunate that the frequency domain methods we have studied so far do not appear to apply.

Example 12.2: A helicopter is intrinsically an unstable system, requiring an electronic or mechanical feedback control system to stabilize it. It has two rotors, one above, which provides lift, and one on the tail. Without the rotor on the tail, the body of the helicopter would start to spin. The rotor on the tail counteracts that spin. However, the force produced by the tail rotor must perfectly counteract the torque of the main rotor, or the body will spin.

A highly simplified version of the helicopter is shown in figure 12.1. The body of the helicopter is modeled as a horizontal arm with moment of inertia M . The tail rotor goes on the end of this arm. The body of the helicopter rotates freely around

the main rotor shaft. Due to **Newton's third law**, the main rotor will tend to cause the body to rotate by applying a torque as suggested by the curved arrow. The tail rotor will have to counter that torque to keep the body of the helicopter from spinning.

Let the input x to the system be the net torque on the tail of the helicopter, as a function of time. That is, at time t , $x(t)$ is the sum of the torque induced by the main rotor shaft and the counteracting torque exerted by the tail rotor. Let the output y be the velocity of rotation of the body. From basic physics, torque equals moment of inertia times rotational acceleration. The rotational acceleration is \dot{y} , the derivative of y , so

$$\dot{y}(t) = x(t)/M.$$

Integrating both sides, assuming that the initial velocity of rotation is zero, we get the output as a function of the input,

$$\forall t \in \mathbb{R}, \quad y(t) = \frac{1}{M} \int_0^t x(\tau) d\tau.$$

It is now easy to see that this system is unstable. Let the input be $x = u$, where u is the **unit step**, given by

$$\forall t \in \mathbb{R}, \quad u(t) = \begin{cases} 0, & t < 0 \\ 1, & t \geq 0 \end{cases}. \quad (12.4)$$

This input is clearly bounded. It never exceeds one in magnitude. However, the output grows without bound.

In practice, a helicopter uses a feedback system to determine how much torque to apply at the tail rotor to keep the body of the helicopter straight. We will see how to do this in Chapter 14.

In this chapter we develop the basics of modeling unstable systems in the frequency domain. We define two new transforms, called the **Z transform** and **Laplace transform**. The Z transform is a generalization of the DTFT and applies to discrete-time signals. The Laplace transform is a generalization of the CTFT and applies to continuous-time signals. These generalizations support frequency-domain analysis of signals that do not have a Fourier transform, and thus allow analysis of unstable systems.

In particular, let \hat{X} denote the Laplace or Z transform of x , depending on whether it is a continuous or discrete-time signal. Then the Laplace or Z transform of the output of an LTI system is given by $\hat{Y} = \hat{H}\hat{X}$, where \hat{H} is the Laplace or Z transform of the impulse response. This relation applies even when the system is unstable. Thus, these transforms take the place of the Fourier transform when the Fourier transform cannot be used. \hat{H} is called the **transfer function** of the LTI system, and it is a generalization of the frequency response.

12.1 Boundedness and stability

In this section, we identify a simple condition for the existence of the DTFT, which is that the signal be **absolutely summable**. We then define a **stable system** and show that an LTI system is stable if and only if its impulse response is absolutely summable. Continuous-time signals are slightly more complicated, requiring slightly more than that they be **absolutely integrable**. The conditions for the existence of the CTFT are called the **Dirichlet conditions**, and once again, if the impulse response of an LTI system satisfies these conditions, then it is stable.

12.1.1 Absolutely summable and absolutely integrable

A discrete-time signal x is said to be **absolutely summable** if

$$\sum_{n=-\infty}^{\infty} |x(n)|$$

exists and is finite. The “absolutely” in “absolutely summable” refers to the absolute value (or magnitude) in the summation. The sum is said to **converge absolutely**. The following simple fact gives a condition for the existence of the DTFT:

If a discrete-time signal x is absolutely summable, then its DTFT exists and is finite for all ω .

To see that this is true, note that the DTFT exists and is finite if and only if

$$\forall \omega \in \mathbb{R}, \quad |X(\omega)| = \left| \sum_{n=-\infty}^{\infty} x(n)e^{-i\omega n} \right|$$

exists and is finite. But

$$\left| \sum_{n=-\infty}^{\infty} x(n)e^{-i\omega n} \right| \leq \sum_{n=-\infty}^{\infty} |x(n)e^{-i\omega n}| \quad (12.5)$$

$$= \sum_{n=-\infty}^{\infty} |x(n)| \cdot |e^{-i\omega n}| \quad (12.6)$$

$$= \sum_{n=-\infty}^{\infty} |x(n)|. \quad (12.7)$$

This follows from the following facts about complex (or real) numbers:

$$|a+b| \leq |a| + |b|,$$

which is known as the **triangle inequality** (and generalizes to infinite sums),

$$|ab| = |a| \cdot |b|,$$

and

$$\forall \theta \in \mathbb{R}, \quad |e^{i\theta}| = 1.$$

We can conclude from (12.5) that

$$\forall \omega \in \mathbb{R}, \quad |X(\omega)| \leq \sum_{n=-\infty}^{\infty} |x(n)|.$$

This means that if x is absolutely summable, then the DTFT exists and is finite. It follows from the fact that if a sum converges absolutely, then it also converges (without the absolute value).

A continuous-time signal x is said to be **absolutely integrable** if

$$\int_{-\infty}^{\infty} |x(t)| dt$$

exists and is finite. A similar argument to that above (with summations replaced by integrals) suggests that if a continuous-time signal x is absolutely integrable, then its CTFT should exist and be finite for all ω . However, caution is in order. Integrals are more complicated than summations, and we need some additional conditions to ensure that the integral is well defined. We can use essentially the same conditions given on page 297 for the convergence of the continuous-time Fourier series. These are called the **Dirichlet conditions**, and require three things:

- x is absolutely integrable;
- in any finite interval, x is of **bounded variation**, meaning that there are no more than a finite number of maxima or minima; and
- in any finite interval, x is continuous at all but a finite number of points.

Most any signal of practical engineering importance satisfies the last two conditions, so the important condition is that it be absolutely integrable. We will henceforth assume without comment that all continuous-time signals satisfy the last two conditions, so the only important condition becomes the first one. Under this assumption, the following simple fact gives a condition for the existence of the CTFT:

An absolutely integrable continuous-time signal x has a CTFT X , and its CTFT $X(\omega)$ is finite for all $\omega \in \mathbb{R}$.

12.1.2 Stability

A system is said to be **bounded-input bounded-output stable (BIBO stable or just stable)** if the output signal is bounded for all input signals that are bounded.

Consider a discrete-time system with input x and output y . An input is bounded if there is a real number $M < \infty$ such that $|x(k)| \leq M$ for all $k \in \mathbb{Z}$. An output is bounded if there is a real number $N < \infty$ such that $|y(n)| \leq N$ for all $n \in \mathbb{Z}$. The system is stable if for any input bounded by M , there is some bound N on the output.

Consider a discrete-time LTI system with impulse response h . The output y corresponding to the input x is given by the convolution sum,

$$\forall n \in \mathbb{Z}, \quad y(n) = (h * x)(n) = \sum_{m=-\infty}^{\infty} h(m)x(n-m). \quad (12.8)$$

Suppose that the input x is bounded with bound M . Then, applying the triangle inequality, we see that

$$|y(n)| \leq \sum_{m=-\infty}^{\infty} |h(m)||x(n-m)| \leq M \sum_{m=-\infty}^{\infty} |h(m)|.$$

Thus, if the impulse response is absolutely summable, then the output is bounded with bound

$$N = M \sum_{m=-\infty}^{\infty} |h(m)|.$$

Thus, if the impulse response of an LTI system is absolutely summable, then the system is stable. The converse is also true, but more difficult to show. That is, if the system is stable, then the impulse response is absolutely summable (see box on page 507). The same argument applies for continuous-time signals, so in summary:

A discrete-time LTI system is stable if and only if its impulse response is absolutely summable. A continuous-time LTI system is stable if and only if its impulse response is absolutely integrable.

The following example makes use of the **geometric series identity**, valid for any real or complex a where $|a| < 1$,

$$\sum_{m=0}^{\infty} a^m = \frac{1}{1-a}. \quad (12.9)$$

To verify this identity, just multiply both sides by $1 - a$ to get

$$\sum_{m=0}^{\infty} a^m - a \sum_{m=0}^{\infty} a^m = 1.$$

This can be written

$$a^0 + \sum_{m=1}^{\infty} a^m - \sum_{m=1}^{\infty} a^m = 1.$$

Now note that $a^0 = 1$ and that the two sums are identical. Since $|a| < 1$, the sums converge, and hence they cancel, so the identity is true.

Example 12.3: As in example 12.1, the impulse response of the bank account of example 5.12 is

$$h(n) = \begin{cases} 0, & n \leq 0 \\ a^{n-1}, & n > 0 \end{cases},$$

where $a > 1$ is a constant that reflects the interest rate. This impulse response is not absolutely summable, so this system is not stable. A system with the same impulse response, but where $0 < a < 1$, however, would be stable, as is easily verified using

Probing Further: Stable systems and their impulse response

Consider a discrete-time LTI system with real-valued impulse response h . In this box, we show that if the system is stable, then its impulse response is absolutely summable. To show this, we show the contrapositive.^a That is, we show that if the impulse response is not absolutely summable, then the system is not stable. To do this, suppose that the impulse response is not absolutely summable. That is, the sum

$$\sum_{n=-\infty}^{\infty} |h(n)|$$

is not bounded. To show that the system is not stable, we need only to find one bounded input for which the output either does not exist or is not bounded. Such an input is given by

$$\forall n \in \mathbb{Z}, \quad x(n) = \begin{cases} h(-n)/|h(-n)|, & h(n) \neq 0 \\ 0, & h(n) = 0 \end{cases}$$

This input is clearly bounded, with bound $M = 1$. Plugging this input into the convolution sum (12.8) and evaluating at $n = 0$ we get

$$\begin{aligned} y(0) &= \sum_{m=-\infty}^{\infty} h(m)x(-m) \\ &= \sum_{m=-\infty}^{\infty} (h(m))^2 / |h(m)| \\ &= \sum_{m=-\infty}^{\infty} |h(m)|, \end{aligned}$$

where the last step follows from the fact that for real-valued $h(m)$, $(h(m))^2 = |h(m)|^2$. But since the impulse response is not absolutely summable, $y(0)$ does not exist or is not finite, so the system is not stable.

A nearly identical argument works for continuous-time systems.

^aThe contrapositive of a statement “if p then q ” is “if not q then not p .” The contrapositive is true if and only if the original statement is true.

(12.9). To use this identity, note that

$$\begin{aligned}\sum_{n=-\infty}^{\infty} |h(n)| &= \sum_{n=1}^{\infty} a^{n-1} \\ &= \sum_{m=0}^{\infty} a^m \\ &= \frac{1}{1-a},\end{aligned}$$

where the second step results from a change of variables, letting $m = n - 1$.

Example 12.4: Consider an LTI system with impulse response $h(t) = a^t u(t)$, for all $t \in \mathbb{R}$. where $a > 0$ is a real number and u is the unit step, given by (12.4). To determine whether this system is stable, we need to determine whether the impulse response is absolutely integrable. That is, we need to determine whether the following integral exists and is finite,

$$\int_{-\infty}^{\infty} |a^t u(t)| dt.$$

Since $a > 0$ and u is the unit step, this simplifies to

$$\int_0^{\infty} a^t dt.$$

From calculus, we know that this integral is infinite if $a \geq 1$, so the system is unstable if $a \geq 1$. The integral is finite if $0 < a < 1$ and is equal to

$$\int_0^{\infty} a^t dt = -1/\ln(a).$$

Thus, the system is stable if $0 < a < 1$.

As we see, when all pertinent signals are absolutely summable (or absolutely integrable), then we can use Fourier transform techniques with confidence. However, many useful signals do not fall in this category (the unit step and sinusoidal signals, for example). Moreover, many useful systems have impulse responses that are not absolutely summable (or absolutely integrable). Fortunately, we can generalize the DTFT and CTFT to get the Z transform and Laplace transform, which easily handle signals that are not absolutely summable.

12.2 The Z transform

Consider a discrete-time signal x that is not absolutely summable. Consider the scaled signal x_r given by

$$\forall n \in \mathbb{Z}, \quad x_r(n) = x(n)r^{-n}, \quad (12.10)$$

for some real number $r \geq 0$. Often, this signal is absolutely summable when r is chosen appropriately. This new signal, therefore, will have a DTFT, even if x does not.

Example 12.5: Continuing with example 12.3, the impulse response of the bank account is

$$h(n) = \begin{cases} 0, & n \leq 0 \\ a^{n-1}, & n > 0 \end{cases},$$

where $a > 1$. This system is not stable. However, the scaled signal

$$h_r(n) = h(n)r^{-n}$$

is absolutely summable if $r > a$. Its DTFT is

$$\begin{aligned}
 \forall r > a, \forall \omega \in \mathbb{R}, \quad H_r(\omega) &= \sum_{m=-\infty}^{\infty} h(m)r^{-m}e^{-i\omega m} \\
 &= \sum_{m=1}^{\infty} a^{m-1}(re^{i\omega})^{-m} \\
 &= \sum_{n=0}^{\infty} a^n(re^{i\omega})^{-n-1} \\
 &= (re^{i\omega})^{-1} \sum_{n=0}^{\infty} (a(re^{i\omega})^{-1})^n \\
 &= \frac{(re^{i\omega})^{-1}}{1 - a(re^{i\omega})^{-1}}.
 \end{aligned}$$

The second step is by change of variables, $n = m - 1$, and the final step applies the geometric series identity (12.9).

In general, the DTFT of the scaled signal x_r in (12.10) is

$$\forall \omega \in \mathbb{R}, \quad X_r(\omega) = \sum_{m=-\infty}^{\infty} x(m)(re^{i\omega})^{-m}.$$

Notice that this is a function not just of ω , but also of r , and in fact, we are only sure it is valid for values of r that yield an absolutely summable signal h_r . If we define the complex number

$$z = re^{i\omega}$$

then we can write this DTFT as

$$\boxed{\forall z \in \text{RoC}(x), \quad \hat{X}(z) = \sum_{m=-\infty}^{\infty} x(m)z^{-m}}, \quad (12.11)$$

where \hat{X} is a function called the **Z transform** of x ,

$$\hat{X}: \text{RoC}(x) \rightarrow \mathbb{C}$$

where $\text{RoC}(x) \subset \mathbb{C}$ is given by

$$\boxed{\text{RoC}(x) = \{z = re^{i\omega} \in \mathbb{C} \mid x(n)r^{-n} \text{ is absolutely summable.}\}} \quad (12.12)$$

The term *RoC* is shorthand for **region of convergence**.

Example 12.6: Continuing example 12.5, we can recognize from the form of $H_r(\omega)$ that the Z transform of the impulse response h is

$$\forall z \in \text{RoC}(h), \quad \hat{H}(z) = \frac{z^{-1}}{1 - az^{-1}} = \frac{1}{z - a},$$

where the last step is the result of multiplying top and bottom by z . The *RoC* is

$$\text{RoC}(h) = \{z = re^{i\omega} \in \mathbb{C} \mid r > a\}$$

The Z transform \hat{H} of the impulse response h of an LTI system is called the **transfer function** of the system.

12.2.1 Structure of the region of convergence

When a signal has a Fourier transform, then knowing the Fourier transform is equivalent to knowing the signal. The signal can be obtained from its Fourier transform, and the Fourier transform can be obtained from the signal. The same is true of a Z transform, but there is a complication. The Z transform is a function $\hat{X}: \text{RoC} \rightarrow \mathbb{C}$, and it is necessary to know the set *RoC* to know the function \hat{X} . The region of convergence is a critical part of the Z transform. We will see that very different signals can have very similar Z transforms that differ only in the region of convergence.

Given a discrete-time signal x , $\text{RoC}(x)$ is defined to be the set of all complex numbers $z = re^{i\omega}$ for which the following series converges:

$$\sum_{m=-\infty}^{\infty} |x(m)r^{-m}|.$$

Notice that if this series converges, then so does

$$\sum_{m=-\infty}^{\infty} |x(m)z^{-m}|$$

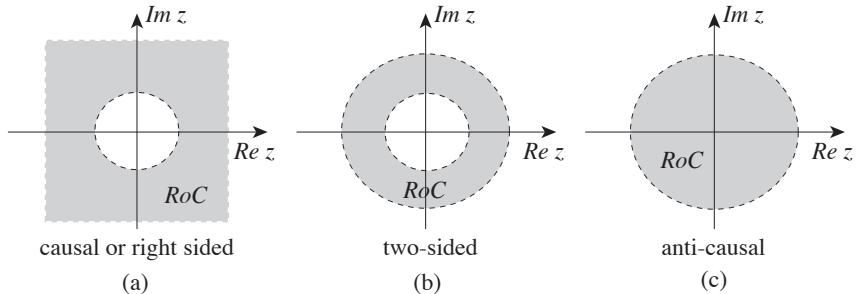


Figure 12.2: Three possible structures for the region of convergence of a Z transform.

for any complex number z with magnitude r . This is because

$$|x(m)z^{-m}| = |x(m)(re^{i\omega})^{-m}| = |x(m)| \cdot |r^{-m}| \cdot |e^{-i\omega m}| = |x(m)| \cdot |r^{-m}|.$$

Thus, the set RoC could equally well be defined to be the set of all complex numbers z such that $x(n)z^{-n}$ is absolutely summable.

Notice that whether this series converges depends only on r , the magnitude of the complex number $z = re^{i\omega}$, and not on ω , its angle. Thus, if any point $z = re^{i\omega}$ is in the set RoC , then all points z' with the same magnitude are also in RoC . This implies that the set RoC , a subset of \mathbb{C} , will have circular symmetry.

The set RoC turns out to have even more structure. There are only three possible patterns, illustrated by the shaded areas in Figure 12.2. Each figure illustrates the complex plane, and the shaded area is a region of convergence. Each possibility has circular symmetry, in that whether a point is in the RoC depends only on its magnitude.

Figure 12.2(a) shows the RoC of a causal signal. A discrete-time signal x is **causal** if $x(n) = 0$ for all $n < 0$. The RoC is the set of complex numbers $z = re^{i\omega}$ where following series converges:

$$\sum_{m=-\infty}^{\infty} |x(m)r^{-m}|.$$

But if x is causal, then

$$\sum_{m=-\infty}^{\infty} |x(m)r^{-m}| = \sum_{m=0}^{\infty} |x(m)r^{-m}|.$$

If this series converges for some given r , then it must also converge for any $\tilde{r} > r$ (because for all $m \geq 0$, $\tilde{r}^{-m} < r^{-m}$). Thus, if $z \in \text{RoC}$, then the RoC must include all points in the complex plane on the circle passing through z and every point outside that circle.

Note further that not only must the RoC include every point outside the circle, but the series must also converge in the limit as z goes to infinity. Thus, for example, $H(z) = z$ cannot be the Z transform of a causal signal because its RoC cannot possibly include infinity ($H(z)$ is not finite there).

Figure 12.2(c) shows the RoC of an anti-causal signal. A discrete-time signal x is **anti-causal** if $x(n) = 0$ for all $n > 0$. By a similar argument, if $z \in \text{RoC}$, then the RoC must include all points in the complex plane on the circle passing through z and every point inside that circle.

Figure 12.2(b) shows the RoC of a signal that is neither causal nor anti-causal. Such a signal is called a **two-sided signal**. Such a signal can always be expressed as a sum of a causal signal and an anti-causal signal. The RoC is the intersection of the regions of convergence for these two components. To see this, just note that the RoC is the set of complex numbers $z = re^{j\omega}$ where following series converges:

$$\sum_{m=-\infty}^{\infty} |x(m)r^{-m}| = \sum_{m=-\infty}^{-1} |x(m)r^{-m}| + \sum_{m=0}^{\infty} |x(m)r^{-m}|.$$

The first sum on the right corresponds to an anti-causal signal, and the second sum on the right to a causal signal. For this series to converge, both sums must converge. Thus, for a two-sided signal, the RoC has a ring structure.

Example 12.7: Consider the discrete-time **unit step** signal u , given by

$$u(n) = \begin{cases} 0, & n < 0 \\ 1, & n \geq 0 \end{cases}. \quad (12.13)$$

The Z transform is, using geometric series identity (12.9),

$$\hat{U}(z) = \sum_{m=-\infty}^{\infty} u(m)z^{-m} = \sum_{m=0}^{\infty} z^{-m} = \frac{1}{1-z^{-1}} = \frac{z}{z-1},$$

with domain

$$\text{RoC}(u) = \{z \in \mathbb{C} \mid \sum_{m=1}^{\infty} |z|^{-m} < \infty\} = \{z \mid |z| > 1\}.$$

This region of convergence has the structure of Figure 12.2(a), where the dashed circle has radius one (that circle is called the **unit circle**). Indeed, this signal is causal, so this structure makes sense.

Example 12.8: The signal v given by

$$v(n) = \begin{cases} -1, & n < 0 \\ 0, & n \geq 0 \end{cases},$$

has Z transform

$$\hat{V}(z) = \sum_{m=-\infty}^{\infty} v(m)z^{-m} = - \sum_{m=-\infty}^{-1} z^{-m} = -z \sum_{k=0}^{\infty} z^k = \frac{z}{z-1},$$

with domain

$$RoC(v) = \{z \in \mathbb{C} \mid \sum_{m=-\infty}^{-1} |z|^{-m} < \infty\} = \{z \mid |z| < 1\}.$$

This region of convergence has the structure of Figure 12.2(c), where the dashed circle is again the unit circle. Indeed, this signal is anti-causal, so this structure makes sense.

Notice that although the Z transform \hat{U} of u and \hat{V} of v have the *same* algebraic form, namely, $z/(z-1)$, they are *different* functions, because their domains are different. Thus the Z transform of a signal comprises *both* the algebraic form of the Z transform as well as its *RoC*.

A **right-sided signal** x is where for some integer N ,

$$x(n) = 0, \quad \forall n < N.$$

Of course, if $N \geq 0$, then this signal is also causal. However, if $N < 0$, then the signal is two sided. Suppose $N < 0$. Then we can write the Z transform of x as

$$\sum_{m=-\infty}^{\infty} |x(m)r^{-m}| = \sum_{m=N}^{-1} |x(m)r^{-m}| + \sum_{m=0}^{\infty} |x(m)r^{-m}|.$$

The left summation on the right side is finite, and each term is finite for all $z \in \mathbb{C}$, so therefore it converges for all $z \in \mathbb{C}$. Thus, the region of convergence is determined entirely by the right summation, which is the Z transform of the causal part of x . Thus, the region of convergence of a right-sided signal has the same form as that of a causal sequence, as shown in figure 12.2(a). (However, if the signal is not causal, the Z transform does not converge at infinity.)

A **left-sided signal** x is where for some integer N ,

$$x(n) = 0, \quad \forall n > N.$$

Of course, if $N \leq 0$, then this signal is also anti-causal. However, if $N > 0$, then the signal is two sided. Suppose $N > 0$. Then we can write the Z transform of x as

$$\sum_{m=-\infty}^{\infty} |x(m)r^{-m}| = \sum_{m=-\infty}^0 |x(m)r^{-m}| + \sum_{m=1}^N |x(m)r^{-m}|.$$

The right summation is finite, and therefore converges for all $z \in \mathbb{C}$ except $z = 0$, where the individual terms of the sum are not finite. Thus, the region of convergence is that of the left summation, except for the point $z = 0$. Thus, the region of convergence of a left-sided signal has the same form as that of an anti-causal sequence, as shown in figure 12.2(c), except that the origin ($z = 0$) is excluded. This, of course, is simply the structure of 12.2(b) where the inner circle has zero radius.

Some signals have no meaningful Z transform.

Example 12.9: The signal x with $x(n) = 1$, for all n , does not have a Z transform. We can write $x = u - v$, where u and v are defined in the previous examples. Thus, the region of convergence of x must be the intersection of the regions of convergence of u and v . However, these two regions of convergence have an empty intersection, so $\text{RoC}(x) = \emptyset$.

Viewed another way, the set $\text{RoC}(x)$ is the set of complex numbers z where

$$\sum_{m=-\infty}^{\infty} |x(m)z^{-m}| = \sum_{m=-\infty}^{\infty} |z^{-m}| < \infty.$$

But there is no such complex number z .

Note that the signal x in example 12.9 is periodic with any integer period p (because $x(n+p) = x(n)$ for any $p \in \mathbb{Z}$). Thus, it has a Fourier series representation. In fact, as shown in Section 10.6.3, a periodic signal also has a Fourier transform representation, as long as we are willing to allow Dirac delta functions in the Fourier transform. (Recall that this means that there are values of ω where $X(\omega)$ will not be finite.) With periodic signals, the Fourier series is by far the simplest frequency-domain tool to use. The Fourier transform can also be used if we allow Dirac delta functions. The Z transform, however, is more problematic, because the region of convergence is empty.

12.2.2 Stability and the Z transform

If a discrete-time signal x is absolutely summable, then it has a DTFT X that is finite for all $\omega \in \mathbb{R}$. Moreover, the DTFT is equal to the Z transform evaluated on the unit circle,

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = \hat{X}(z)|_{z=e^{i\omega}} = \hat{X}(e^{i\omega}).$$

The complex number $z = e^{i\omega}$ has magnitude one, and therefore lies on the unit circle. Recall that an LTI system is stable if and only if its impulse response is absolutely summable. Thus,

A discrete-time LTI system with impulse response h is stable if and only if the transfer function \hat{H} , which is the Z transform of h , has a region of convergence that includes the unit circle.

Example 12.10: Continuing example 12.6, the transfer function of the bank account system has region of convergence given by

$$RoC(h) = \{z = re^{i\omega} \in \mathbb{C} \mid r > a\},$$

where $a > 1$. Thus, the region of convergence includes only complex numbers with magnitude greater than one, and therefore does not include the unit circle. The bank account system is therefore not stable.

12.2.3 Rational Z transforms and poles and zeros

All of the Z transforms we have seen so far are **rational polynomials** in z . A rational polynomial is simply the ratio of two finite-order polynomials. For example, the bank account system has transfer function

$$\hat{H}(z) = \frac{1}{z-a}$$

(see example 12.6). The unit step of example 12.7 and its anti-causal cousin of example 12.8 have Z transforms given by

$$\hat{U}(z) = \frac{z}{z-1}, \quad \hat{V}(z) = \frac{z}{z-1},$$

albeit with different regions of convergence.

In practice, most Z transforms of practical interest can be written as the ratio of two finite order polynomials in z ,

$$\hat{X}(z) = \frac{A(z)}{B(z)}.$$

The **order** of the polynomial A or B is the power of the highest power of z . For the unit step, the numerator polynomial is $A(z) = z$, a first-order polynomial, and the denominator is $B(z) = z - 1$, also a first-order polynomial.

Recall from algebra that a polynomial of order N has N (possibly complex-valued) **roots**, which are values of z where the polynomial evaluates to zero. The roots of the numerator A are called the **zeroes** of the Z transform, and the roots of the denominator B are called the **poles** of the Z transform. The term “zero” refers to the fact that the Z transform evaluates to zero at a zero. The term “pole” suggests an infinitely high tent pole, where the Z transform evaluates to infinity. The locations in the complex plane of the poles and zeros turn out to yield considerable insight about a Z transform. A plot of these locations is called a **pole-zero plot**. The poles are shown as crosses and the zeros as circles.

Example 12.11: The unit step of example 12.7 and its anti-causal cousin of example 12.8 have pole-zero plots shown in Figure 12.3. In each case, the Z transform has the form

$$\frac{z}{z-1} = \frac{A(z)}{B(z)},$$

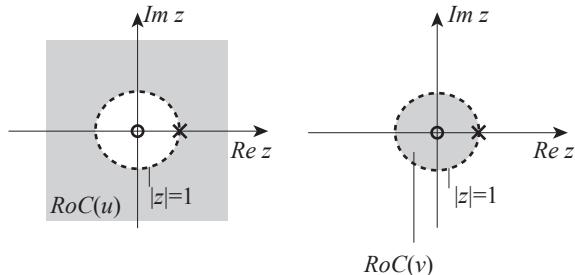


Figure 12.3: Pole-zero plots for the unit step u and its anti-causal cousin v . The regions of convergence are the shaded area in the complex plane, not including the unit circle. Both Z transforms, \hat{U} and \hat{V} , have one pole at $z = 1$ and one zero at $z = 0$.

where $A(z) = z$ and $B(z) = z - 1$. $A(z)$ has only one root, at $z = 0$, so the Z transforms each have one zero, at the origin in the complex plane. $B(z)$ also has only one root, at $z = 1$, so the Z transform has one pole, at $z = 1$.

These plots also show the unit circle, with a dashed line, and the regions of convergence for the two examples, as shaded areas. Note that $RoC(u)$ has the form of a region of convergence of a causal signal, as it should, and $RoC(v)$ has the form of a region of convergence of an anti-causal signal, as it should (see Figure 12.2). Note that neither RoC includes the unit circle, so if these signals were impulse responses of LTI systems, then these systems would be unstable.

Consider a rational Z transform

$$\hat{X}(z) = \frac{A(z)}{B(z)}.$$

The denominator polynomial B evaluates to zero at a pole. That is, if there is a pole at location $z = p$ (a complex number), then $B(p) = 0$. Assuming that $A(p) \neq 0$, then $\hat{X}(p)$ is not finite. Thus, the region of convergence cannot include any pole p that is not cancelled by a zero. This fact, combined with the fact that a causal signal always has a RoC of the form of the left one in Figure 12.2, leads to the following simple **stability criterion for causal systems**:

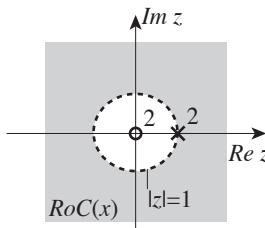


Figure 12.4: Poles and zeros with multiplicity greater than one are indicated by a number next to the cross or circle.

A discrete-time causal system is stable if and only if all the poles of its transfer function lie inside the unit circle.

A subtle fact about rational Z transforms is that the region of convergence is always bordered by the pole locations. This is evident in Figure 12.3, where the single pole at $z = 1$ lies on the boundary of the two possible regions of convergence. In fact, the rational polynomial

$$\frac{z}{z-1}$$

can be associated with only three possible Z transforms, two of which have the two regions of convergence shown in Figure 12.3, plus the one not shown where $RoC = \emptyset$.

Although a polynomial of order N has N roots, these roots are not necessarily distinct. Consider the (rather trivial) polynomial

$$A(z) = z^2.$$

This has order 2, and hence two roots, but both roots are at $z = 0$. Consider a Z transform given by

$$\forall z \in RoC(x), \quad \hat{X}(z) = \frac{z^2}{(z-1)^2}.$$

This has two zeros at $z = 0$, and two poles at $z = 1$. We say that the zero at $z = 0$ has **multiplicity** two. Similarly, the pole at $z = 1$ has multiplicity two. This multiplicity is indicated in a pole-zero plot by a number adjacent to the pole or zero, as shown in Figure 12.4.

Example 12.12: Consider a signal x that is equal to the delayed Kronecker delta function,

$$\forall n \in \mathbb{Z}, \quad x(n) = \delta(n - M),$$

where $M \in \mathbb{Z}$ is a constant. Its Z transform is easy to find using the sifting rule,

$$\forall z \in \text{RoC}(x), \quad \hat{X}(z) = \sum_{m=-\infty}^{\infty} \delta(m - M)z^{-m} = z^{-M} = 1/z^M.$$

If $M > 0$, then this converges absolutely for any $z \neq 0$. Thus, if $M > 0$,

$$\text{RoC}(x) = \{z \in \mathbb{C} \mid z \neq 0\}.$$

This Z transform has M poles at $z = 0$. Notice that this region of convergence, appropriately, has the form of that of a causal signal, Figure 12.2(a), but where the circle has radius zero.

If $M < 0$, then the region of convergence is the entire set \mathbb{C} , and the Z transform has M zeros at $z = 0$. This signal is anti-causal, and its RoC matches the structure of 12.2(c), where the radius of the circle is infinite. Note that this Z transform does not converge at infinity, which it would have to do if the signal were causal.

If $M = 0$, then $\hat{X}(z) = 1$ for all $z \in \mathbb{C}$, so $\text{RoC} = \mathbb{C}$, and there are no poles or zeros. This is a particularly simple Z transform.

Recall that for a causal signal, the Z transform must converge as $z \rightarrow \infty$. The region of convergence must include everything outside some circle, including infinity.¹ This implies that for a causal signal with a rational Z transform, the Z transform must be **proper**. A rational polynomial is proper when the order of the numerator is smaller than or equal to the order of the denominator. For example, if $M = -1$ in the previous example, then $x(n) = \delta(n + 1)$ and $\hat{H}(z) = z$, which has numerator order one and denominator order zero. It is not proper, and indeed, it does not converge as $z \rightarrow \infty$. Any rational polynomial that has a denominator of higher order than the numerator will not converge as z goes to infinity, and hence cannot be the Z transform of a causal signal.

¹Some texts consider poles and zeros at infinity, in which case a causal signal cannot have a pole at infinity.

In the following chapter, table 13.1 gives many common Z transforms, all of which are rational polynomials. Together with the properties discussed in the that chapter, we can find the Z transforms of many signals.

12.3 The Laplace transform

Consider a continuous-time signal x that is not absolutely integrable. Consider the scaled signal x_σ given by²

$$\forall t \in \mathbb{R}, \quad x_\sigma(t) = x(t)e^{-\sigma t}, \quad (12.14)$$

for some real number σ . Often, this signal is absolutely integrable when σ is chosen appropriately. This new signal, therefore, will have a CTFT, even if x does not.

Example 12.13: Consider the impulse response of the simplified helicopter system described in example 12.2. The output as a function of the input is given by

$$\forall t \in \mathbb{R}, \quad y(t) = \frac{1}{M} \int_0^t x(\tau) d\tau.$$

The impulse response is found by letting the input be a Dirac delta function and using the sifting rule to get

$$\forall t \in \mathbb{R}, \quad h(t) = u(t)/M,$$

where u is the continuous-time **unit step** in (12.4). This is not absolutely integrable, so this system is not stable. However, the scaled signal

$$\forall t \in \mathbb{R}, \quad h_\sigma(t) = h(t)e^{-\sigma t}$$

²The reason that this is different from the scaling by r^{-n} used to get the Z transform is somewhat subtle. The two methods are essentially equivalent, if we let $r = e^\sigma$. But scaling by $e^{-\sigma t}$ turns out to be more convenient for continuous-time systems, as we will see.

is absolutely integrable if $\sigma > 0$. Its CTFT is

$$\begin{aligned}\forall \sigma > 0, \forall \omega \in \mathbb{R}, \quad H_\sigma(\omega) &= \int_{-\infty}^{\infty} h(t)e^{-\sigma t}e^{-i\omega t}dt \\ &= \frac{1}{M} \int_0^{\infty} e^{-\sigma t}e^{-i\omega t}dt \\ &= \frac{1}{M} \int_0^{\infty} e^{-(\sigma+i\omega)t}dt \\ &= \frac{1}{M(\sigma+i\omega)}.\end{aligned}$$

The last step in example 12.13 uses the following useful fact from calculus,

$$\int_a^b e^{ct} dt = \frac{1}{c}(e^{cb} - e^{ca}), \quad (12.15)$$

for any $c \in \mathbb{C}$ and $a, b \in \mathbb{R} \cup \{-\infty, \infty\}$ where e^{cb} and e^{ca} are finite.

In general, the CTFT of the scaled signal x_σ in (12.14) is

$$\forall \omega \in \mathbb{R}, \quad X_\sigma(\omega) = \int_{-\infty}^{\infty} x(t)e^{-(\sigma+i\omega)t}dt.$$

Notice that this is a function not just of ω , but also of σ . We are only sure it is valid for values of σ that yield an absolutely integrable signal h_σ .

Define the complex number

$$s = \sigma + i\omega.$$

Then we can write this CTFT as

$$\forall s \in \text{RoC}(x), \quad \hat{X}(s) = \int_{-\infty}^{\infty} x(t)e^{-st}dt,$$

(12.16)

where \hat{X} is a function called the **Laplace transform** of x ,

$$\hat{X}: \text{RoC}(x) \rightarrow \mathbb{C}$$

where $\text{RoC}(x) \subset \mathbb{C}$ is given by

$$\boxed{\text{RoC}(x) = \{s = \sigma + i\omega \in \mathbb{C} \mid x(t)e^{-\sigma t} \text{ is absolutely integrable.}\}} \quad (12.17)$$

The Laplace transform \hat{H} of the impulse response h of an LTI system is called the **transfer function** of the system, just as with discrete-time systems.

Example 12.14: Continuing example 12.13, we can recognize from the form of $H_\sigma(\omega)$ that the transfer function of the helicopter system is

$$\forall s \in \text{RoC}(h), \quad \hat{H}(s) = \frac{1}{Ms}.$$

The RoC is

$$\text{RoC}(h) = \{s = \sigma + i\omega \in \mathbb{C} \mid \sigma < 0\}$$

12.3.1 Structure of the region of convergence

As with the Z transform, the region of convergence is an essential part of a Laplace transform. It gives the domain of the function \hat{X} . Whether a complex number s is in the RoC depends only on σ , not on ω , as is evident in the definition (12.17). Since $s = \sigma + i\omega$, whether a complex number is in the region of convergence depends only on its real part. Once again, there are only three possible patterns for the region of convergence, shown in Figure 12.5. Each figure illustrates the complex plane, and the shaded area is a region of convergence. Each possibility has vertical symmetry, in that whether a point is in the RoC depends only on its real part.

Figure 12.5(a) shows the RoC of a causal or right-sided signal. A continuous-time signal x is **right-sided** if $x(t) = 0$ for all $t < T$ for some $T \in \mathbb{R}$. The RoC is the set of complex numbers $s = \sigma + i\omega$ where following integral converges:

$$\int_{-\infty}^{\infty} |x(t)e^{-\sigma t}| dt.$$

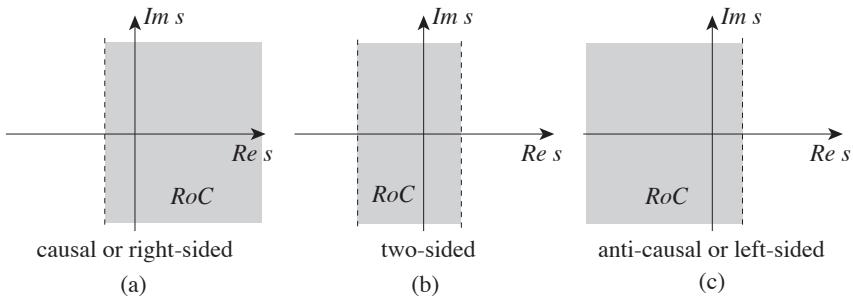


Figure 12.5: Three possible structures for the region of convergence of a Laplace transform.

But if x is right-sided, then

$$\int_{-\infty}^{\infty} |x(t)e^{-\sigma t}| dt = \int_T^{\infty} |x(t)e^{-\sigma t}| dt.$$

If $T \geq 0$ and this integral converges for some given σ , then it must also converge for any $\tilde{\sigma} > \sigma$ because for all $t \geq 0$, $e^{-\tilde{\sigma}t} < e^{-\sigma t}$. Thus, if $s = \sigma + i\omega \in \text{RoC}(x)$, then the $\text{RoC}(x)$ must include all points in the complex plane on the vertical line passing through s and every point to the right of that line.³

If $T < 0$, then

$$\int_T^{\infty} |x(t)e^{-\sigma t}| dt = \int_T^0 |x(t)e^{-\sigma t}| dt + \int_0^{\infty} |x(t)e^{-\sigma t}| dt,$$

then the finite integral exists and is finite for all σ , so the same argument applies.

Figure 12.5(c) shows the RoC of a left-sided signal. A continuous-time signal x is **left-sided** if $x(t) = 0$ for all $t > T$ for some $T \in \mathbb{R}$. By a similar argument, if $s = \sigma + i\omega \in \text{RoC}(x)$, then the $\text{RoC}(x)$ must include all points in the complex plane on the vertical line passing through s and every point to the left of that line.

³It is convenient but coincidental that the region of convergence is the right half of a plane when the sequence is right sided.

Figure 12.5(b) shows the *RoC* of a signal that is a **two-sided signal**. Such a signal can always be expressed as a sum of a right-sided signal and left-sided signal. The *RoC* is the intersection of the regions of convergence for these two components.

Example 12.15: Using the same methods as in examples 12.13 and 12.14 we can find the Laplace transform of the continuous-time **unit step** signal u , given by

$$\forall t \in \mathbb{R}, \quad u(t) = \begin{cases} 0, & t < 0 \\ 1, & t \geq 0 \end{cases}. \quad (12.18)$$

The Laplace transform is

$$\begin{aligned} \forall s \in \text{RoC}(u), \quad \hat{U}(s) &= \int_{-\infty}^{\infty} u(t)e^{-st}dt \\ &= \int_0^{\infty} e^{-st}dt \\ &= \frac{1}{s}, \end{aligned}$$

where again we have used (12.15). The domain of \hat{U} is

$$\text{RoC}(u) = \{s \in \mathbb{C} \mid \text{Re}\{s\} > 0\}.$$

This region of convergence has the structure of Figure 12.5(a), where the dashed line sits exactly on the imaginary axis. The region of convergence, therefore, is simply the right half of the complex plane.

Example 12.16: The signal v given by

$$\forall t \in \mathbb{R}, \quad v(t) = -u(-t) = \begin{cases} -1, & t < 0 \\ 0, & t \geq 0 \end{cases},$$

has Laplace transform

$$\begin{aligned}\forall s \in \text{RoC}(v), \quad \hat{V}(s) &= \int_{-\infty}^{\infty} v(t)e^{-st} dt \\ &= - \int_{-\infty}^0 e^{-st} dt \\ &= \frac{1}{s}\end{aligned}$$

with domain $\text{RoC}(v) = \{s \in \mathbb{C} \mid \text{Re}\{s\} < 0\}$. This region of convergence looks like Figure 12.5(c), where the dashed line coincides with the imaginary axis.

Notice that although the Laplace transforms \hat{U} and \hat{V} have the same algebraic form, namely, $1/s$, they are in fact different functions, because their domains are different.

Some signals have no meaningful Laplace transform.

Example 12.17: The signal x with $x(t) = 1$, for all $t \in \mathbb{R}$, does not have a Laplace transform. We can write $x = u - v$, where u and v are defined in the previous examples. Thus, the region of convergence of x must be the intersection of the regions of convergence of u and v . However, these two regions have an empty intersection, so $\text{RoC}(x) = \emptyset$.

Viewed another way, the set $\text{RoC}(x)$ is the set of complex numbers s where

$$\int_{-\infty}^{\infty} |x(t)e^{-st}| dt = \int_{-\infty}^{\infty} |e^{-st}| dt < \infty.$$

But there is no such complex number s .

Note that the signal x in example 12.17 is periodic with any period $p \in \mathbb{R}$ (because $x(t+p) = x(t)$ for any $p \in \mathbb{R}$). Thus, it has a Fourier series representation. In fact, as shown in Section 10.6.3, a periodic signal also has a Fourier transform representation, as long as we

are willing to allow Dirac delta functions in the Fourier transform. (Recall that this means that there are values of ω where $X(\omega)$ will not be finite.) In the continuous-time case as in the discrete-time case, with periodic signals, the Fourier series is by far the simplest frequency-domain tool to use. The Fourier transform can also be used if we allow Dirac delta functions. The Laplace transform, however, is more problematic, because the region of convergence is empty.

12.3.2 Stability and the Laplace transform

If a continuous-time signal x is absolutely integrable, then it has a CTFT X that is finite for all $\omega \in \mathbb{R}$. Moreover, the CTFT is equal to the Laplace transform evaluated on the imaginary axis,

$$\forall \omega \in \mathbb{R}, \quad X(\omega) = \hat{X}(s)|_{s=i\omega} = \hat{X}(i\omega).$$

The complex number $s = i\omega$ is pure imaginary, and therefore lies on the imaginary axis. Recall that an LTI system is stable if and only if its impulse response is absolutely integrable. Thus

A continuous-time LTI system with impulse response h is stable if and only if the transfer function \hat{H} , which is the Laplace transform of h , has a region of convergence that includes the imaginary axis.

Example 12.18: Consider the exponential signal h given by

$$\forall t \in \mathbb{R}, \quad h(t) = e^{-at} u(t),$$

for some real or complex number a , where, as usual, u is the unit step. The Laplace transform is

$$\begin{aligned}\forall s \in \text{RoC}(h), \quad \hat{H}(s) &= \int_{-\infty}^{\infty} h(t)e^{-st} dt \\ &= \int_0^{\infty} e^{-at} e^{-st} dt \\ &= \int_0^{\infty} e^{-(s+a)t} dt \\ &= \frac{1}{s+a},\end{aligned}$$

where again we have used (12.15). It is evident from (12.15) that for this integral to be valid, the domain of \hat{H} must be

$$\text{RoC}(h) = \{s \in \mathbb{C} \mid \text{Re}\{s\} > -\text{Re}\{a\}\}.$$

This region of convergence has the structure of Figure 12.5(a), where the vertical dashed line passes through a .

Now suppose that h is the impulse response of an LTI system. That LTI system is stable if and only if $\text{Re}\{a\} > 0$. Indeed, if $\text{Re}\{a\} < 0$, then the impulse response grows without bound, because e^{-at} grows without bound as t gets large.

12.3.3 Rational Laplace transforms and poles and zeros

All of the Laplace transforms we have seen so far are **rational polynomials** in s . In practice, most Laplace transforms of interest can be written as the ratio of two finite order polynomials in s ,

$$\hat{X}(s) = \frac{A(s)}{B(s)}.$$

An exception is illustrated in the following example.

Example 12.19: Consider a signal x that is equal to the delayed Dirac delta function,

$$\forall t \in \mathbb{R}, \quad x(t) = \delta(t - \tau),$$

where $\tau \in \mathbb{R}$ is a constant. Its Laplace transform is easy to find using the sifting rule,

$$\forall s \in \text{RoC}(x), \quad \hat{X}(s) = \int_{-\infty}^{\infty} \delta(t - \tau) e^{-st} dt = e^{-s\tau}.$$

This has no finite-order rational polynomial representation.

Unlike the discrete-time case, pure time delays turn out to be rather difficult to realize in many physical systems that are studied using Laplace transforms, so we need not be overly concerned with them. We focus henceforth on rational Laplace transforms.

For a rational Laplace transform, the **order** of the polynomial A or B is the power of the highest power of s . For the exponential of example 12.18, the numerator polynomial is $A(s) = 1$, a zero-order polynomial, and the denominator is $B(s) = s + a$, a first-order polynomial. As with the Z transform, the roots of the numerator polynomial are called the **zeros** of the Laplace transform, and the roots of the denominator polynomial are called the **poles**.

Example 12.20: The exponential of example 12.18 has a single pole at $s = -a$, and no zeros. Note that as s approaches infinity, this Laplace transform approaches zero, and hence we could say that there is a zero at infinity. Equivalently, we might say that this Laplace transform has no finite zeros.

A pole-zero plot is shown in Figure 12.6, where we assume that a is a complex number with a positive real part. The region of convergence includes the imaginary axis, so this signal is absolutely integrable.

As with Z transforms, the region of convergence of a rational Laplace transform bordered by the pole locations. Hence,

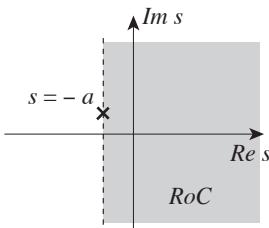


Figure 12.6: Pole-zero plot for the exponential signal of example 12.18, assuming a has a positive real part.

A continuous-time causal system is stable if and only if all the poles of its transfer function lie in the left half of the complex plane. That is, all the poles must have negative real parts.

Table 13.3 in the following chapter gives many common Laplace transforms.

12.4 Summary

Many useful signals have no Fourier transform. A sufficient condition for a signal to have a Fourier transform that is finite at all frequencies is that the signal be absolutely summable (if it is a discrete-time signal) or absolutely integrable (if it is a continuous-time system).

Many useful systems are not stable, which means that even with a bounded input, the output may be unbounded. An LTI system is stable if and only if its impulse response is absolutely summable (discrete-time) or absolutely integrable (continuous-time).

Many signals that are not absolutely summable (integrable) can be scaled by an exponential to get a new signal that is absolutely summable (integrable). The DTFT (CTFT) of the scaled signal is called the Z transform (Laplace transform) of the signal.

The Z transform (Laplace transform) is defined over a region of convergence, where the structure of the region of convergence depends on whether the signal is causal, anti-causal, or two-sided. The Z transform (Laplace transform) of the impulse response is called the transfer function of an LTI system. The region of convergence includes the unit circle (imaginary axis), if and only if the system is stable.

A rational Z transform (Laplace transform) has poles and zeros, and the poles bound the region of convergence. The locations of the poles and zeros yield considerable information about the system, including whether it is stable.

Exercises

Each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **E** Consider the signal x given by

$$\forall n \in \mathbb{Z}, \quad x(n) = a^n u(-n),$$

where a is a complex constant.

- (a) Find the Z transform of x . Be sure to give the region of convergence.
- (b) Where are the poles and zeros?
- (c) Under what conditions on a is x absolutely summable?
- (d) Assuming that x is absolutely summable, find its DTFT.

2. **T** Consider the signal x given by

$$\forall n \in \mathbb{Z}, \quad x(n) = \begin{cases} 1, & |n| \leq M \\ 0, & \text{otherwise} \end{cases},$$

for some integer $M > 0$.

- (a) Find the Z transform of x . Simplify so that there remain no summations. Be sure to give the region of convergence.
- (b) Where are the poles and zeros? Do not give poles and zeros that cancel each other out.
- (c) Under what conditions is x absolutely summable?
- (d) Assuming that x is absolutely summable, find its DTFT.

3. **T** Consider the **unit ramp** signal w given by

$$\forall n \in \mathbb{Z}, \quad w(n) = nu(n),$$

where u is the unit step. The following identity will be useful,

$$\sum_{m=0}^{\infty} (m+1)a^m = \left(\sum_{m=0}^{\infty} a^m \right)^2 = \frac{1}{(1-a)^2}. \quad (12.19)$$

This is a generalization of the geometric series identity, given by (12.9). This series converges for any complex number a with $|a| < 1$, because

$$\begin{aligned}\sum_{m=0}^{\infty} (m+1)|a|^m &= 1 + 2|a| + 3|a|^2 + \dots \\ &= (1 + |a| + |a|^2 + \dots)(1 + |a| + |a|^2 + \dots) \\ &= \left(\sum_{m=0}^{\infty} |a|^m\right)^2 \\ &< \infty.\end{aligned}$$

- (a) Use the given identity to find the Z transform of the unit ramp. Be sure to give the region of convergence. Check your answer against that given on page 597.
 - (b) Sketch the pole-zero plot of the Z transform.
 - (c) Is the unit ramp absolutely summable?
4. E Sketch the pole-zero plots and regions of convergence for the Z transforms of the following impulse responses, and indicate whether a discrete-time LTI system with these impulse responses is stable:
- (a) $h_1(n) = \delta(n) + 0.5\delta(n-1)$.
 - (b) $h_2(n) = (0.5)^n u(n)$.
 - (c) $h_3(n) = 2^n u(n)$.
5. E Consider the anti-causal continuous-time exponential signal x given by

$$\forall t \in \mathbb{R}, \quad x(t) = -e^{-at}u(-t),$$

for some real or complex number a , where, as usual, u is the unit step.

- (a) Show that the Laplace transform of x is

$$\hat{X}(s) = \frac{1}{s+a}$$

with region of convergence

$$RoC(x) = \{s \in \mathbb{C} \mid Re\{s\} < -Re\{a\}\}.$$

- (b) Where are the poles and zeros?

- (c) Under what conditions on a is x absolutely integrable?
(d) Assuming that x is absolutely integrable, find its CTFT.
6. **E** This exercise demonstrates that the Laplace transform is linear. Show that if x and y are continuous-time signals, a and b are complex (or real) constants, and w is given by

$$\forall t \in \mathbb{R}, \quad w(t) = ax(t) + by(t),$$

then the Laplace transform is

$$\forall s \in \text{RoC}(w), \quad \hat{W}(s) = a\hat{X}(s) + b\hat{Y}(s),$$

where

$$\text{RoC}(w) \supset \text{RoC}(x) \cap \text{RoC}(y).$$

7. **T** Let the causal sinusoidal signal y be given by

$$\forall t \in \mathbb{R}, \quad y(t) = \cos(\omega_0 t)u(t),$$

where ω_0 is a real number and u is the unit step.

- (a) Show that the Laplace transform is

$$\forall s \in \{s \mid \text{Re}\{s\} > 0\}, \quad \hat{Y}(s) = \frac{s}{s^2 + \omega_0^2}.$$

Hint: Use linearity, demonstrated in exercise 6, and Euler's relation.

- (b) Sketch the pole-zero plot and show the region of convergence.

8. **E** Consider a discrete-time LTI system with impulse response

$$\forall n, \quad h(n) = a^n \cos(\omega_0 n)u(n),$$

for some $\omega_0 \in \mathbb{R}$. Determine for what values of a this system is stable.

9. **T** The continuous-time unit ramp signal w is given by

$$\forall t \in \mathbb{R}, \quad x(t) = tu(t),$$

where u is the unit step.

- (a) Find the Laplace transform of the unit ramp, and give the region of convergence.

Hint: Use integration by parts in (12.16) and the fact that $\int_0^\infty te^{-\sigma t} dt < \infty$ for $\sigma > 0$.

- (b) Sketch the pole-zero plot of the Laplace transform.

10. **E** Let h and g be the impulse response of two stable systems. They may be discrete-time or continuous-time. Let a and b be two complex numbers. Show that the system with impulse response $ah + bg$ is stable.

11. **T** Consider a series composition of two (continuous- or discrete-time) systems with impulse response h and g . The output v of the first system is related to its input x by $v = h * x$. The output y of the second system (and of the series composition) is $y = g * v$. Suppose both systems are stable. Show that the series composition is stable.

Hint: Use the definition of stability.

12. **T** Let h be the impulse response of a stable discrete-time system, so it is absolutely summable, and denote

$$\|h\| = \sum_{n=-\infty}^{\infty} |h(n)|.$$

($\|h\|$ is called the **norm** of the impulse response.)

- (a) Suppose the input signal x is bounded by M , i.e. $\forall n, |x(n)| \leq M$. Show that the output $y = h * x$ is bounded by $\|h\|M$.

- (b) Consider the input signal x where

$$\forall n \in \mathbb{Z}, \quad x(n) = \begin{cases} h(-n)/|h(-n)|, & h(n) \neq 0 \\ 0, & h(n) = 0. \end{cases}$$

Show that $\|h\|$ is the smallest bound of the output $y = h * x$.

- (c) Let g be the impulse response of another stable system with norm $\|g\|$. Show that the norm satisfies the triangle inequality,

$$\|h + g\| \leq \|h\| + \|g\|.$$

- (d) Suppose the two systems are placed in series. The composition has the impulse response $h * g$. Show that

$$\|h * g\| \leq \|h\| \times \|g\|.$$

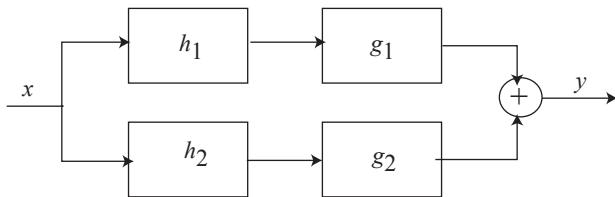


Figure 12.7: System composition for Exercise 13.

13. **E** Show that the series-parallel composition of Figure 12.7 is stable if the four component systems are stable. Let h be the impulse response of the composition. Express h in terms of the component impulse responses and then estimate $\|h\|$ in terms of the norms of the components.
14. **E** Let x be a discrete-time signal of finite duration, i.e. $x(n) = 0$ for $n < M$ and $n > N$ where M and N are finite integers (positive or negative). Let \hat{X} be its Z transform.
- Show that all its poles (if any) are at $z = 0$.
 - Show that if x is causal it has N poles at $z = 0$.
15. **T** This problem relates the Z and Laplace transforms. Let x be a discrete-time signal with Z transform $\hat{X} : \text{RoC}(x) \rightarrow \mathbb{C}$. Consider the continuous-time signal y related to x by

$$\forall t \in \mathbb{R}, \quad y(t) = \sum_{n=-\infty}^{\infty} x(n)\delta(t - nT).$$

Here $T > 0$ is a fixed period. So y comprises delta functions located at $t = nT$ of magnitude $x(n)$.

- Use the sifting property and the definition (12.16) to find the Laplace transform \hat{Y} of y . What is $\text{RoC}(y)$?
- Show that $\hat{Y}(s) = \hat{X}(e^{sT})$, where $\hat{X}(e^{sT})$ is $\hat{X}(z)$ evaluated at $s = e^{sT}$.
- Suppose $\hat{X}(z) = \frac{1}{z-1}$ with $\text{RoC}(x) = \{z \mid |z| > 1\}$. What are \hat{Y} and $\text{RoC}(y)$?

13

Laplace and Z Transforms

Contents

13.1 Properties of the Z transform	538
13.1.1 Linearity	541
13.1.2 Delay	544
13.1.3 Convolution	545
13.1.4 Conjugation	546
13.1.5 Time reversal	547
13.1.6 Multiplication by an exponential	548
13.1.7 Causal signals and the initial value theorem	548
13.2 Frequency response and pole-zero plots	550
13.3 Properties of the Laplace transform	552
13.3.1 Integration	555
13.3.2 Sinusoidal signals	555
13.3.3 Differential equations	556
13.4 Frequency response and pole-zero plots	557
13.5 The inverse transforms	559
13.5.1 Inverse Z transform	559
13.5.2 Inverse Laplace transform	568
13.6 Steady state response	570
13.7 Linear difference and differential equations	573
13.7.1 LTI differential equations	579
13.8 State-space models	584
13.8.1 Continuous-time state-space models	590
13.9 Summary	596
<i>Probing Further: Derivatives of Z transforms</i>	<i>597</i>
<i>Probing Further: Inverse transform as an integral</i>	<i>600</i>
<i>Probing Further: (Continued) Inverse transform</i>	<i>601</i>

<i>Probing Further: Differentiation and Laplace transforms</i>	602
Exercises	603

In the previous chapter, we defined Laplace and Z transforms to deal with signals that are not absolutely summable and systems that are not stable. The Z transform of the discrete-time signal x is given by

$$\forall z \in \text{RoC}(x), \quad \hat{X}(z) = \sum_{m=-\infty}^{\infty} x(m)z^{-m},$$

where $\text{RoC}(x)$ is the **region of convergence**, the region in which the sum above converges absolutely.

The Laplace transform of the continuous-time signal x is given by

$$\forall s \in \text{RoC}(x), \quad \hat{X}(s) = \int_{-\infty}^{\infty} x(t)e^{-st} dt,$$

where $\text{RoC}(x)$ is again the region of convergence, the region in which the integral above converges absolutely.

In this chapter, we explore key properties of the Z and Laplace transforms and give examples of transforms. We will also explain how, given a rational polynomial in z or s , plus a region of convergence, one can find the corresponding time-domain function. This **inverse transform** proves particularly useful, because compositions of LTI systems, studied in the next chapter, often lead to rather complicated rational polynomial descriptions of a transfer function.

Z transforms of common signals are given in table 13.1. Properties of the Z transform are summarized in table 13.2 and elaborated in the first section below.

13.1 Properties of the Z transform

The Z transform has useful properties that are similar to those of the four Fourier transforms. They are summarized in table 13.2 and elaborated in this section.

Discrete-time signal $\forall n \in \mathbb{Z}$	Z transform $\forall z \in \text{RoC}(x)$	$\text{Roc}(x) \subset \mathbb{C}$	Reference
$x(n) = \delta(n - M)$	$\hat{X}(z) = z^{-M}$	\mathbb{C}	Example 12.12
$x(n) = u(n)$	$\hat{X}(z) = \frac{z}{z - 1}$	$\{z \mid z > 1\}$	Example 12.7
$x(n) = a^n u(n)$	$\hat{X}(z) = \frac{z}{z - a}$	$\{z \mid z > a \}$	Example 13.3
$x(n) = a^n u(-n)$	$\hat{X}(z) = \frac{1}{1 - a^{-1}z}$	$\{z \mid z < a \}$	Exercise 1 in Chapter 12
$x(n) = \cos(\omega_0 n)u(n)$	$\hat{X}(z) = \frac{z^2 - z \cos(\omega_0)}{z^2 - 2z \cos(\omega_0) + 1}$	$\{z \mid z > 1\}$	Example 13.3
$x(n) = \sin(\omega_0 n)u(n)$	$\hat{X}(z) = \frac{z \sin(\omega_0)}{z^2 - 2z \cos(\omega_0) + 1},$	$\{z \mid z > 1\}$	Exercise 1
$x(n) = \frac{1}{(N-1)!} (n-1) \cdots (n-N+1) a^{n-N} u(n-N)$	$\hat{X}(z) = \frac{1}{(z-a)^N}$	$\{z \mid z > a \}$	(13.13)
$x(n) = \frac{(-1)^N}{(N-1)!} (N-1-n) \cdots (1-n) a^{n-N} u(-n)$	$\hat{X}(z) = \frac{1}{(z-a)^N}$	$\{z \mid z < a \}$	(13.14)

Table 13.1: Z transforms of key signals. The signal u is the unit step (12.13), δ is the Kronecker delta, a is any complex constant, ω_0 is any real constant, M is any integer constant, and $N > 0$ is any integer constant.

Time domain $\forall n \in \mathbb{Z}$	Frequency domain $\forall z \in \text{RoC}$	RoC	Name (reference)
$w(n) = ax(n) + by(n)$	$\hat{W}(z) = a\hat{X}(z) + b\hat{Y}(z)$	$\text{RoC}(w) \supset \text{RoC}(x) \cap \text{RoC}(y)$	Linearity (Section 13.1.1)
$y(n) = x(n - N)$	$\hat{Y}(z) = z^{-N}\hat{X}(z)$	$\text{RoC}(y) = \text{RoC}(x)$	Delay (Section 13.1.2)
$y(n) = (x * h)(n)$	$\hat{Y}(z) = \hat{X}(z)\hat{H}(z)$	$\text{RoC}(y) \supset \text{RoC}(x) \cap \text{RoC}(h)$	Convolution (Section 13.1.3)
$y(n) = x^*(n)$	$\hat{Y}(z) = [\hat{X}(z^*)]^*$	$\text{RoC}(y) = \text{RoC}(x)$	Conjugation (Section 13.1.4)
$y(n) = x(-n)$	$\hat{Y}(z) = \hat{X}(z^{-1})$	$\text{RoC}(y) = \{z \mid z^{-1} \in \text{RoC}(x)\}$	Time reversal (Section 13.1.5)
$y(n) = nx(n)$	$\hat{Y}(z) = -z \frac{d}{dz} \hat{X}(z)$	$\text{RoC}(y) = \text{RoC}(x)$	Scaling by n (page 597)
$y(n) = a^{-n}x(n)$	$\hat{Y}(z) = \hat{X}(az)$	$\text{RoC}(y) = \{z \mid az \in \text{RoC}(x)\}$	Exponential scaling (Section 13.1.6)

Table 13.2: Properties of the Z transform. In this table, a, b are complex constants, and N is an integer constant.

13.1.1 Linearity

Suppose x and y have Z transforms \hat{X} and \hat{Y} , that a, b are two complex constants, and that

$$w = ax + by.$$

Then the Z transform of w is

$$\forall z \in \text{RoC}(w), \quad \hat{W}(z) = a\hat{X}(z) + b\hat{Y}(z).$$

This follows immediately from the definition of the Z transform,

$$\begin{aligned}\hat{W}(z) &= \sum_{m=-\infty}^{\infty} w(m)z^{-m} \\ &= \sum_{m=-\infty}^{\infty} (ax(m) + by(m))z^{-m} \\ &= a\hat{X}(z) + b\hat{Y}(z).\end{aligned}$$

The region of convergence of w must include at least the regions of convergence of x and y , since if $x(n)r^{-n}$ and $y(n)r^{-n}$ are absolutely summable, then certainly $(ax(n) + by(n))r^{-n}$ is absolutely summable. Conceivably, however, the region of convergence may be larger. Thus, all we can assert in general is

$$\text{RoC}(w) \supset \text{RoC}(x) \cap \text{RoC}(y). \quad (13.1)$$

Linearity is extremely useful because it makes it easy to find the Z transform of complicated signals that can be expressed a linear combination of signals with known Z transforms.

Example 13.1: We can use the results of example 12.12 plus linearity to find, for example, the Z transform of the signal x given by

$$\forall n \in \mathbb{Z}, \quad x(n) = \delta(n) + 0.9\delta(n-4) + 0.8\delta(n-5).$$

This is simply

$$\hat{X}(z) = 1 + 0.9z^{-4} + 0.8z^{-5}.$$

We can identify the poles by writing this as a rational polynomial in z (multiply top and bottom by z^5),

$$\hat{X}(z) = \frac{z^5 + 0.9z + 0.8}{z^5},$$

from which we see that there are 5 poles at $z = 0$. The signal is causal, so the region of convergence is the region outside the circle passing through the pole with the largest magnitude, or in this case,

$$RoC(x) = \{z \in \mathbb{C} \mid z \neq 0\}.$$

Example 13.1 illustrates how to find the transfer function of any finite impulse response (FIR) filter. It also suggests that the transfer function of an FIR filter always has a region of convergence that includes the entire complex plane, except possibly $z = 0$. The region of convergence will also not include $z = \infty$ if the FIR filter is not causal.

Linearity can also be used to invert a Z transform. That is, given a rational polynomial and a region of convergence, we can find the time-domain function that has this Z transform. The general method for doing this will be considered in the next chapter, but for certain simple cases, we just have to recognize familiar Z transforms.

Example 13.2: Suppose we are given the Z transform

$$\forall z \in \{z \in \mathbb{C} \mid z \neq 0\}, \quad \hat{X}(z) = \frac{z^5 + 0.9z + 0.8}{z^5}.$$

We can immediately recognize this as the Z transform of a causal signal, because it is a proper rational polynomial and the region of convergence includes the entire complex plane except $z = 0$ (thus, it has the form of Figure 12.2(a)).

If we divide through by z^5 , this becomes

$$\forall z \in \{z \in \mathbb{C} \mid z \neq 0\}, \quad \hat{X}(z) = 1 + 0.9z^{-4} + 0.8z^{-5}.$$

By linearity, we can see that

$$\forall n \in \mathbb{Z}, \quad x(n) = x_1(n) + 0.9x_2(n) + 0.8x_3(n),$$

where x_1 has Z transform 1, x_2 has Z transform z^{-4} , and x_3 has Z transform z^{-5} . The regions of convergence for each Z transform must be at least that of x , or at least $\{z \in \mathbb{C} \mid z \neq 0\}$. From example 12.12, we recognize these Z transforms, and hence obtain

$$\forall n \in \mathbb{Z}, \quad x(n) = \delta(n) + 0.9\delta(n-4) + 0.8\delta(n-5).$$

Another application of linearity uses Euler's relation to deal with sinusoidal signals.

Example 13.3: Consider the exponential signal x given by

$$\forall n \in \mathbb{Z}, \quad x(n) = a^n u(n),$$

where a is a complex constant. Its Z transform is

$$\hat{X}(z) = \sum_{m=-\infty}^{\infty} x(m)z^{-m} = \sum_{m=0}^{\infty} a^m z^{-m} = \frac{1}{1 - az^{-1}} = \frac{z}{z - a}, \quad (13.2)$$

where we have used the geometric series identity (12.9). This has a zero at $z = 0$ and a pole at $z = a$. The region of convergence is

$$RoC(x) = \{z \in \mathbb{C} \mid \sum_{m=0}^{\infty} |a|^m |z|^{-m} < \infty\} = \{z \mid |z| > |a|\}, \quad (13.3)$$

the region of the complex plane outside the circle that passes through the pole. A pole-zero plot is shown in Figure 13.1(a).

We can use this result plus linearity of the Z transform to determine the Z transform of the causal sinusoidal signal y given by

$$\forall n \in \mathbb{Z}, \quad y(n) = \cos(\omega_0 n)u(n).$$

Euler's relation implies that

$$y(n) = \frac{1}{2} \{e^{i\omega_0 n} u(n) + e^{-i\omega_0 n} u(n)\}.$$

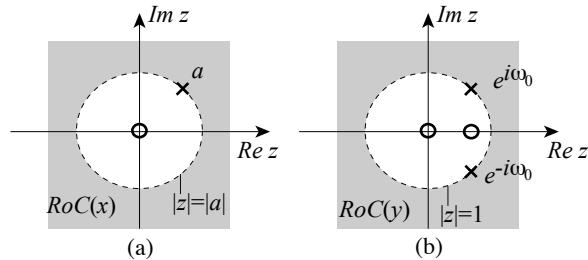


Figure 13.1: Pole-zero plots for the exponential signal x and the sinusoidal signal y of example 13.3.

Using (13.2) and linearity,

$$\begin{aligned}\hat{Y}(z) &= \frac{1}{2} \left\{ \frac{z}{z - e^{i\omega_0}} + \frac{z}{z - e^{-i\omega_0}} \right\} \\ &= \frac{1}{2} \frac{2z^2 - z(e^{i\omega_0} + e^{-i\omega_0})}{(z - e^{i\omega_0})(z - e^{-i\omega_0})} \\ &= \frac{z(z - \cos(\omega_0))}{z^2 - 2z\cos(\omega_0) + 1}.\end{aligned}$$

This has a zero at $z = 0$, another zero at $z = \cos(\omega_0)$, and two poles, one at $z = e^{i\omega_0}$ and the other at $z = e^{-i\omega_0}$. Both of these poles lie on the unit circle. A pole-zero plot is shown in Figure 13.1(b), where we assume that $\omega_0 = \pi/4$. We know from (13.1) and (13.3) that the region of convergence is at least the area outside the unit circle. In this case, we can conclude that it is exactly the area outside the unit circle, because it must be bordered by the poles, and it must have the form of a region of convergence of a causal signal.

13.1.2 Delay

For any integer N (positive or negative) and signal x , let $y = D_N(x)$ be the signal given by

$$\forall n \in \mathbb{Z}, \quad y(n) = x(n - N).$$

Suppose x has Z transform \hat{X} with domain $\text{RoC}(x)$. Then $\text{RoC}(y) = \text{RoC}(x)$ and

$$\forall z \in \text{RoC}(y), \quad \hat{Y}(z) = \sum_{m=-\infty}^{\infty} y(m)z^{-m} = \sum_{m=-\infty}^{\infty} x(m-N)z^{-m} = z^{-N}\hat{X}(z). \quad (13.4)$$

Thus

If a signal is delayed by N samples, its Z transform is multiplied by z^{-N} .

13.1.3 Convolution

Suppose x and h have Z transforms \hat{X} and \hat{H} . Let

$$y = x * h.$$

Then

$$\forall z \in \text{RoC}(y), \quad \hat{Y}(z) = \hat{X}(z)\hat{H}(z). \quad (13.5)$$

This follows from using the definition of convolution,

$$\forall n \in \mathbb{Z}, \quad y(n) = \sum_{m=-\infty}^{\infty} x(m)h(n-m),$$

in the definition of the Z transform,

$$\begin{aligned} \hat{Y}(z) &= \sum_{n=-\infty}^{\infty} y(n)z^{-n} = \sum_{n=-\infty}^{\infty} \sum_{m=-\infty}^{\infty} x(m)z^{-m}h(n-m)z^{-(n-m)} \\ &= \sum_{l=-\infty}^{\infty} \sum_{m=-\infty}^{\infty} x(m)z^{-m}h(l)z^{-l} = \hat{X}(z)\hat{H}(z). \end{aligned}$$

The Z transform of y converges absolutely at least at values of z where both \hat{X} and \hat{H} converge absolutely. Thus,

$$\text{RoC}(y) \supset \text{RoC}(x) \cap \text{RoC}(h).$$

This is true because the double sum above can be written as

$$\sum_{n=-\infty}^{\infty} y(n)z^{-n} = \left(\sum_{m=-\infty}^{\infty} x(m)z^{-m} \right) \left(\sum_{l=-\infty}^{\infty} h(l)z^{-l} \right).$$

This obviously converges absolutely if each of the two factors converges absolutely. Note that the region of convergence may actually be larger than $\text{RoC}(x) \cap \text{RoC}(h)$. This can occur, for example, if the product (13.5) results in zeros of $\hat{X}(z)$ cancelling poles of $\hat{H}(z)$ (see Exercise 3).

If h is the impulse response of an LTI system, then its Z transform is called the **transfer function** of the system. The result (13.5) tells us that the Z transform of the output is the product of the Z transform of the input and the transfer function. The transfer function, therefore, serves the same role as the frequency response. It converts convolution into simple multiplication.

13.1.4 Conjugation

Suppose x is a complex-valued signal. Let y be defined by

$$\forall n \in \mathbb{Z}, \quad y(n) = [x(n)]^*.$$

Then

$$\forall z \in \text{RoC}(y), \quad \hat{Y}(z) = [\hat{X}(z^*)]^*,$$

where

$$\text{RoC}(y) = \text{RoC}(x).$$

This follows because

$$\begin{aligned} \forall z \in \text{RoC}(x), \quad \hat{Y}(z) &= \sum_{n=-\infty}^{\infty} y(n)z^{-n} \\ &= \sum_{n=-\infty}^{\infty} x^*(n)z^{-n} \\ &= \left[\sum_{n=-\infty}^{\infty} x(n)(z^*)^{-n} \right]^* \\ &= [\hat{X}(z^*)]^*. \end{aligned}$$

If x happens to be a real signal, then $y = x$, so $\hat{Y} = \hat{X}$, so

$$\hat{X}(z) = [\hat{X}(z^*)]^*.$$

The key consequence is:

For the Z transform of a real-valued signal, poles and zeros occur in complex-conjugate pairs. That is, if there is a zero at $z = q$, then there must be a zero at $z = q^*$, and if there is a pole at $z = p$, then there must be a pole at $z = p^*$.

This is because

$$0 = \hat{X}(q) = (\hat{X}(q^*))^*$$

Similarly, if there is a pole at $z = p$, then there must also be a pole at $z = p^*$.

Example 13.4: Example 13.3 gave the Z transform of a signal of the form $x(n) = a^n u(n)$, where a is allowed to be complex, and the Z transform of a signal of the form $y(n) = \cos(\omega_0 n)u(n)$, which is real-valued. The pole-zero plots are shown in Figure 13.1. In that figure, the complex signal has a pole at $z = a$, and none at $z = a^*$. But the real signal has a pole at $z = e^{i\omega_0}$ and a matching pole at the complex conjugate, $z = e^{-i\omega_0}$.

13.1.5 Time reversal

Suppose x has Z transform \hat{X} and y is obtained from x by reversing time, so that

$$\forall n \in \mathbb{Z}, \quad y(n) = x(-n).$$

Then

$$\forall z \in \{z \in \mathbb{C} \mid z^{-1} \in \text{Roc}(x)\}, \quad \hat{Y}(z) = \hat{X}(z^{-1}).$$

This is evident from the definition of the Z transform, which implies that

$$\hat{Y}(z) = \sum_{m=-\infty}^{\infty} x(-m)z^{-m} = \sum_{n=-\infty}^{\infty} x(n)(z^{-1})^{-n} = \hat{X}(z^{-1}),$$

where $\hat{X}(z^{-1})$ is \hat{X} evaluated at z^{-1} .

//

13.1.6 Multiplication by an exponential

Suppose x has Z transform \hat{X} , a is a complex constant, and $y(n) = a^{-n}x(n)$ for all n . Then

$$\forall z \in \{z \in \mathbb{C} \mid az \in \text{RoC}(x)\}, \quad \hat{Y}(z) = \hat{X}(az),$$

where $\hat{X}(az)$ is \hat{X} evaluated at az . This is because

$$\hat{Y}(z) = \sum_{m=-\infty}^{\infty} y(m)z^{-m} = \sum_{m=-\infty}^{\infty} x(m)(az)^{-m} = \hat{X}(az).$$

Note that if \hat{X} has a pole at p (or a zero at q), then \hat{Y} has a pole at p/a (or a zero at q/a).

Example 13.5: Suppose x is given by

$$\forall n \in \mathbb{Z}, \quad x(n) = a^n u(n).$$

Then we know from example 13.3 that

$$\forall z \in \{z \mid |z| > |a|\}, \quad \hat{X}(z) = \frac{z}{z-a}.$$

This has a pole at $z = a$. Now let $y(n) = a^{-n}x(n) = u(n)$. The Z transform is

$$\hat{Y}(z) = \hat{X}(az) = \frac{az}{az-a} = \frac{z}{z-1},$$

as expected. Moreover, this has a pole at $z = a/a = 1$, as expected, and the region of convergence is indeed given by

$$\{z \in \mathbb{C} \mid az \in \text{RoC}(x)\} = \{z \in \mathbb{C} \mid |z| > 1\}.$$

13.1.7 Causal signals and the initial value theorem

Consider a causal discrete-time signal x . Its Z transform is

$$\forall z \in \{z \in \mathbb{C} \mid |z| > r\}, \quad \hat{X}(z) = \sum_{m=0}^{\infty} x(m)z^{-m},$$

for some r (the largest magnitude of a pole). Then

$$\lim_{z \rightarrow \infty} \sum_{m=0}^{\infty} x(m)z^{-m} = x(0) + \lim_{z \rightarrow \infty} \sum_{m=1}^{\infty} x(m)z^{-m} = x(0).$$

This is because as z goes to ∞ , each term $x(m)z^{-m}$ goes to zero. Thus

$$\text{If } x \text{ is causal, } x(0) = \lim_{z \rightarrow \infty} \hat{X}(z).$$

This is called the **initial value theorem**.

Example 13.6: The Z transform of the unit step $x(n) = u(n)$ is $\hat{X}(z) = z/(z - 1)$, so, as expected,

$$x(0) = \lim_{z \rightarrow \infty} \hat{X}(z) = \lim_{z \rightarrow \infty} \frac{z}{z - 1} = \lim_{z \rightarrow \infty} \frac{1}{1 - z^{-1}} = 1,$$

because

$$\lim_{z \rightarrow \infty} z^{-1} = 0.$$

Suppose a Z transform \hat{X} is the rational polynomial

$$\hat{X}(z) = \frac{a_M z^M + a_{M-1} z^{M-1} + \cdots + a_0}{z^N + b_{N-1} z^{N-1} + \cdots + b_0}.$$

If x is causal, then this rational polynomial must be **proper**. Were this not the case, if $M > N$, then by the initial value theorem, we would have

$$x(0) = \lim_{z \rightarrow \infty} \hat{X}(z) = \infty,$$

which is certainly not right.

Example 13.7: Consider the Z transform

$$\forall z \in \mathbb{C}, \quad \hat{X}(z) = z.$$

This is not a proper rational polynomial (the numerator has order 1 and the denominator, which is 1, has order 0). From example 12.12, we know that this corresponds to

$$\forall n \in \mathbb{Z}, \quad x(n) = \delta(n+1).$$

This is not a causal signal.

13.2 Frequency response and pole-zero plots

A pole-zero plot can be used to get a quick estimate of key properties of an LTI system. We have already seen that it reveals whether the system is stable. It also reveals key features of the frequency response, such as whether the system is highpass or lowpass.

Consider a stable discrete-time LTI system with impulse response h , frequency response H , and rational transfer function \hat{H} . We know that the frequency response and transfer function are related by

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \hat{H}(e^{i\omega}).$$

That is, the frequency response is equal to the Z transform evaluated on the unit circle. The unit circle is in the region of convergence because the system is stable.

Assume that \hat{H} is a rational polynomial, in which case we can express it in terms of the first-order factors of the numerator and denominator polynomials,

$$\hat{H}(z) = \frac{(z - q_1) \cdots (z - q_M)}{(z - p_1) \cdots (z - p_N)},$$

with zeros at q_1, \dots, q_M and poles at p_1, \dots, p_N . The zeros and poles may be repeated (i.e., they may have multiplicity greater than one). The frequency response is therefore

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \frac{(e^{i\omega} - q_1) \cdots (e^{i\omega} - q_M)}{(e^{i\omega} - p_1) \cdots (e^{i\omega} - p_N)}.$$

The magnitude response is

$$\forall \omega \in \mathbb{R}, \quad |H(\omega)| = \frac{|e^{i\omega} - q_1| \cdots |e^{i\omega} - q_M|}{|e^{i\omega} - p_1| \cdots |e^{i\omega} - p_N|}.$$

Each of these factors has the form

$$|e^{i\omega} - b|$$

where b is the location of either a pole or a zero. The factor $|e^{i\omega} - b|$ is just the distance from $e^{i\omega}$ to b in the complex plane.

Of course, $e^{i\omega}$ is a point on the unit circle. If that point is close to a zero at location q , then the factor $|e^{i\omega} - q|$ is small, so the magnitude response will be small. If that point is close to a pole at p , then the factor $|e^{i\omega} - p|$ is small, but since this factor is in the denominator, the magnitude response will be large. Thus,

The magnitude response of a stable LTI system may be estimated from the pole-zero plot of its transfer function. Starting at $\omega = 0$, trace counterclockwise around the unit circle as ω increases. If you pass near a zero, then the magnitude response should dip. If you pass near a pole, then the magnitude response should rise.

Example 13.8: Consider the causal LTI system of example 9.16, which is defined by the difference equation

$$\forall n \in \mathbb{Z}, \quad y(n) = x(n) + 0.9y(n-1).$$

We can find the transfer function by taking Z transforms on both sides, using linearity, to get

$$\hat{Y}(z) = \hat{X}(z) + 0.9z^{-1}\hat{Y}(z).$$

The transfer function is

$$\hat{H}(z) = \frac{\hat{Y}(z)}{\hat{X}(z)} = \frac{1}{1 - 0.9z^{-1}} = \frac{z}{z - 0.9}.$$

This has a pole at $z = 0.9$, which is closest to $z = 1$ on the unit circle, and a zero at $z = 0$, which is equidistant from all points on the unit circle. The zero, therefore, has no effect on the magnitude response. The pole is closest to $z = 1$, which corresponds to $\omega = 0$, so the magnitude response peaks at $\omega = 0$, as shown in Figure 9.12.

Example 13.9: Consider a length-4 moving average. Using methods like those in example 9.12, we can show that the transfer function is

$$\forall z \in \{z \in \mathbb{C} \mid z \neq 0\}, \quad \hat{H}(z) = \frac{1}{4} \cdot \frac{1 - z^{-4}}{1 - z^{-1}} = \frac{1}{4} \frac{z^4 - 1}{z^3(z - 1)}.$$

The numerator polynomial has roots at the four roots of unity, which are $z = 1$, $z = e^{i\pi/2}$, $z = -1$, and $z = e^{i3\pi/2}$. Thus, we can write this transfer function as

$$\begin{aligned} & \forall z \in \{z \in \mathbb{C} \mid z \neq 0\}, \\ \hat{H}(z) &= \frac{1}{4} \frac{(z-1)(z-e^{i\pi/2})(z+1)(z-e^{i3\pi/2})}{z^3(z-1)} \\ &= \frac{1}{4} \frac{(z-e^{i\pi/2})(z+1)(z-e^{i3\pi/2})}{z^3}. \end{aligned}$$

The $(z - 1)$ factors in the numerator and denominator cancel (fortunately, or we would have a pole at $z = 1$, on the unit circle, and we would have to conclude that the system was unstable). A pole-zero plot is shown in Figure 13.2.

The magnitude response is shown in Figure 9.8. Relating that figure to the pole-zero plot, we see that the frequency response peaks at $z = 1$, and as we move around the unit circle, we pass through zero at $\omega = \pi/2$, or $z = e^{i\pi/2}$, and again through zero at $\omega = \pi$. The magnitude response is periodic with period 2π , so the zero at $z = e^{3i\pi/2}$ is also a zero at $z = e^{-i\pi/2}$, corresponding to a frequency of $\omega = -\pi/2$.

13.3 Properties of the Laplace transform

The Laplace transform has useful properties that are similar to those of the Z transform. They are summarized in table 13.4 and elaborated mostly in the exercises at the end of this chapter. In this section, we elaborate on one of the properties that is not shared by the Z transform, namely integration, and then use the properties to develop some examples. Key Laplace transforms are given in table 13.3.

Continuous-time signal $\forall t \in \mathbb{R}$	Laplace transform $\forall s \in \text{RoC}(x)$	$\text{Roc}(x)$	Reference
$x(t) = \delta(t - \tau)$	$\hat{X}(s) = e^{-s\tau}$	\mathbb{C}	Exercise 12.19
$x(t) = u(t)$	$\hat{X}(s) = 1/s$	$\{s \in \mathbb{C} \mid \text{Re}\{s\} > 0\}$	Example 12.15
$x(t) = e^{-at}u(t)$	$\hat{X}(s) = \frac{1}{s+a}$	$\{s \in \mathbb{C} \mid \text{Re}\{s\} > -\text{Re}\{a\}\}$	Example 12.18
$x(t) = -e^{-at}u(-t)$	$\hat{X}(s) = \frac{1}{s+a}$	$\{s \in \mathbb{C} \mid \text{Re}\{s\} < -\text{Re}\{a\}\}$	Exercise 5
$x(t) = \cos(\omega_0 t)u(t)$	$\hat{X}(s) = \frac{s}{s^2 + \omega_0^2}$	$\{s \mid \text{Re}\{s\} > 0\}$	Exercise 7
$x(t) = \sin(\omega_0 t)u(t)$	$\hat{X}(s) = \frac{\omega_0}{s^2 + \omega_0^2}$	$\{s \mid \text{Re}\{s\} > 0\}$	Example 13.10
$x(t) = \frac{t^{N-1}}{(N-1)!}e^{-at}u(t)$	$\hat{X}(z) = \frac{1}{(s+a)^N}$	$\{s \in \mathbb{C} \mid \text{Re}\{s\} > -\text{Re}\{a\}\}$	—
$x(t) = -\frac{t^{N-1}}{(N-1)!}e^{-at}u(-t)$	$\hat{X}(z) = \frac{1}{(s+a)^N}$	$\{s \in \mathbb{C} \mid \text{Re}\{s\} < -\text{Re}\{a\}\}$	—

Table 13.3: Laplace transforms of key signals. The signal u is the unit step (12.18), δ is the Dirac delta, a is any complex constant, ω_0 is any real constant, τ is any real constant, and N is a positive integer.

Time domain $\forall t \in \mathbb{R}$	s domain $\forall s \in \text{RoC}$	RoC	Name (reference)
$w(t) = ax(t) + by(t)$	$\hat{W}(s) = a\hat{X}(s) + b\hat{Y}(s)$	$\text{RoC}(w) \supset \text{RoC}(x) \cap \text{RoC}(y)$	Linearity (Exercise 6)
$y(t) = x(t - \tau)$	$\hat{Y}(s) = e^{-s\tau}\hat{X}(s)$	$\text{RoC}(y) = \text{RoC}(x)$	Delay (Exercise 7)
$y(t) = (x * h)(t)$	$\hat{Y}(s) = \hat{X}(s)\hat{H}(s)$	$\text{RoC}(y) \supset \text{RoC}(x) \cap \text{RoC}(h)$	Convolution (Exercise 8)
$y(t) = x^*(t)$	$\hat{Y}(s) = [\hat{X}(s^*)]^*$	$\text{RoC}(y) = \text{RoC}(x)$	Conjugation (Exercise 9)
$y(t) = x(ct)$	$\hat{Y}(s) = \hat{X}(s/c)/ c $	$\text{RoC}(y) = \{s \mid s/c \in \text{RoC}(x)\}$	Time scaling (Exercise 10)
$y(t) = tx(t)$	$\hat{Y}(s) = -\frac{d}{ds}\hat{X}(s)$	$\text{RoC}(y) = \text{RoC}(x)$	Scaling by t —
$y(t) = e^{at}x(t)$	$\hat{Y}(s) = \hat{X}(s-a)$	$\text{RoC}(y) = \{s \mid s-a \in \text{RoC}(x)\}$	Exponential scaling (Exercise 11)
$y(t) = \int_{-\infty}^t x(\tau)d\tau$	$\hat{Y}(s) = \hat{X}(s)/s$	$\text{RoC}(y) \supset \text{RoC}(x) \cap \{s \mid \text{Re}\{s\} > 0\}$	Integration (Section 13.3.1)
$y(t) = \frac{d}{dt}x(t)$	$\hat{Y}(s) = s\hat{X}(s)$	$\text{RoC}(y) \supset \text{RoC}(x)$	Differentiation (page 13.5.2)

Table 13.4: Properties of the Laplace transform. In this table, a, b are complex constants, c and τ are real constants.

13.3.1 Integration

Let y be defined by

$$\forall t \in \mathbb{R}, \quad y(t) = \int_{-\infty}^t x(\tau) d\tau.$$

The Laplace transform is

$$\forall s \in \text{RoC}(y), \quad \hat{Y}(s) = \hat{X}(s)/s,$$

where

$$\text{RoC}(y) \supset \text{RoC}(x) \cap \{s \mid \text{Re}\{s\} > 0\}.$$

This follows from the convolution property in table 13.4. We recognize that

$$y(t) = (x * u)(t),$$

where u is the unit step. Hence, from the convolution property,

$$\hat{Y}(s) = \hat{X}(s)\hat{U}(s)$$

and

$$\text{RoC}(y) \supset \text{RoC}(x) \cap \text{RoC}(u).$$

\hat{U} and $\text{RoC}(u)$ are given in example 12.15, from which the property follows.

13.3.2 Sinusoidal signals

Sinusoidal signals have Laplace transforms with poles on the imaginary axis, as illustrated in the following example.

Example 13.10: Let the causal sinusoidal signal y be given by

$$\forall t \in \mathbb{R}, \quad y(t) = \sin(\omega_0 t)u(t),$$

where ω_0 is a real number and u is the unit step. Euler's relation implies that

$$y(t) = \frac{1}{2i}[e^{i\omega_0 t}u(t) - e^{-i\omega_0 t}u(t)].$$

Using (12.18) and linearity,

$$\begin{aligned}\hat{Y}(s) &= \frac{1}{2i} \left\{ \frac{1}{s+i\omega_0} - \frac{1}{s-i\omega_0} \right\} \\ &= \frac{\omega_0}{s^2 + \omega_0^2}.\end{aligned}$$

This has no finite zeros and two poles, one at $s = i\omega_0$ and the other at $s = -i\omega_0$. Both of these poles lie on the imaginary axis, as shown in Figure 13.3. The region of convergence is the right half of the complex plane. Note that if this were the impulse response of an LTI system, that system would not be stable. The region of convergence does not include the imaginary axis.

13.3.3 Differential equations

We can use the differentiation property in table 13.4 to solve differential equations with constant coefficients.

Example 13.11: In the tuning fork example of example 2.16, the displacement y of a tine is related to the acceleration of the tine by

$$\ddot{y}(t) = -\omega_0^2 y(t),$$

where ω_0 is a real constant. Let us assume that the tuning fork is initially at rest, and an external input x (representing say, a hammer strike) adds to the acceleration as follows,

$$\ddot{y}(t) = -\omega_0^2 y(t) + x(t).$$

We can use Laplace transforms to find the impulse response of this LTI system. Taking Laplace transforms on both sides, using linearity and the differentiation property,

$$\forall s \in \text{RoC}(y) \cap \text{RoC}(x), \quad s^2 \hat{Y}(s) = -\omega_0^2 \hat{Y}(s) + \hat{X}(s).$$

From this, we can find the transfer function of the system,

$$\hat{H}(s) = \frac{\hat{Y}(s)}{\hat{X}(s)} = \frac{1}{s^2 + \omega_0^2}.$$

Comparing this with example 13.10, we see that this differs only by a scaling by ω_0 from the Laplace transform in that example. Thus, the pole-zero plot of the tuning fork is shown in Figure 13.3, and the impulse response is given by

$$\forall t \in \mathbb{R}, \quad h(t) = \sin(\omega_0 t)u(t)/\omega_0.$$

Interestingly, this implies that the tuning fork is not stable. This impulse response is not absolutely integrable. However, this model of the tuning fork is idealized. It fails to account for loss of energy due to friction. A more accurate model would be stable.

The above example can be easily generalized to find the transfer function of any LTI system described by a differential equation. In fact, Laplace transforms offer a powerful and effective way to solve differential equations.

In the previous example, we inverted the Laplace transform by recognizing that it matched the example before that. In the next chapter, we will give a more general method for inverting a Laplace transform.

13.4 Frequency response and pole-zero plots

Just as with Z transforms, the pole-zero plot of a Laplace transform can be used to get a quick estimate of key properties of an LTI system. Consider a stable continuous-time LTI system with impulse response h , frequency response H , and rational transfer function \hat{H} . We know that the frequency response and transfer function are related by

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \hat{H}(i\omega).$$

That is, the frequency response is equal to the Laplace transform evaluated on the imaginary axis. The imaginary axis is in the region of convergence because the system is stable.

Assume that \hat{H} is a rational polynomial, in which case we can express it in terms of the first-order factors of the numerator and denominator polynomials,

$$\hat{H}(s) = \frac{(s - q_1) \cdots (s - q_M)}{(s - p_1) \cdots (s - p_N)},$$

with zeros at q_1, \dots, q_M and poles at p_1, \dots, p_N . The zeros and poles may be repeated (i.e., they may have multiplicity greater than one). The frequency response is therefore

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \frac{(i\omega - q_1) \cdots (i\omega - q_M)}{(i\omega - p_1) \cdots (i\omega - p_N)}.$$

The magnitude response is

$$\forall \omega \in \mathbb{R}, \quad |H(\omega)| = \frac{|i\omega - q_1| \cdots |i\omega - q_M|}{|i\omega - p_1| \cdots |i\omega - p_N|}.$$

Each of these factors has the form

$$|i\omega - b|$$

where b is the location of either a pole or a zero. The factor $|i\omega - b|$ is just the distance from $i\omega$ to b in the complex plane.

Of course, $i\omega$ is a point on the imaginary axis. If that point is close to a zero at location q , then the factor $|i\omega - q|$ is small, so the magnitude response will be small. If that point is close to a pole at p , then the factor $|i\omega - p|$ is small, but since this factor is in the denominator, the magnitude response will be large. Thus,

The magnitude response of a stable LTI system may be estimated from the pole-zero plot of its transfer function. Starting at $i\omega = 0$, trace upwards and downwards along the imaginary axis to increase or decrease ω . If you pass near a zero, then the magnitude response should dip. If you pass near a pole, then the magnitude response should rise.

Example 13.12: Consider an LTI system with transfer function given by

$$\forall s \in \{s \mid \operatorname{Re}\{s\} > \operatorname{Re}\{a\}\}, \quad H(s) = \frac{s}{(s-a)(s-a^*)}.$$

Suppose that $a = c + i\omega_0$. Figure 13.4 shows three pole-zero plots for $\omega_0 = 1$ and three values of c , namely $c = -1$, $c = -0.5$, and $c = -0.1$. The magnitude frequency responses can be calculated and plotted using the following Matlab code:

```

1 w = [-10:0.05:10];
2 a1 = -1.0 + i;
3 H1 = i*w./((i*w - a1).* (i*w-conj(a1)));
4 a2 = -0.5 + i;
```

```

5 H2 = i*w./((i*w - a2).* (i*w-conj(a2)));
6 a3 = -0.1 + i;
7 H3 = i*w./((i*w - a3).* (i*w-conj(a3)));
8 plot(w, abs(H1), w, abs(H2), w, abs(H3));

```

The plots are shown together at the bottom of Figure 13.4. The plot with the higher peaks corresponds to the pole-zero plot with the poles closer to the imaginary axis.

13.5 The inverse transforms

There are two inverse transforms. The inverse Z transform recovers the discrete-time signal x from its Z transform \hat{X} . The inverse Laplace transform recovers the continuous-time signal x from its Laplace transform \hat{X} . We study the inverse Z transform in detail. The inverse Laplace transform is almost identical. The general approach is to break down a complicated rational polynomial into a sum of simple rational polynomials whose inverse transforms we recognize. We consider only the case where \hat{X} can be expressed as a rational polynomial.

13.5.1 Inverse Z transform

The procedure is to construct the **partial fraction expansion** of \hat{X} , which breaks it down into a sum of simpler rational polynomials.

Example 13.13: Consider a Z transform given by

$$\forall z \in \text{RoC}(x), \quad \hat{X}(z) = \frac{1}{(z-1)(z-2)} = \frac{-1}{z-1} + \frac{1}{z-2}. \quad (13.6)$$

This sum is called the **partial fraction expansion** of \hat{X} , and we will see below how to find it systematically. We can write this as

$$\forall z \in \text{RoC}(x), \quad \hat{X}(z) = \hat{X}_1(z) + \hat{X}_2(z),$$

where $\hat{X}_1(z) = -1/(z-1)$ and $\hat{X}_2(z) = 1/(z-2)$ are the two terms.

To determine the inverse Z transforms of the two terms, we need to know their regions of convergence. Recall from the linearity property that $RoC(x)$ includes the intersection of the regions of convergence of the two terms,

$$RoC(x) \supset RoC(x_1) \cap RoC(x_2). \quad (13.7)$$

Once we know these two regions of convergence, we can use table 13.1 to obtain the inverse Z transform of each term. By the linearity property the sum of these inverses is the inverse Z transform of \hat{X} .

\hat{X} given by (13.6) has one pole at $z = 1$ and one pole at $z = 2$. From section 12.2.3 we know that $RoC(x)$ is bordered by these poles, so it has one of three forms:

1. $RoC(x) = \{z \in \mathbb{C} \mid |z| < 1\}$,
2. $RoC(x) = \{z \in \mathbb{C} \mid 1 < |z| < 2\}$, or
3. $RoC(x) = \{z \in \mathbb{C} \mid |z| > 2\}$.

Suppose we have case (1), which implies that x is anti-causal. From (13.7), the region of convergence of the term $-1/(z-1)$ must be $\{z \in \mathbb{C} \mid |z| < 1\}$. The only other possibility is $\{z \in \mathbb{C} \mid |z| > 1\}$, which would violate (13.7) unless the intersection is empty (which would not be an interesting case). Thus, from table 13.1, the inverse Z transform of the first term must be the anti-causal signal $x_1(n) = u(-n)$, for all $n \in \mathbb{Z}$.

For the second term, $1/(z-2)$, its region of convergence could be either $\{z \in \mathbb{C} \mid |z| < 2\}$ or $\{z \in \mathbb{C} \mid |z| > 2\}$. Again, the second possibility would violate (13.7), so we must have the first possibility. This results in $x_2(n) = -2^{n-1}u(-n)$, from the last entry in table 13.1. Hence, the inverse Z transform is

$$\forall n \in \mathbb{Z}, \quad x(n) = u(-n) - 2^{n-1}u(-n).$$

If $RoC(x)$ is given by case (2), we rewrite (13.6) slightly as

$$\hat{X}(z) = -z^{-1} \frac{z}{z-1} + \frac{1}{z-2}.$$

The inverse Z transform of the first term is obtained from table 13.1, together with the delay property in table 13.2. The inverse Z transform of the second term is the

same as in case (1). We conclude that in case (2) the inverse Z transform is the two-sided signal

$$\forall n, \quad x(n) = -u(n-1) - 2^{n-1}u(-n).$$

In case (3), we write (13.6) as

$$\hat{X}(z) = -z^{-1} \frac{z}{z-1} + z^{-1} \frac{z}{z-2},$$

and conclude that the inverse Z transform is the causal signal

$$\forall n, \quad x(n) = -u(n-1) + 2^{n-1}u(n-1).$$

We can generalize this example. Consider any **strictly proper** rational polynomial

$$\hat{X}(z) = \frac{A(z)}{B(z)} = \frac{a_M z^M + \cdots + a_1 z + a_0}{z^N + b_{N-1} z^{N-1} + \cdots + b_1 z + b_0}.$$

The numerator is of order M , the denominator is of order N . ‘Strictly proper’ means that $M < N$. We can factor the denominator,

$$\hat{X}(z) = \frac{a_M z^M + \cdots + a_1 z + a_0}{(z - p_1)^{m_1} (z - p_2)^{m_2} \cdots (z - p_k)^{m_k}}. \quad (13.8)$$

Thus \hat{X} has k distinct poles at p_i , each with multiplicity m_i . Since the order of the denominator is N , it must be true that

$$N = \sum_{i=1}^k m_i. \quad (13.9)$$

The partial fraction expansion of (13.8) is

$$\hat{X}(z) = \sum_{i=1}^k \left[\frac{R_{i1}}{(z - p_i)} + \frac{R_{i2}}{(z - p_i)^2} + \cdots + \frac{R_{im_i}}{(z - p_i)^{m_i}} \right]. \quad (13.10)$$

A pole with multiplicity m_i contributes m_i terms to the partial fraction expansion, so the total number of terms is N , the order of the denominator, from (13.9). The coefficients R_{ij} are complex numbers called the **residues** of the pole p_i .

We assume that the poles p_1, \dots, p_N are indexed so that $|p_1| \leq \dots |p_N|$. The $RoC(x)$ must have one of the following three forms:

1. $\text{RoC} = \{z \in \mathbb{C} \mid |z| < |p_1|\}$,
2. $\text{RoC} = \{z \in \mathbb{C} \mid |p_{j-1}| < |z| < |p_j|\}$, for $j \in \{2, \dots, k\}$, or
3. $\text{RoC} = \{z \in \mathbb{C} \mid |z| > |p_k|\}$.

As in example 13.13, each term in the partial fraction expansion has two possible regions of convergence, only one of which overlaps with $\text{RoC}(x)$. Thus, if we know $\text{RoC}(x)$, we can determine the region of convergence of each term of the partial fraction expansion, and then use table 13.1 to find its inverse.

The following example illustrates how to find the residues.

Example 13.14: We will find the inverse Z transform of

$$\hat{X}(z) = \frac{2z+3}{(z-1)(z+2)} = \frac{R_1}{z-1} + \frac{R_2}{z+2}.$$

The residues R_1, R_2 can be found by matching coefficients on both sides. Rewrite the right-hand side as

$$\frac{(R_1 + R_2)z + (2R_1 - R_2)}{(z-1)(z+2)}.$$

Matching the coefficients of the numerator polynomials on both sides we conclude that $R_1 + R_2 = 2$ and $2R_1 - R_2 = 3$. We can solve these simultaneous equations to determine that $R_1 = 5/3$ and $R_2 = 1/3$.

Alternatively, we can find residue R_1 by multiplying both sides by $(z-1)$ and evaluating at $z=1$. That is,

$$R_1 = \left. \frac{2z+3}{z+2} \right|_{z=1} = \frac{5}{3}.$$

Similarly, we can find R_2 by multiplying both sides by $z+2$ and evaluating at $z=-2$, to get

$$\left. \frac{2z+3}{z-1} \right|_{z=-2} = R_2,$$

so $R_2 = 1/3$. Thus the partial fraction expansion is

$$\hat{X}(z) = \frac{5/3}{z-1} + \frac{1/3}{z+2}.$$

$\text{RoC}(x)$ is either

1. $\{z \in \mathbb{C} \mid |z| < 1\}$,
2. $\{z \in \mathbb{C} \mid 1 < |z| < 2\}$, or
3. $\{z \in \mathbb{C} \mid |z| > 2\}$.

Knowing which case holds, we can find the inverse Z transform of each term from table 13.1. In the first case, x is the anti-causal signal

$$\forall n, \quad x(n) = -\frac{5}{3}u(-n) - \frac{1}{3}(-2)^{n-1}u(-n).$$

In the second case it is the two-sided signal

$$\forall n, \quad x(n) = \frac{5}{3}u(n-1) - \frac{1}{3}(-2)^{n-1}u(-n).$$

In the third case it is the causal signal

$$\forall n, \quad x(n) = \frac{5}{3}u(n-1) + \frac{1}{3}(-2)^{n-1}u(n-1).$$

If some pole of \hat{X} has multiplicity greater than one, it is slightly more difficult to carry out the partial fraction expansion. The following example illustrates the method.

Example 13.15: Consider the expansion

$$\hat{X}(z) = \frac{2z+3}{(z-1)(z+2)^2} = \frac{R_1}{z-1} + \frac{R_{21}}{z+2} + \frac{R_{22}}{(z+2)^2}.$$

Again we can match coefficients and determine the residues. Alternatively, to obtain R_1 we multiply both sides by $(z-1)$ and evaluate the result at $z=1$, to get $R_1 = 5/9$. To obtain R_{22} we multiply both sides by $(z+2)^2$ and evaluate the result at $z=-2$, to get $R_{22} = 1/3$.

To obtain R_{21} we multiply both sides by $(z+2)^2$,

$$\frac{2z+3}{z-1} = \frac{(z+2)^2 R_1}{z-1} + R_{21}(z+2) + R_{22},$$

and then differentiate both sides with respect to z . We evaluate the result at $z = -2$, to get

$$\frac{d}{dz} \left. \frac{2z+3}{z-1} \right|_{z=-2} = R_{21}.$$

Hence $R_{21} = -5/9$. So the partial fraction expansion is

$$\frac{2z+3}{(z-1)(z+2)^2} = \frac{5/9}{z-1} - \frac{5/9}{z+2} + \frac{1/3}{(z+2)^2}.$$

Knowing the RoC , we can now obtain the inverse Z transform of \hat{X} . For instance, in the case where $\text{RoC} = \{z \in \mathbb{C} \mid |z| > 2\}$, the inverse Z transform is the causal signal

$$\forall n, \quad x(n) = \frac{5}{9}u(n-1) - \frac{5}{9}(-2)^{n-1}u(n-1) + \frac{1}{3}(n-1)(-2)^{n-2}u(n-2).$$

In example 13.15, we used the next to the last entry in table 13.1 to find the inverse transform of the term $(1/3)/(z+2)^2$. That entry in the table is based on a generalization of the geometric series identity, given by (12.9). The first generalization is

$$\sum_{n=0}^{\infty} (n+1)a^n = \left(\sum_{n=0}^{\infty} a^n \right)^2 = \frac{1}{(1-a)^2}. \quad (13.11)$$

The series above converges for any complex number a with $|a| < 1$ (see Exercise 3 of Chapter 12). The broader generalization, for any integer $k \geq 1$, is

$$\frac{1}{k!} \sum_{n=0}^{\infty} (n+k)(n+k-1)\cdots(n+1)a^n = \frac{1}{(1-a)^{k+1}}, \quad (13.12)$$

for any complex number a with $|a| < 1$.

Consider then a Z transform \hat{X} that has a pole at p of multiplicity m and no zeros. Since the pole p cannot belong to RoC , the RoC is either

$$\{z \in \mathbb{C} \mid |z| > |p|\} \text{ or } \{z \in \mathbb{C} \mid |z| < |p|\}.$$

In the first case we expand \hat{X} in a series involving only the terms $z^{-n}, n \geq 0$,

$$\begin{aligned}\hat{X}(z) &= \frac{1}{(z-p)^m} \\ &= \frac{z^{-m}}{(1-pz^{-1})^m} \\ &= z^{-m} \frac{1}{(m-1)!} \sum_{n=0}^{\infty} (m+n-1)\cdots(n+1)(pz^{-1})^n, \text{ using (13.12)} \\ &= \frac{1}{(m-1)!} \sum_{k=m}^{\infty} (k-1)\cdots(k-m+1)p^{k-m}z^{-k}, \text{ defining } k=n+m,\end{aligned}$$

and the series converges for any z with $|z| > |p|$. We can match the coefficients of the powers of z in the Z transform definition,

$$\hat{X}(z) = \sum_{k=-\infty}^{\infty} x(k)z^{-k},$$

from which we can recognize that

$$\begin{aligned}\forall k \in \mathbb{Z}, \quad x(k) &= \begin{cases} 0, & k < m \\ \frac{1}{(m-1)!}(k-1)\cdots(k-m+1)p^{k-m}, & k \geq m \end{cases} \\ &= \frac{1}{(m-1)!}(k-1)\cdots(k-m+1)p^{k-m}u(k-m).\end{aligned}\tag{13.13}$$

In the second case, $RoC = \{z \in \mathbb{C} \mid |z| < |p|\}$, we expand \hat{X} in a series involving only the terms $z^{-n}, n \leq 0$,

$$\begin{aligned}\hat{X}(z) &= \frac{1}{(z-p)^m} \\ &= \frac{1}{(-p)^m} \frac{1}{(1-p^{-1}z)^m} \\ &= \frac{1}{(-p)^m} \frac{1}{(m-1)!} \sum_{n=0}^{\infty} (m+n-1)\cdots(n+1)(p^{-1}z)^n, \text{ using (13.12)} \\ &= \frac{(-1)^m}{(m-1)!} \sum_{k=-\infty}^0 (m-k-1)\cdots(1-k)p^{k-m}z^{-k}, \text{ defining } k=-n,\end{aligned}$$

and the series converges for any z with $|z| < |p|$. Again, we match powers of z in the Z transform definition to get

$$\begin{aligned} \forall k \in \mathbb{Z}, \quad x(k) &= \begin{cases} \frac{(-1)^m}{(m-1)!} (m-1-k) \cdots (1-k) p^{k-m}, & k \leq 0 \\ 0, & k > 0 \end{cases} \\ &= \frac{(-1)^m}{(m-1)!} (m-1-k) \cdots (1-k) p^{k-m} u(-k). \end{aligned} \tag{13.14}$$

Example 13.16: Suppose

$$\hat{X}(z) = \frac{1}{(z-2)^2}$$

with $\text{RoC} = \{z \in \mathbb{C} \mid |z| > 2\}$. Then, by (13.13), \hat{X} is the Z transform of the signal

$$\forall k \in \mathbb{Z}, \quad x(k) = \begin{cases} 0, & k < 2 \\ (k-1)2^{k-2}, & k \geq 2 \end{cases}.$$

Suppose

$$\hat{Y}(z) = \frac{1}{(z-2)^2}$$

with $\text{RoC} = \{z \in \mathbb{C} \mid |z| < 2\}$. Then, by (13.14), \hat{Y} is the Z transform of the signal

$$\forall k \in \mathbb{Z}, \quad y(k) = \begin{cases} (1-k)2^{k-2}, & k \leq 0 \\ 0, & k > 0 \end{cases}.$$

Since the unit circle $\{z \in \mathbb{C} \mid |z| = 1\} \subset \text{RoC}$, the DTFT of y is defined and given by

$$\forall \omega \in \mathbb{R}, \quad Y(\omega) = \hat{Y}(e^{j\omega}) = \frac{1}{(e^{j\omega}-2)^2}.$$

Now that we know how to inverse transform all the terms of the partial fraction expansion, we can generalize the method used in example 13.15 to calculate the inverse Z transform

of any \hat{X} of the form

$$\hat{X}(z) = \frac{a_M z^M + \cdots + a_0}{z^N + b_{N-1} z^{N-1} + \cdots + b_0}.$$

Step 1 If $M \geq N$, divide through to obtain

$$\hat{X}(z) = c_{M-N} z^{M-N} + \cdots + c_0 + \hat{W}(z),$$

where \hat{W} is strictly proper.

Step 2 Carry out the partial fraction expansion of \hat{W} and, knowing the *RoC*, obtain the inverse Z transform w . Then from table 13.1,

$$\forall n, \quad x(n) = c_{m+l-N} \delta(n+m+l-N) + \cdots + c_0 \delta(n) + w(n).$$

Example 13.17: We follow the procedure for

$$\hat{X}(z) = \frac{z^2 + z + 1 + z^{-1}}{(z+2)^2}.$$

First, to get this into the proper form, as a rational polynomial in z , notice that

$$\hat{X}(z) = z^{-1} \hat{Y}(z),$$

where

$$\hat{Y}(z) = \frac{z^3 + z^2 + z + 1}{(z+2)^2}.$$

Since z^{-1} corresponds to a one-step delay,

$$x(n) = y(n-1),$$

so if we find the inverse Z transform of \hat{Y} , then we have found the inverse Z transform of \hat{X} .

Working now with \hat{Y} , step 1 yields

$$\hat{Y}(z) = z - 3 + \frac{9z + 13}{z^2 + 4z + 4}.$$

Step 2 gives

$$\hat{W}(z) = \frac{9z+13}{(z+2)^2} = \frac{-5}{(z+2)^2} + \frac{9}{z+2}.$$

Suppose $\text{RoC} = \{z \in \mathbb{C} \mid |z| > 2\}$. Then from table 13.1,

$$\begin{aligned}\forall n, \quad w(n) &= -5(n-1)(-2)^{n-2}u(n-2) + 9(-2)^{n-1}u(n-1), \\ \forall n, \quad y(n) &= \delta(n+1) - 3\delta(n) + w(n), \\ \forall n, \quad x(n) &= y(n-1).\end{aligned}$$

Hence, for all $n \in \mathbb{Z}$,

$$x(n) = \delta(n) - 3\delta(n-1) - 5(n-2)(-2)^{n-3}u(n-3) + 9(-2)^{n-2}u(n-2).$$

13.5.2 Inverse Laplace transform

The procedure to calculate the inverse Laplace transform is virtually identical. Suppose the Laplace transform \hat{X} is a rational polynomial

$$\hat{X}(s) = \frac{a_M s^M + \cdots + a_0}{s^N + b_{N-1} s^{N-1} + \cdots + b_0}.$$

We follow Steps 1 and 2 above. We divide through in case $M \geq N$ to obtain

$$\hat{X}(s) = c_{M-N} s^{M-N} + \cdots + c_0 + \hat{W}(s),$$

where \hat{W} is strictly proper. We carry out the partial fraction expansion of \hat{W} . Knowing $\text{RoC}(x)$, we can again infer the region of convergence of each term. We then obtain the inverse Laplace transform term by term using table 13.3,

$$\forall t \in \mathbb{R}, \quad x(t) = c_{m-n} \delta^{(M-N)}(t) + \cdots + c_0 \delta(t) + w(t).$$

Here w is the inverse Laplace transform of \hat{W} , δ is the Dirac delta function, and $\delta^{(i)}$ is the i th derivative of the Dirac delta function.¹

¹The derivative of δ is a function only in a formal sense, and we obtain its Laplace transform using the differentiation property in table 13.4.

Example 13.18: We follow the procedure and obtain the partial fraction expansion of

$$\begin{aligned}\hat{X}(s) &= \frac{s^3 + s^2 + s + 1}{s(s+2)^2} \\ &= 1 + \frac{-3s^2 - 3s + 1}{s(s+2)^2} \\ &= 1 + \frac{1/4}{s} + \frac{-13/4}{s+2} + \frac{5/2}{(s+2)^2}.\end{aligned}$$

\hat{X} has one pole at $s = 0$ and a pole at $s = -2$ of multiplicity two. So its RoC has one of three forms:

1. $RoC = \{s \in \mathbb{C} \mid Re\{s\} < -2\}$,
2. $RoC = \{s \in \mathbb{C} \mid -2 < Re\{s\} < 0\}$, or
3. $RoC = \{s \in \mathbb{C} \mid Re\{s\} > 0\}$.

We now use table 13.3 to obtain the inverse Laplace transform of each term. In case (1), the continuous-time signal is the anti-causal signal

$$\forall t, \quad x(t) = \delta(t) - \frac{1}{4}u(-t) + \frac{13}{4}e^{-2t}u(-t) - \frac{5}{2}te^{-2t}u(-t).$$

In case (2), it is the two-sided signal,

$$\forall t, \quad x(t) = \delta(t) - \frac{1}{4}u(-t) - \frac{13}{4}e^{-2t}u(t) + \frac{5}{2}te^{-2t}u(t).$$

In case (3), it is the causal signal,

$$\forall t, \quad x(t) = \delta(t) + \frac{1}{4}u(t) - \frac{13}{4}e^{-2t}u(t) + \frac{5}{2}te^{-2t}u(t).$$

13.6 Steady state response

Although it has been a fair amount of work, being able to compute an inverse transform for an arbitrary rational polynomial proves useful. Our first use will be to study the **steady-state response** of a causal and stable LTI system that has a sinusoidal input that starts at time zero.

If the input to an LTI system is a complex exponential,

$$\forall t \in \mathbb{R}, \quad x(t) = e^{i\omega t},$$

then the output y is an exponential of the same frequency but with amplitude and phase given by $H(\omega)$,

$$\forall t \in \mathbb{R}, \quad y(t) = H(\omega)e^{i\omega t},$$

where H is the frequency response. However, this result requires the exponential input to start at $t = -\infty$. In practice, of course, an input may start at some finite time, say at $t = 0$, but this result does not describe the output if the input is

$$\forall t \in \mathbb{R}, \quad x(t) = e^{i\omega t}u(t). \tag{13.17}$$

We will see that if the system is stable and causal,² then the output y decomposes into two parts, a **transient output** and a **steady state output**,

$$y = y_{tr} + y_{ss},$$

where the transient becomes vanishingly small for large t . That is,

$$\lim_{t \rightarrow \infty} y_{tr}(t) = 0.$$

Moreover, the steady state signal is the exponential,

$$\forall t, \quad y_{ss}(t) = H(\omega)e^{i\omega t}u(t). \tag{13.18}$$

Thus for stable systems, we can use the frequency response to describe the eventual output to sinusoidal signals that start at some finite time.

For the special case $\omega = 0$, the input (13.17) is the unit step, $x = u$, and $y_{ss} = H(0)u$. So for stable systems, the steady state response to a unit step input is a step of size $H(0)$.

²This result can be generalized to non-causal systems, but causal systems will be sufficient for our purposes.

($H(0)$ is called the **dc gain**.) This case is important in the design of feedback control, considered in the next chapter.

Let h be the impulse response and \hat{H} be the Laplace transform of a stable and causal LTI system. We assume for simplicity that \hat{H} is a strictly proper rational polynomial all of whose poles have multiplicity one,

$$\hat{H}(s) = \frac{A(s)}{(s - p_1) \cdots (s - p_N)} .$$

Because the system is causal, $RoC(h)$ has the form

$$RoC(h) = \{s \mid Re\{s\} > q\},$$

where q is the largest real part of any pole. Since the system is stable, $q < 0$, so that the region of convergence includes the imaginary axis.

From table 13.3 the Laplace transform \hat{X} of the signal (13.17) is

$$\hat{X}(s) = \frac{1}{s - i\omega},$$

with $RoC(x) = \{s \in \mathbb{C} \mid Re\{s\} > 0\}$.

The Laplace transform of the output $y = h * x$ is

$$\hat{Y} = \hat{H}\hat{X},$$

with

$$RoC(y) \supset RoC(h) \cap RoC(x) = \{s \in \mathbb{C} \mid Re\{s\} > 0\}.$$

The partial fraction expansion of \hat{Y} is

$$\hat{Y}(s) = \hat{H}(s)\hat{X}(s) = \frac{A(s)}{(s - p_1) \cdots (s - p_N)} \cdot \frac{1}{s - i\omega} \quad (13.19)$$

$$= \frac{R_1}{s - p_1} + \cdots + \frac{R_N}{s - p_N} + \frac{R_\omega}{s - i\omega} . \quad (13.20)$$

Because everything is causal, each term must be causal, so from table 13.3 we obtain

$$\forall t, \quad y(t) = \sum_{k=1}^N R_k e^{p_k t} u(t) + R_\omega e^{i\omega t} u(t).$$

We decompose $y = y_{tr} + y_{ss}$, with

$$\begin{aligned}\forall t, \quad y_{tr}(t) &= \sum_{k=1}^N R_k e^{p_k t} u(t), \\ \forall t, \quad y_{ss}(t) &= R_\omega e^{i\omega t} u(t).\end{aligned}$$

Since $\operatorname{Re}\{p_k\} < 0$ for $k = 1, \dots, N$,

$$\lim_{t \rightarrow \infty} y_{tr}(t) = 0.$$

Thus, the steady-state response y_{ss} is eventually all that is left.

Finally, the residue R_ω is obtained by multiplying both sides of (13.19) by $s - i\omega$ and evaluating at $s = i\omega$ to get $R_\omega = \hat{H}(i\omega) = H(\omega)$, so that

$$\forall t, \quad y_{ss}(t) = H(\omega) e^{i\omega t} u(t).$$

This analysis reveals several interesting features of the total response y . First, from (13.20) we see the poles p_1, \dots, p_N of the transfer function contribute to the transient response y_{tr} , and the pole of the input \hat{X} at $i\omega$ contributes to the steady state response. Second we can determine how quickly the transient response dies down. The transient response is

$$\forall t, \quad y_{tr}(t) = R_1 e^{p_1 t} u(t) + \dots + R_N e^{p_N t} u(t).$$

The magnitude of the terms is

$$|R_1| e^{\operatorname{Re}\{p_1\}t}, \dots, |R_N| e^{\operatorname{Re}\{p_N\}t}.$$

Each term decreases exponentially with t , since the real parts of the poles are negative. The slowest decrease is due to the pole with the least negative part. Thus the pole of the stable, causal transfer function with the least negative part determines how fast the transient response goes to zero. Indeed for large t , we can approximate the response y as

$$y(t) \approx R_i e^{p_i t} + H(\omega) e^{i\omega t},$$

where p_i is the pole with the largest (least negative) real part.

There is a similar result for discrete-time systems, and it is obtained in the same way. Suppose an exponential input

$$\forall n \in \mathbb{Z}, \quad x(n) = e^{i\omega n} u(n),$$

is applied to a stable and causal system with impulse response h , transfer function \hat{H} , and frequency response H . Then the output $y = h * x$ can again be decomposed as

$$\forall n, \quad y(n) = y_{tr}(n) + y_{ss}(n),$$

where the transient $y_{tr}(n) \rightarrow 0$ as $n \rightarrow \infty$, and the steady state response is

$$\forall n, \quad y_{ss}(n) = \hat{H}(e^{i\omega}) e^{i\omega n} u(n) = H(\omega) e^{i\omega n} u(n).$$

For large n , the transient response decays exponentially as p_i^n , i.e.

$$y(n) \approx R_i p_i^n + y_{ss}(n),$$

where p_i is the pole with the largest magnitude (which must be less than one, since the system is stable).

13.7 Linear difference and differential equations

Many natural and man-made systems can be modeled as linear differential equations or difference equations. We have seen that when such systems are initially at rest, they are LTI systems. Hence, we can use their transfer functions (which are Z transforms or Laplace transforms) to analyze the response of these systems to external inputs.

However, physical systems are often not initially at rest. Dealing with non-zero initial conditions introduces some complexity in the analysis. Mathematicians call such systems with non-zero initial conditions **initial value problems**. We can adapt our methods to deal with initial conditions. The rest of this chapter is devoted to these methods.

Example 13.19: In example 13.8 we considered the LTI system described by the difference equation

$$y(n) - 0.9y(n-1) = x(n).$$

The transfer function of this system is $\hat{H}(z) = z/(z - 0.9)$. If the system is initially at rest, we can calculate its response y from its Z transform $\hat{Y} = \hat{H}\hat{X}$. For instance, if the input is the unit step, $\hat{X}(z) = z/(z - 1)$,

$$\hat{Y}(z) = \frac{z^2}{(z - 0.9)(z - 1)} = \frac{-9z}{z - 0.9} + \frac{10z}{z - 1},$$

and so $y(n) = -9(0.9)^n + 10, n \geq 0$.

We cannot use the transfer function, however, to determine the response if the initial condition at time $n = 0$ is $y(-1) = \bar{y}(-1)$, and the input is $x(n) = 0, n \geq 0$. The response to this initial condition is

$$y(n) = \bar{y}(-1)(0.9)^{n+1}, n \geq -1.$$

We can check that this expression is correct by verifying that it satisfies both the initial condition and the difference equation.

If the initial condition is $y(-1) = \bar{y}(-1)$ and the input is a unit step, the response turns out to be the sum of the response due to the input (with zero initial condition) and the response due to the initial condition (with zero input),

$$y(n) = [-9(0.9)^n + 10] + [\bar{y}(-1)(0.9)^{n+1}], n \geq 0.$$

For small values of n the response depends heavily on the initial condition, especially if $\bar{y}(0)$ is large. Because this system is stable, the effect of the initial condition becomes vanishingly small for large n .

An **LTI difference equation** has the form

$$y(n) + a_1y(n-1) + \cdots + a_my(n-m) = b_0x(n) + \cdots + b_kx(n-k), n \geq 0. \quad (13.21)$$

We interpret this equation as describing a causal discrete-time LTI system in which $x(n)$ is the input and $y(n)$ is the output at time n . The a_i and b_j are constant coefficients that specify the system.

We have used difference equations before. In section 8.2.1 we used this form and the discrete time Fourier transform to find the frequency response of this system. In section 9.5 we showed how to realize such systems as IIR filters. In example 13.19 we used the transfer function to find the response. But in all these cases, we had to assume that the system was initially at rest. We now develop a method to find the response for arbitrary initial conditions.

We assume the input signal x starts at some finite time, which we take to be zero, $x(n) = 0, n < 0$. We wish to calculate $y(n), n \geq 0$. From (13.21) we can see that we need to be given m initial conditions,

$$y(-1) = \bar{y}(-1), \dots, y(-m) = \bar{y}(-m).$$

Given the input signal and these initial conditions, there is a straightforward procedure to calculate the output response $y(n), n \geq 0$: Rewrite (13.21) as

$$y(n) = -a_1y(n-1) - \cdots - a_my(n-m) + b_0x(n) + \cdots + b_kx(n-k), \quad (13.22)$$

and recursively use (13.22) to obtain $y(0), y(1), y(2), \dots$. For $n = 0$, (13.22) yields

$$\begin{aligned} y(0) &= -a_1y(-1) - \cdots - a_my(-m) + b_0x(0) + \cdots + b_kx(-k) \\ &= -a_1\bar{y}(-1) - \cdots - a_m\bar{y}(-m) + b_0x(0). \end{aligned}$$

All the terms on the right are known from the initial conditions and the input $x(0)$, so we can calculate $y(0)$. Next, taking $n = 1$ in (13.22),

$$y(1) = -a_1y(0) + \cdots + a_my(1-m) + b_0x(1) + \cdots + b_kx(1-k).$$

All the terms on the right are known either from the given data or from precalculated values— $y(0)$ in this case. Proceeding in this way we can calculate the remaining values of the output sequence $y(2), y(3), \dots$, one at a time.

We now use the Z transform to calculate the *entire* output sequence. Multiplying both sides of (13.21) by $u(n)$, the unit step, gives us a relation that holds among signals whose domain is \mathbb{Z} :

$$\begin{aligned} y(n)u(n) + a_1y(n-1)u(n) + \cdots + a_my(n-m)u(n) \\ = b_0x(n)u(n) + \cdots + b_kx(n-k)u(n), \quad n \in \mathbb{Z}. \end{aligned}$$

We can now take the Z transforms of both sides. We multiply both sides by z^{-n} and sum,

$$\begin{aligned} \sum_{n=0}^{\infty} y(n)z^{-n} + a_1 \sum_{n=0}^{\infty} y(n-1)z^{-n} + \cdots + a_m \sum_{n=0}^{\infty} y(n-m)z^{-n} \\ = b_0 \sum_{n=0}^{\infty} x(n)z^{-n} + \cdots + b_k \sum_{n=0}^{\infty} x(n-k)z^{-n}. \end{aligned} \quad (13.23)$$

Define

$$\hat{X}(z) = \sum_{n=0}^{\infty} x(n)z^{-n}, \quad \hat{Y}(z) = \sum_{n=0}^{\infty} y(n)z^{-n}.$$

Each sum in (13.23) can be expressed in terms of \hat{Y} or \hat{X} . In evaluating the Z transforms of the signals $y(n-1)u(n), y(n-2)u(n), \dots$ we need to include the initial conditions:

$$\begin{aligned}\sum_{n=0}^{\infty} y(n-1)z^{-n} &= \bar{y}(-1)z^0 + z^{-1} \sum_{n=1}^{\infty} y(n-1)z^{-(n-1)} = \bar{y}(-1)z^0 + z^{-1}\hat{Y}(z), \\ \sum_{n=0}^{\infty} y(n-2)z^{-n} &= \bar{y}(-2)z^0 + \bar{y}(-1)z^{-1} + z^{-2} \sum_{n=2}^{\infty} y(n-2)z^{-(n-2)} \\ &= \bar{y}(-2)z^0 + \bar{y}(-1)z^{-1} + z^{-2}\hat{Y}(z), \\ &\dots \\ \sum_{n=0}^{\infty} y(n-m)z^{-n} &= \bar{y}(-m)z^0 + \dots + \bar{y}(-1)z^{-(m-1)} + z^{-m} \sum_{n=m}^{\infty} y(n-m)z^{-(n-m)} \\ &= \bar{y}(-m)z^0 + \dots + \bar{y}(-1)z^{-(m-1)} + z^{-m}\hat{Y}(z).\end{aligned}$$

Because $x(n) = 0, n < 0$, by assumption, the sums on the right in (13.23) are simpler:

$$\begin{aligned}\sum_{n=0}^{\infty} x(n-1)z^{-n} &= x(-1)z^0 + z^{-1}\hat{X}(z) = z^{-1}\hat{X}(z) \\ \sum_{n=0}^{\infty} x(n-2)z^{-n} &= x(-2)z^0 + x(-1)z^{-1} + z^{-2}\hat{X}(z) = z^{-2}\hat{X}(z) \\ &\dots \\ \sum_{n=0}^{\infty} x(n-k)z^{-n} &= x(-k)z^0 + \dots + x(-1)z^{-(k-1)} + z^{-k}\hat{X}(z) = z^{-k}\hat{X}(z).\end{aligned}$$

(If there were non-zero initial conditions for $x(-1), \dots, x(-k)$, we could include them in the Z transforms of $x(n-1)u(n), \dots, x(n-k)u(n)$.) Substituting these relations in (13.23) yields

$$\begin{aligned}\hat{Y}(z) &+ a_1[z^{-1}\hat{Y}(z) + \bar{y}(-1)z^0] \\ &+ \dots \\ &+ a_m[z^{-m}\hat{Y}(z) + \bar{y}(-m)z^0 + \dots + \bar{y}(-1)z^{-(m-1)}] \\ &= b_0\hat{X}(z) + b_1z^{-1}\hat{X}(z) + \dots + b_kz^{-k}\hat{X}(z),\end{aligned}\tag{13.24}$$

from which, by rearranging terms, we obtain

$$[1 + a_1z^{-1} + \dots + a_mz^{-m}]\hat{Y}(z) = [b_0 + b_1z^{-1} + \dots + b_kz^{-k}]\hat{X}(z) + \hat{C}(z),$$

where $\hat{C}(z)$ is an expression involving only the initial conditions

$$\bar{y}(-1), \dots, \bar{y}(-m).$$

Therefore,

$$\hat{Y}(z) = \frac{b_0 + b_1 z^{-1} + \cdots + b_k z^{-k}}{1 + a_1 z^{-1} + \cdots + a_m z^{-m}} \hat{X}(z) + \frac{\hat{C}(z)}{1 + a_1 z^{-1} + \cdots + a_m z^{-m}}.$$

We rewrite this relation as

$$\hat{Y}(z) = \hat{H}(z) \hat{X}(z) + \frac{\hat{C}(z)}{1 + a_1 z^{-1} + \cdots + a_m z^{-m}}. \quad (13.25)$$

where

$$\hat{H}(z) = \frac{b_0 + b_1 z^{-1} + \cdots + b_k z^{-k}}{1 + a_1 z^{-1} + \cdots + a_m z^{-m}}.$$

(13.26)

Observe that if the initial conditions are all zero, $\hat{C}(z) = 0$, and we only have the first term on the right in (13.25); and if the input is zero—i.e., $x(n) = 0$ for all n , then $\hat{X}(z) = 0$, and we only have the second term.

By definition, $\hat{Y}(z)$ is the Z transform of the causal signal $y(n)u(n), n \in \mathbb{Z}$. So its $RoC = \{z \in \mathbb{C} \mid |z| > |p|\}$ in which p is the pole of the right side of (13.25) with the largest magnitude. The inverse Z transform of \hat{Y} can be expressed as

$$\forall n \geq 0, \quad y(n) = y_{zs}(n) + y_{zi}(n),$$

where $y_{zs}(n)$, the inverse Z transform of $\hat{H}\hat{X}$, is the **zero-state response**, and $y_{zi}(n)$, the inverse Z transform of $\hat{C}(z)/[1 + a_1 z^{-1} + \cdots + a_m z^{-m}]$, is the **zero-input response**. The zero-state response, also called the **forced response**, is the output when all initial conditions are zero. The zero-input response, also called the **natural response**, is the output when the input is zero.

Thus the (total) response is the sum of the zero-state and zero-input response. We first encountered this property of linearity in Chapter 5.

By definition, the **transfer function** is the Z transform of the zero-state impulse response. Taking $\hat{C} = 0$ and $\hat{X} = 1$ in (13.25) shows that the transfer function is $\hat{H}(z)$. From (13.26) we see that \hat{H} can be written down by inspection of the difference equation (13.21). If the system is stable—all poles of \hat{H} are inside the unit circle—the frequency response is

$$\forall \omega, \quad H(\omega) = \hat{H}(e^{j\omega}) = \frac{b_0 + b_1 e^{-j\omega} + \cdots + b_k e^{-jk\omega}}{1 + a_1 e^{-j\omega} + \cdots + a_m e^{-jm\omega}}.$$

We saw this relation in (8.21).

Example 13.20: Consider the difference equation

$$y(n) - \frac{5}{6}y(n-1) + \frac{1}{6}y(n-2) = x(n), \quad n \geq 0.$$

Taking Z transforms as in (13.24) yields

$$\hat{Y}(z) - \frac{5}{6}[z^{-1}\hat{Y}(z) + \bar{y}(-1)] + \frac{1}{6}[z^{-2}\hat{Y}(z) + \bar{y}(-2) + \bar{y}(-1)z^{-1}] = \hat{X}(z).$$

Therefore

$$\begin{aligned}\hat{Y}(z) &= \frac{1}{1 - \frac{5}{6}z^{-1} + \frac{1}{6}z^{-2}}\hat{X}(z) + \frac{\frac{5}{6}\bar{y}(-1) + \frac{1}{6}\bar{y}(-2) + \frac{1}{6}\bar{y}(-1)z^{-1}}{1 - \frac{5}{6}z^{-1} + \frac{1}{6}z^{-2}} \\ &= \frac{z^2}{z^2 - \frac{5}{6}z + \frac{1}{6}}\hat{X}(z) + \frac{[\frac{5}{6}\bar{y}(-1) + \frac{1}{6}\bar{y}(-2)]z^2 + \frac{1}{6}\bar{y}(-1)z}{z^2 - \frac{5}{6}z + \frac{1}{6}},\end{aligned}$$

from which we can obtain \hat{Y} for a specified \hat{X} and initial conditions $\bar{y}(-1), \bar{y}(-2)$. The transfer function is

$$\hat{H}(z) = \frac{z^2}{z^2 - \frac{5}{6}z + \frac{1}{6}} = \frac{z^2}{(z - \frac{1}{3})(z - \frac{1}{2})},$$

which has poles at $z = 1/3$ and $z = 1/2$ (and two zeros at $z = 0$). The system is stable. The zero-state impulse response h is the inverse Z transform of $\hat{H}(z)$, which we obtain using partial fraction expansion,

$$\hat{H}(z) = z \left[\frac{-2}{z - \frac{1}{3}} + \frac{3}{z - \frac{1}{2}} \right]$$

so that

$$\forall n \in \mathbb{Z}, \quad h(n) = -2 \left(\frac{1}{3} \right)^n u(n) + 3 \left(\frac{1}{2} \right)^n u(n).$$

We can recognize that the impulse response consists of two terms, each contributed by one pole of the transfer function.

Suppose the initial conditions are $\bar{y}(-1) = 1, \bar{y}(-2) = 1$ and the input x is the unit step, so $\hat{X}(z) = z/(z-1)$. Then the zero-input response, y_{zi} , has Z transform

$$\begin{aligned}\hat{Y}_{zi}(z) &= \frac{[\frac{5}{6}\bar{y}(-1) + \frac{1}{6}\bar{y}(-2)]z^2 + \frac{1}{6}\bar{y}(-1)z}{(z - \frac{1}{3})(z - \frac{1}{2})} \\ &= \frac{z^2 + \frac{1}{6}z}{(z - \frac{1}{3})(z - \frac{1}{2})} = z \left[\frac{-3}{z - \frac{1}{3}} + \frac{4}{z - \frac{1}{2}} \right],\end{aligned}$$

so

$$\forall n, \quad y_{zi}(n) = -3\left(\frac{1}{3}\right)^n u(n) + 4\left(\frac{1}{2}\right)^n u(n).$$

The zero-state response, y_{zs} , has Z transform

$$\begin{aligned} \hat{Y}_{zs}(z) &= \hat{H}(z)\hat{X}(z) = \frac{z^3}{(z - \frac{1}{3})(z - \frac{1}{2})(z - 1)} \\ &= z \left[\frac{1}{z - \frac{1}{3}} + \frac{-3}{z - \frac{1}{2}} + \frac{3}{z - 1} \right], \end{aligned}$$

so

$$\forall n, \quad y_{zs}(n) = \left(\frac{1}{3}\right)^n u(n) - 3\left(\frac{1}{2}\right)^n u(n) + 3u(n).$$

The (total) response

$$\forall n \in \mathbb{Z}, \quad y(n) = y_{zs}(n) + y_{zi}(n) = 3u(n) + [-2(1/3)^n + (1/2)^n]u(n),$$

can also be expressed as the sum of the steady-state and the transient response with $y_{ss}(n) = 3u(n)$ and $y_{tr}(n) = -2(1/3)^n u(n) + (1/2)^n u(n)$. Note that the decomposition of the response into the sum of the zero-state and zero-input responses is different from its decomposition into the steady-state and transient responses.

13.7.1 LTI differential equations

The analogous development for continuous time concerns systems described by a **LTI differential equation** of the form

$$\begin{aligned} \frac{d^m y}{dt^m}(t) + a_{m-1} \frac{d^{m-1} y}{dt^{m-1}}(t) + \cdots + a_1 \frac{dy}{dt}(t) + a_0 y(t) \\ = b_k \frac{d^k x}{dt^k}(t) + \cdots + b_1 \frac{dx}{dt}(t) + b_0 x(t), \quad t \geq 0. \end{aligned} \tag{13.27}$$

We interpret this equation as describing a causal continuous-time LTI system in which $x(t)$ is the input and $y(t)$ is the output at time t . The constant coefficients a_i and b_j specify the system.

In section 8.2.1 we used this form to find the frequency response. In example 13.11, we used the Laplace transform to find the transfer function of a tuning force. But in both cases, we assumed that the system was initially at rest. We now develop a method to find the response to arbitrary initial conditions. We begin with a simple circuit example.

Example 13.21: A series connection of a resistor R , a capacitor C , and a voltage source x , is described by the differential equation

$$\frac{dy}{dt}(t) + \frac{1}{RC}y(t) = x(t),$$

in which y is the voltage across the capacitor. The differential equation is obtained from Kirchhoff's voltage law. The transfer function of this system is $\hat{H}(s) = 1/(s + 1/RC)$. So if the system is initially at rest, we can calculate the response y from its Laplace transform $\hat{Y} = \hat{H}\hat{X}$. For instance, if the input is a unit step, $\hat{X}(s) = 1/s$,

$$\hat{Y}(s) = \frac{1}{(s + 1/RC)s} = \frac{-RC}{s + 1/RC} + \frac{RC}{s},$$

therefore, $y(t) = -RCe^{-t/RC} + RC, t \geq 0$.

We cannot use this transfer function, however, to determine the response if the initial capacitor voltage is $y(0) = \bar{y}(0)$ and $x(t) = 0, t \geq 0$. The response in this case is

$$y(t) = \bar{y}(0)e^{-t/RC}, t \geq 0.$$

We can check that expression is correct by verifying that it satisfies the given initial condition and the differential equation.

If the initial condition is $y(0) = \bar{y}(0)$ and the input is a unit step, the response turns out to be the sum of the response due to the input (with zero initial condition) and the response due to the initial condition (with zero input),

$$y(t) = [-RCe^{-t/RC} + RC] + [\bar{y}(0)e^{-t/RC}], t \geq 0.$$

For the general case (13.27) we assume that the input x starts at some finite time which we take to be zero, so $x(t) = 0, t < 0$. We wish to calculate $y(t), t \geq 0$. From the theory of

differential equations we know that we need to be given m initial conditions,

$$y(0) = \bar{y}(0), \frac{dy}{dt}(0) = \bar{y}^{(1)}(0), \dots, \frac{d^{m-1}y}{dt^{m-1}}(0) = \bar{y}^{(m-1)}(0),$$

in order to calculate $y(t), t \geq 0$.

Because time is continuous, there is no recursive procedure for calculating the output from the given data as we did in (13.22). Instead we calculate the output signal using the Laplace transform. We define the Laplace transforms of the signals $y(t)u(t), y^{(1)}(t)u(t), \dots, y^{(m)}(t)u(t)$

$$\begin{aligned}\hat{Y}(s) &= \int_{-\infty}^{\infty} y(t)u(t)e^{-st}dt = \int_0^{\infty} y(t)e^{-st}dt \\ \hat{Y}^{(i)}(s) &= \int_{-\infty}^{\infty} y^{(i)}(t)u(t) = \int_0^{\infty} y^{(i)}(t)e^{-st}dt, i = 1, \dots, m \\ \hat{X}(s) &= \int_{-\infty}^{\infty} x(t)u(t)e^{-st}dt = \int_0^{\infty} x(t)e^{-st}dt.\end{aligned}$$

Here we use the notation $y^{(i)}(t) = \frac{d^i y}{dt^i}(t), t \geq 0$. We now derive the relations between these Laplace transforms.

The derivative $y^{(1)}(t) = \frac{dy}{dt}(t)$ and y are related by

$$y(t)u(t) = y(0)u(t) + \int_0^t y^{(1)}(\tau)u(\tau)d\tau = \bar{y}(0)u(t) + \int_0^t y^{(1)}(\tau)u(\tau)d\tau, t \in \mathbb{R}.$$

Using integration by parts,

$$\begin{aligned}\hat{Y}(s) &= \int_0^{\infty} y(t)e^{-st}dt = \int_0^{\infty} \bar{y}(0)e^{-st}dt + \int_0^{\infty} \left(\int_0^t y^{(1)}(\tau)d\tau \right) e^{-st}dt \\ &= \frac{1}{s}\bar{y}(0) - \frac{1}{s} \int_0^t y^{(1)}(\tau)d\tau e^{-st} \Big|_{t=0} + \frac{1}{s} \int_0^{\infty} y^{(1)}(t)e^{-st}dt \\ &= \frac{1}{s}[\hat{Y}^{(1)}(s) + \bar{y}(0)].\end{aligned}$$

Therefore,

$$\boxed{\hat{Y}^{(1)}(s) = s\hat{Y}(s) - \bar{y}(0).} \quad (13.28)$$

Repeating this procedure, we get the Laplace transforms of the higher-order derivatives,

$$\begin{aligned}\hat{Y}^{(2)}(s) &= s\hat{Y}^{(1)}(s) - \bar{y}^{(1)}(0) \\ &= s^2\hat{Y}(s) - s\bar{y}(0) - \bar{y}^{(1)}(0) \\ &\quad \dots \\ \hat{Y}^{(m)}(s) &= s^m\hat{Y}(s) - s^{m-1}\bar{y}(0) - s^{m-2}\bar{y}^{(1)}(0) - \dots - \bar{y}^{(m-1)}(0).\end{aligned}$$

On the other hand, because $x^{(i)}(t) = \frac{d^i x}{dt^i}(t)$ for all $t \in \mathbb{R}$, using the differentiation property in table 13.4, we obtain

$$\begin{aligned}\hat{X}^{(1)}(s) &= s\hat{X}(s) \\ &\dots \\ \hat{X}^{(k)}(s) &= s^k\hat{X}(s).\end{aligned}$$

By substituting from the relations just derived, we obtain the Laplace transforms of all the terms in (13.27),

$$\begin{aligned}&[s^m\hat{Y}(s) - s^{m-1}\bar{y}(0) - \dots - \bar{y}^{m-1}(0)] \\ &+ a_{m-1}[s^{m-1}\hat{Y}(s) - s^{m-2}\bar{y}(0) - \dots - \bar{y}^{m-2}(0)] \\ &\dots \\ &+ a_1[s\hat{Y}(s) - \bar{y}(0)] \\ &+ a_0\hat{Y}(s) \\ &= b_k s^k \hat{X}(s) + \dots + b_1 s \hat{X}(s) + b_0 \hat{X}(s).\end{aligned}\tag{13.29}$$

Rearranging terms yields

$$[s^m + a_{m-1}s^{m-1} + \dots + a_1s + a_0]\hat{Y}(s) = [b_k s^k + \dots + b_1 s + b_0]\hat{X}(s) + \hat{C}(s),$$

in which \hat{C} is an expression involving only the intial conditions

$$\bar{y}(0), \dots, \bar{y}^{(m-1)}(0).$$

Therefore,

$$\hat{Y}(s) = \frac{b_k s^k + b_{k-1}s^{k-1} + \dots + b_1 s + b_0}{s^m + a_{m-1}s^{m-1} + \dots + a_1s + a_0} \hat{X}(s) + \frac{\hat{C}(s)}{s^m + a_{m-1}s^{m-1} + \dots + a_1s + a_0},\tag{13.30}$$

which we also write as

$$\hat{Y}(s) = \hat{H}(s)\hat{X}(s) + \frac{\hat{C}(s)}{s^m + a_{m-1}s^{m-1} + \dots + a_1s + a_0},\tag{13.31}$$

in which

$$\hat{H}(s) = \frac{b_k s^k + \dots + b_1 s + b_0}{s^m + \dots + a_1 s + a_0}.$$

(13.32)

If the initial conditions are all zero, $\hat{C}(s) = 0$, and we only have the first term on the right in (13.31); if the input is zero—i.e., $x(t) = 0$ for all t , then $\hat{X}(s) = 0$, and we only get the second term in (13.31).

By definition, $\hat{Y}(s)$ is the Laplace transform of the causal signal $y(t)u(t), t \in \mathbb{R}$. So its $RoC = \{s \in \mathbb{C} \mid Re\{s\} > Re\{p\}\}$, where p is a pole of the right side of (13.31) with the largest real part.

Taking the inverse Laplace transform of \hat{Y} , we can decompose the output signal y as

$$\forall t, \quad y(t) = y_{zs}(t) + y_{zi}(t),$$

where y_{zs} , the inverse Laplace transform of $\hat{H}\hat{X}$, is the **zero-state or forced response** and y_{zi} , the inverse Laplace transform of $\hat{C}(s)/[s^m + \dots + a_0]$, is the **zero-input or natural response**. The (total) response is the sum of the zero-state and zero-input response, which is a general property of linear systems.

By definition, the **transfer function** is the Laplace transform of the zero-state impulse response. Taking $\hat{C} = 0$ and $\hat{X} = 1$ (the Laplace transform of the unit impulse) in (13.31) shows that the transfer function is $\hat{H}(s)$ which, as we see from (13.32), can be written down by inspection of the differential equation (13.27). If the system is stable—all poles of $\hat{H}(s)$ have real parts strictly less than zero—the frequency response is, as in (8.23)

$$\forall \omega, \quad H(\omega) = \hat{H}(i\omega) = \frac{b_k(i\omega)^k + \dots + b_1 i\omega + b_0}{(i\omega)^m + \dots + a_1 i\omega + a_0}.$$

Example 13.22: We find the response $y(t), t \geq 0$, for the differential equation

$$\frac{d^2y}{dt^2} + 3\frac{dy}{dt} + 2y = 3x(t) + \frac{dx}{dt},$$

when the input is a unit step $x(t) = u(t)$ and the initial conditions are $y(0) = 1, y^{(1)}(0) = 2$. Taking Laplace transforms of both sides as in (13.29),

$$[s^2\hat{Y}(s) - s\bar{y}(0) - \bar{y}^{(1)}(0)] + 3[s\hat{Y}(s) - \bar{y}(0)] + 2\hat{Y}(s) = 3\hat{X}(s) + s\hat{X}(s).$$

Therefore,

$$\hat{Y}(s) = \frac{s+3}{s^2+3s+2} \hat{X}(s) + \frac{s\bar{y}(0) + \bar{y}^{(1)}(0) + 3\bar{y}(0)}{s^2+3s+2}.$$

Substituting $\hat{X}(s) = 1/s$, $\bar{y}(0) = 1$, $\bar{y}^{(1)} = 2$, yields

$$\begin{aligned}\hat{Y}(s) &= \frac{s+3}{s(s^2+3s+2)} + \frac{s+5}{s^2+3s+2} \\ &= \left[\frac{3/2}{s} - \frac{2}{s+1} + \frac{1/2}{s+2} \right] + \left[\frac{4}{s+1} - \frac{3}{s+2} \right].\end{aligned}$$

Taking inverse Laplace transforms gives

$$\begin{aligned}\forall t, \quad y(t) &= y_{zs}(t) + y_{zi}(t) \\ &= \left[\frac{3}{2}u(t) - 2e^{-t}u(t) + \frac{1}{2}e^{-2t}u(t) \right] + \left[4e^{-t}u(t) - 3e^{-2t}u(t) \right] \\ &= \frac{3}{2}u(t) + \left[2e^{-t} - \frac{5}{2}e^{-2t} \right]u(t) \\ &= y_{ss}(t) + y_{tr}(t).\end{aligned}$$

As in the case of difference equations, the decomposition of the response into zero-state and zero-input responses is different from the decomposition into transient and steady-state responses. (Indeed, the steady-state response does not exist if the system is unstable, whereas the former decomposition always exists.)

13.8 State-space models

This section is mathematically more advanced in that it uses the operation of matrix inverse.

In section 5.3 we introduced single-input, single-output (SISO) multidimensional state-space models of discrete-time and continuous-time LTI systems. For LTI systems, state-space models provide an alternative description to difference or differential equation representations. The advantage of state-space models is that by using matrix notation we have a very compact representation of the response, independent of the order of the system. We develop a method that combines this matrix notation with transform techniques to calculate the response.

The discrete-time SISO state-space model is

$$\forall n \geq 0, \quad s(n+1) = As(n) + bx(n), \quad (13.33)$$

$$y(n) = c^T s(n) + dx(n), \quad (13.34)$$

in which $s(n) \in \mathbb{R}^N$ is the state, $x(n) \in \mathbb{R}$ is the input, and $y(n) \in \mathbb{R}$ is the output at time n . In this $[A, b, c, d]$ representation, A is an $N \times N$ (square) matrix, b, c are N -dimensional column vectors, and d is a scalar. If the initial state is $s(0)$, and the input sequence is $x(0), x(1), \dots$, by recursively using (13.33) and (13.34) we obtain the state and output responses:

$$s(n) = A^n s(0) + \sum_{m=0}^{n-1} A^{n-1-m} b x(m), \quad (13.35)$$

$$y(n) = c^T A^n s(0) + \left\{ \sum_{m=0}^{n-1} c^T A^{n-1-m} b x(m) + d x(n) \right\}, \quad (13.36)$$

for all $n \geq 0$. Notice that these “closed-form” formulas for the response are independent of the order N . Difference equation representations do not have such a closed-form formula.

Example 13.23: Consider the system described by the difference equation

$$y(n) - 2y(n-1) - 3y(n-2) = x(n).$$

As in section 5.3, we can construct a state-space model for this system by noting that the state at time n should remember the previous two inputs $y(n-1), y(n-2)$. Define the two-dimensional state vector $s(n) = [s_1(n) \ s_2(n)]^T$ by $s_1(n) = y(n-1), s_2(n) = ay(n-2)$, in which $a \neq 0$ is a constant. Problem 23 at the end of this chapter asks you to show that the $[A, b, c, d]$ representation for this choice of state is given by

$$A = \begin{bmatrix} 2 & 3/a \\ a & 0 \end{bmatrix}, \quad b = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \quad c^T = [2 \ 3/a], \text{ and } d = 1.$$

Different choices of a give a different state-space model. However, they all have the same input-output relation because they all have the same transfer function.

We will obtain the Z transforms of the response sequences (13.35), (13.36). The key is to compute the Z transform of the entire $N \times N$ matrix sequence $A^n u(n), n \in \mathbb{Z}$. This Z transform is

$$\sum_{n=0}^{\infty} z^{-n} A^n = [I - z^{-1} A]^{-1} = z[zI - A]^{-1}. \quad (13.37)$$

Here z is a complex number and I is the $N \times N$ identity matrix. The series on the left is an infinite sum of $N \times N$ matrices which converges to the $N \times N$ matrix on the right, for $z \in \text{RoC}$. RoC is determined later.

Assuming the series converges, it is easy to check the equality (13.37): Just multiply both sides by $[I - z^{-1} A]$ and verify that

$$[I - z^{-1} A] \sum_{n=0}^{\infty} z^{-n} A^n = \sum_{n=0}^{\infty} z^{-n} A^{-n} - \sum_{n=0}^{\infty} z^{-(n+1)} A^{n+1} = z^0 A^0 = I.$$

Next, denote by F the matrix inverse,

$$F(z) = [I - z^{-1} A]^{-1} = z[zI - A]^{-1}, \quad (13.38)$$

and the coefficients of A^n and $F(z)$ by

$$A^n = [a_{ij}(n) \mid 1 \leq i, j \leq N], \quad F(z) = [f_{ij}(z) \mid 1 \leq i, j \leq N].$$

Then $f_{ij}(z) = \sum_{n=0}^{\infty} z^{-n} a_{ij}(n)$ is the Z transform of the sequence $a_{ij}(n), n \geq 0, 1 \leq i, j \leq N$. So we can obtain $A^n, n \geq 0$, by taking the inverse Z transform of each of the N^2 coefficients of $F(z)$.

Example 13.24: Let

$$A = \begin{bmatrix} 2 & 1 \\ 3 & 4 \end{bmatrix},$$

then

$$[zI - A]^{-1} = \begin{bmatrix} z-2 & -1 \\ -3 & z-4 \end{bmatrix}^{-1} = \frac{1}{\det[zI - A]} \begin{bmatrix} z-4 & 1 \\ 3 & z-2 \end{bmatrix},$$

in which $\det[zI - A]$ denotes the determinant of $[zI - A]$,

$$\det[zI - A] = (z-2)(z-4) - 3 = z^2 - 6z + 5 = (z-1)(z-5).$$

Hence,

$$\begin{aligned} F(z) = z[zI - A]^{-1} &= \frac{z}{(z-1)(z-5)} \begin{bmatrix} z-4 & 1 \\ 3 & z-2 \end{bmatrix} \\ &= \begin{bmatrix} \frac{z(z-4)}{(z-1)(z-5)} & \frac{z}{(z-1)(z-5)} \\ \frac{3z}{(z-1)(z-5)} & \frac{z(z-2)}{(z-1)(z-5)} \end{bmatrix}. \end{aligned}$$

The partial fraction expansion of the coefficients of F is

$$F(z) = \begin{bmatrix} \frac{(3/4)z}{z-1} + \frac{(1/4)z}{z-5} & \frac{(-1/4)z}{z-1} + \frac{(1/4)z}{z-5} \\ \frac{(-3/4)z}{z-1} + \frac{(3/4)z}{z-5} & \frac{(1/4)z}{z-1} + \frac{(3/4)z}{z-5} \end{bmatrix}.$$

Using table 13.1 we find the inverse Z transform of every coefficient of $F(z)$: for all $n \in \mathbb{Z}$,

$$A^n u(n) = \begin{bmatrix} \frac{3}{4}u(n) + \frac{1}{4}5^n u(n) & -\frac{1}{4}u(n) + \frac{1}{4}5^n u(n) \\ -\frac{3}{4}u(n) + \frac{3}{4}5^n u(n) & \frac{1}{4}u(n) + \frac{3}{4}5^n u(n) \end{bmatrix}.$$

This is more revealingly expressed as

$$A^n = \begin{bmatrix} 3/4 & -1/4 \\ -3/4 & 1/4 \end{bmatrix} + 5^n \begin{bmatrix} 1/4 & 1/4 \\ 3/4 & 3/4 \end{bmatrix}, \quad n \geq 0,$$

because it shows that the variation in n of A^n is determined by the two poles, at $z = 1$ and $z = 5$, in the coefficients of $F(z)$. Moreover, these two poles are the zeros of

$$\det[zI - A] = (z - 1)(z - 5).$$

This determinant is called the **characteristic polynomial** of the matrix A and its zeros are called the **eigenvalues** of A . The domain of convergence is $\text{RoC} = \{z \in \mathbb{C} \mid |z| > 5\}$.

We return to the general case in (13.38). Denote the matrix inverse of $[zI - A]$ as

$$[zI - A]^{-1} = \frac{1}{\det[zI - A]} G(z),$$

in which $G(z)$ is the $N \times N$ matrix of co-factors of $[zI - A]$. It follows that each coefficient $f_{ij}(z)$ of $F(z) = z[zI - A]^{-1}$ is a rational polynomial whose denominator is the characteristic polynomial of A , $\det[zI - A]$. Therefore, if there are no pole-zero cancellations, all coefficients of $F(z)$ have the same poles, which are the zeros of $\det[zI - A]$. These zeros are called the eigenvalues of A . The polynomial $\det[zI - A]$ is of order N , and so A has N eigenvalues.

Because $A^n u(n), n \in \mathbb{Z}$, is a causal sequence, the region of convergence is $RoC = \{z \in \mathbb{C} \mid |z| > |p|\}$, in which p is the pole of F (or eigenvalue of A) with the largest magnitude. For the system (13.33), (13.34) to be stable, the poles of F must have magnitudes strictly smaller than 1.

Suppose A has N distinct eigenvalues p_1, \dots, p_N ,

$$\det[zI - A] = (z - p_1) \cdots (z - p_N).$$

Then the partial fraction expansion of $F(z)$ has the form

$$F(z) = \frac{z}{z - p_1} R_1 + \cdots + \frac{z}{z - p_N} R_N,$$

in which R_i is the matrix of residues of the coefficients of F at the pole p_i . R_i is a constant matrix, possibly with complex coefficients if p_i is complex. Recalling that $\frac{z}{z - p_i}$ is the inverse Z transform of $p_i^n u(n)$, we can take the inverse Z transform of $F(z)$ to conclude that

$$A^n = p_1^n R_1 + \cdots + p_N^n R_N, \quad n \geq 0. \quad (13.39)$$

Thus A^n is a linear combination of p_1^n, \dots, p_N^n .

We can decompose the response (13.36) into the zero-input and zero-state responses, expressing the latter as a convolution sum,

$$y(n) = c^T A^n s(0) + \sum_{m=0}^n h(n-m) x(m), \quad n \geq 0,$$

where the (zero-state) impulse response is

$$h(n) = \begin{cases} 0, & n < 0 \\ d, & n = 0 \\ c^T A^{n-1} b, & n \geq 1 \end{cases}.$$

Let $\hat{X}, \hat{Y}, \hat{H}, \hat{Y}_{zi}$ be the Z transforms:

$$\hat{X}(z) = \sum_{n=0}^{\infty} x(n)z^{-n}, \quad \hat{Y}(z) = \sum_{n=0}^{\infty} y(n)z^{-n},$$

$$\hat{H}(z) = \sum_{n=0}^{\infty} h(n)z^{-n}, \quad \hat{Y}_{zi}(z) = \sum_{n=0}^{\infty} c^T z^{-n} A^n s(0).$$

Then

$$\hat{Y} = \hat{H}\hat{X} + \hat{Y}_{zi}.$$

Because $\sum_{n=0}^{\infty} z^{-n} A^n = z[zI - A]^{-1}$, we obtain

$$\boxed{\hat{H}(z) = c^T [zI - A]^{-1} b + d,}$$

and

$$\boxed{\hat{Y}_{zi}(z) = z c^T [zI - A]^{-1} s(0).}$$

Example 13.25: Suppose A is as in example 13.24, $b^T = [1 \ 1]$, $c^T = [2 \ 0]$, $d = 3$, and $(s(0))^T = [0 \ 4]$. Then the transfer function is

$$\hat{H}(z) = [2 \ 0] \begin{bmatrix} \frac{(z-4)}{(z-1)(z-5)} & \frac{1}{(z-1)(z-5)} \\ \frac{3}{(z-1)(z-5)} & \frac{(z-2)}{(z-1)(z-5)} \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} + 3 = \frac{2(z-4)+2}{(z-1)(z-5)} + 3,$$

and the Z transform of the zero-input response is

$$\hat{Y}_{zi}(z) = [2 \ 0] \begin{bmatrix} \frac{z(z-4)}{(z-1)(z-5)} & \frac{z}{(z-1)(z-5)} \\ \frac{3z}{(z-1)(z-5)} & \frac{z(z-2)}{(z-1)(z-5)} \end{bmatrix} \begin{bmatrix} 0 \\ 4 \end{bmatrix} = \frac{8z}{(z-1)(z-5)}.$$

The transfer function

$$\hat{H}(z) = \frac{2(z-4)+2}{(z-1)(z-5)} + 3 = \frac{3z^2 - 16z + 9}{z^2 - 6z + 5} = \frac{3 - 16z^{-1} + 9z^{-2}}{1 - 6z^{-1} + 5z^{-2}}.$$

From (13.26) we recognize that \hat{H} is also the transfer function of the difference equation

$$y(n) - 6y(n-1) + 5y(n-2) = 3x(n) - 16x(n-1) + 9x(n-2).$$

This difference equation describes the same input-output relation as the state-space model of this example.

13.8.1 Continuous-time state-space models

The continuous-time SISO state-space model introduced in section 5.4 has the representation in terms of $[A, b, c, d]$

$$\dot{v}(t) = Av(t) + bx(t), \quad (13.40)$$

$$y(t) = c^T v(t) + dx(t), \quad (13.41)$$

in which $v(t) \in \mathbb{R}^N$ is the state, $x(t) \in \mathbb{R}$ is the input, and $y(t) \in \mathbb{R}$ is the output at time $t \in \mathbb{R}$. A is an $N \times N$ matrix, and b, c are N -dimensional column vectors, and d is a scalar. (We use v instead of s to denote the state, because s is reserved for the Laplace transform variable.)

Given the initial state $v(0)$ and the input signal $x(t), t \geq 0$, we will show that the state response and the output response obey the formulas

$$v(t) = e^{tA}v(0) + \int_0^t e^{(t-\tau)A}bx(\tau)d\tau, \quad (13.42)$$

$$y(t) = c^T e^{tA}v(0) + \left[\int_0^t c^T e^{(t-\tau)A}bx(\tau)d\tau \right] + dx(t). \quad (13.43)$$

In these formulas, e^{tA} or $\exp(tA)$ is the name of the $N \times N$ matrix

$$e^{tA} = \sum_{k=0}^{\infty} \frac{(tA)^k}{k!} = I + tA + \frac{(tA)^2}{2!} + \frac{(tA)^3}{3!} + \dots, \quad (13.44)$$

where $(tA)^k$ is the matrix tA multiplied by itself k times, and $(tA)^0 = I$, the $N \times N$ identity matrix. Definition (13.44) of the **matrix exponential** is the natural generalization of the exponential of a real or complex number. (The series in (13.44) is absolutely summable because of the factor $k!$ in the denominator.)

Unlike in the discrete-time case, there is no recursive procedure to compute the responses (13.42), (13.43). This is because time is continuous, and the difficulty has to do with the integrals in these formulas. For numerical calculation, one resorts to a finite sum approximation of the integrals, as we indicated in Section 5.4. The Laplace transform provides an alternative approach that is exact.

The key to showing (13.42) is the fact that $e^{tA}, t \geq 0$, is the solution to the differential equation

$$\frac{d}{dt}e^{tA} = Ae^{tA}, \quad t \geq 0, \quad (13.45)$$

with initial condition $e^{0A} = I$. Note that (13.43) follows immediately from (13.42) and (13.41).

To verify (13.45) we substitute for e^{tA} from (13.44) and differentiate the sum term by term,

$$\frac{d}{dt}e^{tA} = \sum_{k=0}^{\infty} \frac{d}{dt} \frac{(tA)^k}{k!} = \sum_{k=1}^{\infty} \frac{kA}{k!} (tA)^{k-1} = A \sum_{k=1}^{\infty} \frac{(tA)^{k-1}}{(k-1)!} = Ae^{tA}.$$

We can now check that (13.42) is indeed the solution of (13.40) by taking derivatives of both sides and using (13.45):

$$\begin{aligned} \dot{v}(t) &= Ae^{tA}v(0) + e^{0A}bx(t) + \int_0^t Ae^{(t-\tau)A}bx(\tau)d\tau \\ &= A[e^{tA}v(0) + \int_0^t Ae^{(t-\tau)A}bx(\tau)d\tau] + bx(t) \\ &= Av(t) + bx(t). \end{aligned}$$

We turn to the main difficulty in calculating the terms on the right in the responses (13.42), (13.43), namely the calculation of the $N \times N$ matrix $e^{tA}, t \geq 0$. We determine the Laplace transform of $e^{tA}u(t), t \in \mathbb{R}$, denoting it by

$$G(s) = \int_0^{\infty} e^{tA}e^{-st}dt.$$

This means that $g_{ij}(s)$ is the Laplace transform of $a_{ij}(t), t \geq 0$, denoting by $a_{ij}(t)$ and $g_{ij}(s)$ the coefficients of the $N \times N$ matrices e^{tA} and $G(s)$, respectively. The region of convergence of G , RoC , is determined later.

Using the derivative formula (13.28) in (13.45) we see that

$$sG(s) - I = AG(s),$$

which gives $G(s) = [sI - A]^{-1}$, so that the Laplace transform of $e^{tA}u(t)$ is

$$\boxed{G(s) = \int_0^\infty e^{tA}e^{-st}dt = [sI - A]^{-1}.} \quad (13.46)$$

Example 13.26: Let

$$A = \begin{bmatrix} 1 & 2 \\ -2 & 1 \end{bmatrix},$$

then

$$[sI - A]^{-1} = \begin{bmatrix} s-1 & -2 \\ 2 & s-1 \end{bmatrix}^{-1} = \frac{1}{\det[sI - A]} \begin{bmatrix} s-1 & 2 \\ -2 & s-1 \end{bmatrix}.$$

The determinant is

$$\det[sI - A] = (s-1)^2 + 4 = (s-1+2i)(s-1-2i),$$

so that

$$\begin{aligned} [sI - A]^{-1} &= \begin{bmatrix} \frac{s-1}{(s-1+2i)(s-1-2i)} & \frac{2}{(s-1+2i)(s-1-2i)} \\ \frac{-2}{(s-1+2i)(s-1-2i)} & \frac{s-1}{(s-1+2i)(s-1-2i)} \end{bmatrix} \\ &= \begin{bmatrix} \frac{1/2}{s-1+2i} + \frac{1/2}{s-1-2i} & \frac{i/2}{s-1+2i} + \frac{-i/2}{s-1-2i} \\ \frac{-i/2}{s-1+2i} + \frac{i/2}{s-1-2i} & \frac{1/2}{s-1+2i} + \frac{1/2}{s-1-2i} \end{bmatrix}. \end{aligned}$$

The region of convergence $RoC = \{s \in \mathbb{C} \mid Re\{s\} > 1\}$. We find the inverse Laplace transform using table 13.3 and express it in two ways: for all $t \geq 0$,

$$\begin{aligned} e^{tA} &= e^{(1-2i)t} \begin{bmatrix} 1/2 & i/2 \\ -i/2 & 1/2 \end{bmatrix} + e^{(1+2i)t} \begin{bmatrix} 1/2 & -i/2 \\ i/2 & 1/2 \end{bmatrix} \\ &= e^t \begin{bmatrix} \cos 2t & \sin 2t \\ -\sin 2t & \cos 2t \end{bmatrix}. \end{aligned}$$

The first expression shows e^{tA} as a linear combination of the exponentials $e^{(1-2i)t}$ and $e^{(1+2i)t}$, in which the exponents, $1-2i$ and $1+2i$, are the two eigenvalues of A —that is, the zeros of its characteristic polynomial, $\det[sI - A]$. The second expression shows that e^{tA} is sinusoidal with frequency 2 radians/sec equal to the imaginary part of the eigenvalues whose amplitude grows exponentially corresponding to the real part of the eigenvalues.

Returning to the general case (13.46), denote the matrix inverse of $[sI - A]$ as

$$G(s) = [sI - A]^{-1} = \frac{1}{\det[sI - A]} K(s),$$

in which $K(s)$ is the $N \times N$ matrix of co-factors of $[sI - A]$. Each coefficient $g_{ij}(s)$ of $G(s)$ is a rational polynomial of A whose denominator is the characteristic polynomial of A , $\det[sI - A]$. Therefore, if there are no pole-zero cancellations, all coefficients of $G(s)$ have the same poles—the eigenvalues of A . Because $e^{tA}u(t), t \in \mathbb{R}$, is a causal signal, the region of convergence of its Laplace transform $G(s)$ is $\{s \in \mathbb{C} \mid \operatorname{Re}\{s\} > \operatorname{Re}\{p\}\}$, in which p is the pole of G with the largest real part.

Because $\det[sI - A]$ is a polynomial of order N , G has N poles. For the system (13.40), (13.41) to be stable, the poles of $G(s)$ must have strictly negative real parts. The system of example (13.26) is unstable, because the real part of the eigenvalues is +1.

Suppose the characteristic polynomial has N distinct zeros p_1, \dots, p_N ,

$$\det[sI - A] = (s - p_1) \cdots (s - p_N).$$

Then the partial fraction expansion of $G(s)$ has the form

$$G(s) = [sI - A]^{-1} = \frac{1}{s - p_1} R_1 + \cdots + \frac{1}{s - p_N} R_N,$$

in which R_i is the matrix of residues at the pole p_i of the coefficients of $G(s)$. R_i is a constant matrix, possibly with complex coefficients, if p_i is complex. Because the inverse Laplace transform of $\frac{1}{s - p_i}$ is $e^{p_i t} u(t)$, the inverse Laplace transform of $[sI - A]^{-1}$ is

$$e^{tA}u(t) = [e^{p_1 t} R_1 + \cdots + e^{p_N t} R_N]u(t). \quad (13.47)$$

Thus the matrix e^{tA} as a function of t is a linear combination of $e^{p_1 t}, \dots, e^{p_N t}$, where the p_i are the eigenvalues of A —that is the zeros of $\det[sI - A]$.

We decompose the response (13.43) into the sum of the zero-input and zero-state responses, expressing the latter as a convolution integral,

$$y(t) = c^T e^{tA} v(0) + \int_0^t h(t - \tau) x(\tau) d\tau, \quad t \geq 0,$$

in which the (zero-state) impulse response is: for all $t \in \mathbb{R}$,

$$h(t) = c^T e^{tA} b u(t) + d \delta(t).$$

(Here δ is the Dirac delta function.) Let $\hat{X}, \hat{Y}, \hat{H}, \hat{Y}_{zi}$ be the Laplace transforms

$$\begin{aligned}\hat{X}(s) &= \int_0^\infty x(t)e^{-st}dt, & \hat{Y}(s) &= \int_0^\infty y(t)e^{-st}dt, \\ \hat{H}(s) &= \int_{-\infty}^\infty h(t)e^{-st}dt, & \hat{Y}_{zi}(s) &= \int_0^\infty c^T e^{tA} v(0)e^{-st}dt.\end{aligned}$$

Then

$$\hat{Y} = \hat{H}\hat{X} + \hat{Y}_{zi},$$

in which

$$\boxed{\hat{H}(s) = c^T [sI - A]^{-1} b + d,}$$

and

$$\boxed{\hat{Y}_{zi}(s) = c^T [sI - A]^{-1} v(0).}$$

We continue with example 13.26.

Example 13.27: Suppose A is as in example 13.26, $b^T = [1 \ 1]^T$, $c^T = [2 \ 0]^T$, $d = 3$, and $v(0)^T = [0 \ 4]^T$. Then the transfer function is

$$\hat{H}(s) = [2 \ 0] \begin{bmatrix} \frac{s-1}{(s-1)^2-4} & \frac{-2}{(s-1)^2-4} \\ \frac{2}{(s-1)^2-4} & \frac{s-1}{(s-1)^2-4} \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} + 3 = \frac{2s-6}{(s-1)^2-4} + 3,$$

and the Laplace transform of the zero-input response is

$$\hat{Y}_{zi}(s) = [2 \ 0] \begin{bmatrix} \frac{s-1}{(s-1)^2-4} & \frac{-2}{(s-1)^2-4} \\ \frac{2}{(s-1)^2-4} & \frac{s-1}{(s-1)^2-4} \end{bmatrix} \begin{bmatrix} 0 \\ 4 \end{bmatrix} = \frac{-16}{(s-1)^2-4}.$$

The transfer function

$$\hat{H}(s) = \frac{2s-6}{(s-1)^2-4} + 3 = \frac{3s^2-4s-15}{s^2-2s-3}.$$

From (13.32) we know that \hat{H} is also the transfer function of the differential equation

$$\frac{d^2y}{dt^2}(t) - 2\frac{dy}{dt}(t) - 3y(t) = 3\frac{d^2x}{dt^2}(t) - 4\frac{dx}{dt}(t) - 15x(t).$$

Thus this differential equation describes the same system as the state-space model of example 13.24.

This example illustrates a general way of obtaining a differential equation description of a continuous-time state-space model by means of its transfer function.

It is easier to obtain a state-space model with a specified proper transfer function,

$$\hat{H}(s) = \frac{b_{N-1}s^{N-1} + \cdots + b_1s + b_0}{s^N + \cdots + a_1s + a_0} + b_N.$$

(The first term in \hat{H} is strictly proper. Some of the coefficients b_i, a_j may be zero.) Then the N -dimensional $[A, b, c, d]$ representation

$$A = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \cdots & \cdots & & \cdots & \cdots \\ 0 & 0 & 0 & \cdots & 1 \\ -a_0 & -a_1 & -a_2 & \cdots & -a_{N-1} \end{bmatrix}, \quad b = \begin{bmatrix} 0 \\ 0 \\ \cdots \\ 0 \\ 1 \end{bmatrix},$$

$$c^T = [b_0 b_1 \cdots b_{N-1}], \quad d = b_N. \quad (13.48)$$

has the same transfer function as \hat{H} , that is

$$c^T [sI - A]^{-1} b + d = \hat{H}(s). \quad (13.49)$$

Exercise 30 at the end of this chapter asks you to verify (13.49).

Simply by interchanging the variables s and z we see that the proper rational polynomial

$$\hat{H}(z) = \frac{b_{N-1}z^{N-1} + \cdots + b_1z + b_0}{z^N + \cdots + a_1z + a_0} + b_N = d + c^T [zI - A]^{-1} b$$

is the transfer function of the discrete-time $[A, b, c, d]$ representation.

Thus we can use any of three equivalent representations of LTI systems:

- difference or differential equations, used to describe many physical systems,
- transfer functions used for frequency-domain analysis, and in feedback design considered in the next chapter,
- state-space models, used in modern control theory.

13.9 Summary

The Z transform and Laplace transform have many of the same properties as the Fourier transforms. They are linear, which greatly facilitates computation of the transforms and their inverses. Moreover, the Z transform (Laplace transform) of the output of an LTI system is the product of the Z transforms (Laplace transforms) of the input and the transfer function. Thus, the Z transform (Laplace transform) plays the same role as the frequency response, describing the relationship between the input and the output as a product rather than a convolution.

Linear difference and differential equations, and state-space models of LTI systems were introduced in Chapter 5 and Chapter 8. However, we lacked a method to calculate the response of these models for non-zero initial conditions. The Z transform and the Laplace transform provide such a method.

Probing Further: Derivatives of Z transforms

Calculus on complex-valued functions of complex variables can be intricate. Suppose \hat{X} is a function of a complex variable. The derivative can be defined as a limit,

$$\frac{d}{dz}\hat{X}(z) = \lim_{\epsilon \rightarrow 0} \frac{\hat{X}(z + \epsilon) - \hat{X}(z)}{\epsilon},$$

where ϵ is a complex variable that can approach zero from any direction in the complex plane. The derivative exists if the limit does not depend on the direction. If the derivative exists at all points within a distance $\epsilon > 0$ of a point z in the complex plane, then \hat{X} is said to be **analytic** at z . A Z transform is a series of the form

$$\forall z \in \text{RoC}(x), \quad \hat{X}(z) = \sum_{n=-\infty}^{\infty} x(n)z^{-n}.$$

This is called a **Laurent series** in the theory of complex variables. It can be shown that a Laurent series is analytic at all points $z \in \text{RoC}(x)$, and that the derivative is

$$\forall z \in \text{RoC}(x), \quad \frac{d}{dz}\hat{X}(z) = \sum_{m=-\infty}^{\infty} -mx(m)z^{-m-1}.$$

We can use this fact to show that the Z transform of y given by $y(n) = nx(n)$ is

$$\forall z \in \text{RoC}(x), \quad \hat{Y}(z) = -z \frac{d}{dz}\hat{X}(z).$$

This is because

$$\hat{Y}(z) = \sum_{n=-\infty}^{\infty} nx(n)z^{-n} = \sum_{n=-\infty}^{\infty} (-z) \frac{d}{dz} x(n)z^{-n} = -z \frac{d}{dz}\hat{X}(z).$$

It is not difficult to show that $\text{RoC}(y) = \text{RoC}(x)$ (see Exercise 5).

This property can be used to find other Z transforms. For example, the Z transform of the unit step, $x = u$, is $\hat{X}(z) = z/(z-1)$, with $\text{RoC}(x) = \{z \in \mathbb{C} \mid |z| > 1\}$. So the Z transform of the **unit ramp** y , given by $y(n) = nu(n)$, is

$$\hat{Y}(z) = -z \frac{d}{dz} \frac{z}{z-1} = \frac{z}{(z-1)^2},$$

with $\text{RoC}(y) = \{z \in \mathbb{C} \mid |z| > 1\}$. Another method for finding the Z transform of the unit ramp is given in Exercise 3 of Chapter 12.

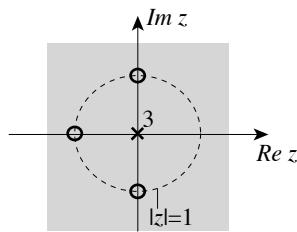
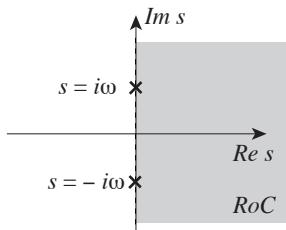


Figure 13.2: Pole-zero plot for a length-4 moving average system.

Figure 13.3: Pole-zero plot for the sinusoidal signal y of example 13.10.

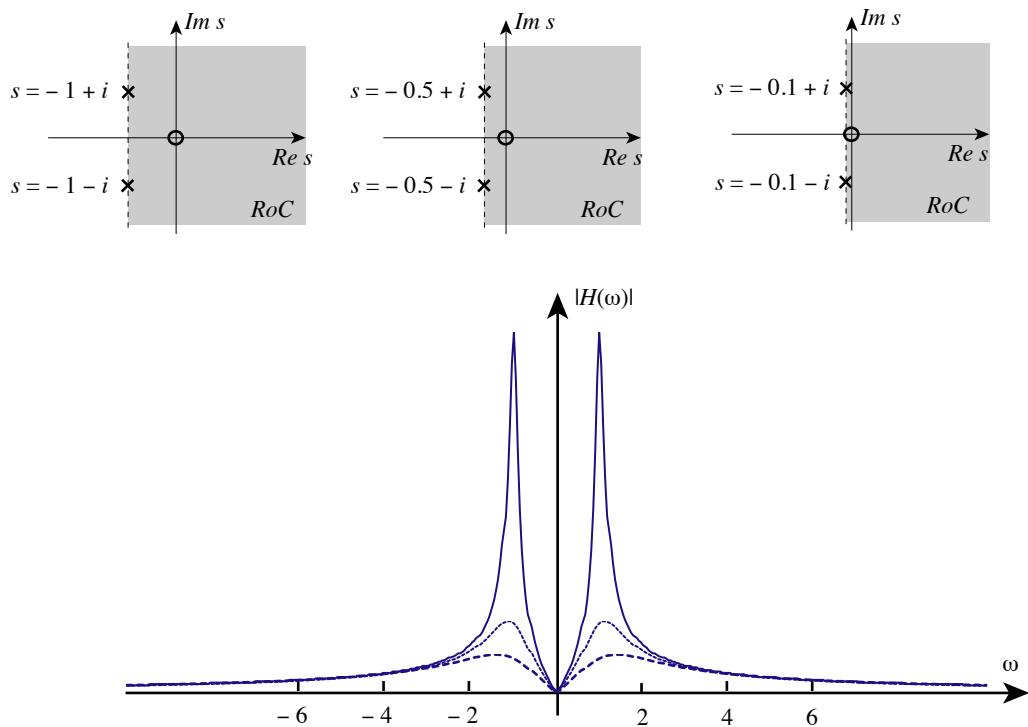


Figure 13.4: Pole-zero plots for the three transfer functions in example 13.12, and the three corresponding magnitude frequency responses.

Probing Further: Inverse transform as an integral

Even if the Z transform is not a rational polynomial, we can recover the signal x from its Z transform, $\hat{X} : \text{RoC}(x) \rightarrow \mathbb{C}$, using the DTFT. A non-empty $\text{RoC}(x)$ contains the circle of radius r for some $r > 0$. So the series in the equation

$$\hat{X}(re^{i\omega}) = \sum_{m=-\infty}^{\infty} x(m)(re^{i\omega})^{-m} = \sum_{m=-\infty}^{\infty} (x(m)r^{-m})e^{-i\omega m}$$

is absolutely summable. Hence the signal x_r : $\forall n, x_r(n) = x(n)r^{-n}$, has DTFT X_r : $\forall \omega, X_r(\omega) = \hat{X}(re^{i\omega})$. We can, therefore, obtain x_r as the inverse DTFT of X_r

$$\forall n, \quad x_r(n) = r^{-n}x(n) = \frac{1}{2\pi} \int_0^{2\pi} \hat{X}(re^{i\omega}) e^{i\omega n} d\omega.$$

Multiplying both sides by r^n , we can recover x as

$$\forall n \in \mathbb{Z}, \quad x(n) = \frac{1}{2\pi} \int_0^{2\pi} \hat{X}(re^{i\omega}) (re^{i\omega})^n d\omega. \quad (13.15)$$

This formula defines the inverse Z transform as an integral of the real variable ω . (Continued on page 601.)

Probing Further: (Continued) Inverse transform

It is conventional to write the inverse Z transform differently. Express z as $z = re^{i\omega}$. Then as ω varies from 0 to 2π , z varies as

$$dz = re^{i\omega}id\omega = zid\omega, \text{ or } d\omega = \frac{dz}{iz}.$$

Substituting this in (13.15) gives,

$$\forall n, \quad x(n) = \frac{1}{2\pi} \oint \hat{X}(z) z^n \frac{dz}{iz} = \frac{1}{2\pi i} \oint \hat{X}(z) z^{n-1} dz.$$

Here the ‘circle’ in the integral sign, \oint , means that the integral in the complex z -plane is along any closed counterclockwise circle contained in $RoC(x)$. (An integral along a closed contour is called a **contour integral**.) In summary,

$$\boxed{\forall n \in \mathbb{Z}, \quad x(n) = \frac{1}{2\pi i} \oint \hat{X}(z) z^{n-1} dz,} \quad (13.16)$$

where the integral is along any closed counterclockwise circle inside $RoC(x)$.

We can similarly use the CTFT to recover any continuous-time signal x from its Laplace transform by

$$\boxed{\forall t \in \mathbb{R}, \quad x(t) = \frac{1}{2\pi i} \int_{\sigma-i\infty}^{\sigma+i\infty} \hat{X}(s) e^{st} ds}$$

where the integral is along any vertical line $(\sigma - i\infty, \sigma + i\infty)$ contained in $RoC(x)$.

Probing Further: Differentiation and Laplace transforms

We can use the inverse Laplace transform as given in the box on page 600 to demonstrate the differentiation property in table 13.4. Let y be defined by

$$\forall t \in \mathbb{R}, \quad y(t) = \frac{d}{dt}x(t).$$

We can write x in terms of its Laplace transform as

$$\forall t \in \mathbb{R}, \quad x(t) = \frac{1}{2\pi i} \int_{\sigma-i\infty}^{\sigma+i\infty} \hat{X}(s)e^{st} ds.$$

Differentiating this with respect to t is easy,

$$\forall t \in \mathbb{R}, \quad \frac{d}{dt}x(t) = \frac{1}{2\pi i} \int_{\sigma-i\infty}^{\sigma+i\infty} s\hat{X}(s)e^{st} ds.$$

Consequently, $y(t) = dx(t)/dt$ is the inverse transform of $s\hat{X}(s)$, so

$$\forall s \in \text{RoC}(y), \quad \hat{Y}(s) = s\hat{X}(s),$$

where $\text{RoC}(y) \supset \text{RoC}(x)$.

Exercises

Each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **E** Consider the signal x given by

$$\forall n, \quad x(n) = \sin(\omega_0 n)u(n).$$

- (a) Show that the Z transform is

$$\forall z \in \text{RoC}(x), \quad \hat{X}(z) = \frac{z \sin(\omega_0)}{z^2 - 2z \cos(\omega_0) + 1},$$

where

$$\text{RoC}(x) = \{z \in \mathbb{C} \mid |z| > 1\}.$$

- (b) Where are the poles and zeros?
(c) Is x absolutely summable?

2. **T** Consider the signal x given by

$$\forall n \in \mathbb{Z}, \quad x(n) = a^{|n|},$$

where $a \in \mathbb{C}$.

- (a) Find the Z transform of x . Be sure to give the region of convergence.
(b) Where are the poles?
(c) Under what conditions is x absolutely summable?

3. **E** Consider a discrete-time LTI system with transfer function given by

$$\forall z \in \{z \mid |z| > 0.9\}, \quad \hat{H}(z) = \frac{z}{z - 0.9}.$$

Suppose that the input x is given by

$$\forall n \in \mathbb{Z}, \quad x(n) = \delta(n) - 0.9\delta(n - 1).$$

Find the Z transform of the output y , including its region of convergence.

4. E Consider the exponentially modulated sinusoid y given by

$$\forall n \in \mathbb{Z}, \quad y(n) = a^{-n} \cos(\omega_0 n) u(n),$$

where a is a real number, ω_0 is a real number, and u is the unit step signal.

- Find the Z transform. Be sure to give the region of convergence. **Hint:** Use example 13.3 and Section 13.1.6.
 - Where are the poles?
 - For what values of a is this signal absolutely summable?
5. T Suppose $x \in DiscSignals$ satisfies

$$\sum_{n=-\infty}^{\infty} |x(n)r^{-n}| < \infty, \quad 0 < r_1 < r < r_2,$$

for some real numbers r_1 and r_2 such that $r_1 < r_2$. Show that

$$\sum_{n=-\infty}^{\infty} |nx(n)r^{-n}| < \infty, \quad 0 < r_1 < r < r_2.$$

Hint: Use the fact that for any $\varepsilon > 0$ there exists $N < \infty$ such that $n(1 + \varepsilon)^{-n} < 1$ for all $n > N$.

6. T Consider a causal discrete-time LTI system where the input x and output y are related by the difference equation

$$\forall n \in \mathbb{Z}, \quad y(n) + b_1 y(n-1) + b_2 y(n-2) = a_0 x(n) + a_1 x(n-1) + a_2 x(n-2),$$

where b_1, b_2, a_0, a_1 , and a_2 are real-valued constants.

- Find the transfer function.
 - Say as much as you can about the region of convergence.
 - Under what conditions is the system stable?
7. E This exercise verifies the time delay property of the Laplace transform. Show that if x is a continuous-time signal, τ is a real constant, and y is given by

$$\forall t \in \mathbb{R}, \quad y(t) = x(t - \tau),$$

then its Laplace transform is

$$\forall s \in \text{RoC}(y), \quad \hat{Y}(s) = e^{-s\tau} \hat{X}(s),$$

with region of convergence

$$\text{RoC}(y) = \text{RoC}(x).$$

8. **E** This exercise verifies the convolution property of the Laplace transform. Suppose x and h have Laplace transforms \hat{X} and \hat{H} . Let y be given by

$$\forall t \in \mathbb{R}, \quad y(t) = (x * h)(t) = \int_{-\infty}^{\infty} x(\tau)h(t - \tau)d\tau.$$

Then show that the Laplace transform is

$$\forall s \in \text{RoC}(y), \quad \hat{Y}(s) = \hat{X}(s)\hat{H}(s),$$

with

$$\text{RoC}(y) \supset \text{RoC}(x) \cap \text{RoC}(h).$$

9. **T** This exercise verifies the conjugation property of the Laplace transform, and then uses this property to demonstrate that for real-valued signals, poles and zeros come in complex-conjugate pairs.

- (a) Let x be a complex-valued continuous-time signal and y be given by

$$\forall t \in \mathbb{R}, \quad y(t) = [x(t)]^*.$$

Show that

$$\forall s \in \text{RoC}(y), \quad \hat{Y}(s) = [\hat{X}(s^*)]^*,$$

where

$$\text{RoC}(y) = \text{RoC}(x).$$

- (b) Use this property to show that if x is real, then complex poles and zeros occur in complex conjugate pairs. That is, if there is a zero at $s = q$, then there must be a zero at $s = q^*$, and if there is a pole at $s = p$, then there must also be a pole at $s = p^*$.

10. **T** This exercise verifies the time scaling property of the Laplace transform. Let y be defined by

$$\forall t \in \mathbb{R}, \quad y(t) = x(ct),$$

for some real number c . Show that

$$\forall s \in \text{RoC}(y), \quad \hat{Y}(s) = \hat{X}(s/c)/|c|,$$

where

$$\text{RoC}(y) = \{s \mid s/c \in \text{RoC}(x)\}.$$

11. **E** This exercise verifies the exponential scaling property of the Laplace transform. Let y be defined by

$$\forall t \in \mathbb{R}, \quad y(t) = e^{at}x(t),$$

for some complex number a . Show that

$$\forall s \in \text{RoC}(y), \quad \hat{Y}(s) = \hat{X}(s - a),$$

where

$$\text{RoC}(y) = \{s \mid s - a \in \text{RoC}(x)\}.$$

12. **T** Consider a discrete-time LTI system with impulse response

$$\forall n, \quad h(n) = a^n \cos(\omega_0 n)u(n),$$

for some $\omega_0 \in \mathbb{R}$. Show that if the input is

$$\forall n \in \mathbb{Z}, \quad x(n) = e^{i\omega_0 n}u(n),$$

then the output y is unbounded.

13. **E** Find and plot the inverse Z transform of

$$\hat{X}(z) = \frac{1}{(z - 3)^3}$$

with

(a) $\text{Roc}(x) = \{z \in \mathbb{C} \mid |z| > 3\}$

(b) $\text{Roc}(x) = \{z \in \mathbb{C} \mid |z| < 3\}.$

14. E Obtain the partial fraction expansions of the following rational polynomials. First divide through if necessary to get a strictly proper rational polynomial.

(a)

$$\frac{z+2}{(z+1)(z+3)}$$

(b)

$$\frac{(z+2)^2}{(z+1)(z+3)}$$

(c)

$$\frac{z+2}{z^2+4}.$$

15. E Find the inverse Z transform x for each of the three possible regions of convergence associated with

$$\hat{X}(z) = \frac{(z+2)^2}{(z+1)(z+3)}.$$

For which region of convergence is x causal? For which is x strictly anti-causal?
For which is x two-sided?

16. E Find the inverse Z transform x for each of the two possible regions of convergence associated with

$$\hat{X}(z) = \frac{z+2}{z^2+4}.$$

17. E Consider a stable system with impulse response

$$h(n) = (0.5)^n x(n).$$

Find the steady-state response to a unit step input.

18. E Let $h(n) = 2^n u(-n)$, all n , and $g(n) = 0.5^n u(n)$, for all n . Find $h * u$ and $g * u$, where u is the unit step.
19. E This exercise shows how we can determine the transfer function and frequency response of an LTI system from its step response. Suppose a causal system with step input $x = u$, produces the output

$$\forall n \in \mathbb{Z}, \quad y(n) = (1 - 0.5^n)u(n).$$

- (a) Find the transfer function (including its region of convergence).

- (b) If the system is stable, find its frequency response.
(c) Find the impulse response of the system.
20. **E** Consider an LTI system with impulse response h given by
- $$\forall n \in \mathbb{Z}, \quad h(n) = 2^n u(n).$$
- (a) Find the transfer function, including its region of convergence.
(b) Use the transfer function to find the Z transform of the step response.
(c) Find the inverse transform of the result of part (b) to obtain the step response in the time domain.
21. **E** Determine the zero-input and zero-state responses, and the transfer function for the following. In both cases take $y(-1) = y(-2) = 0$ and $x(n) = u(n)$.
- (a) $y(n) + y(n-2) = x(n), n \geq 0$.
(b) $y(n) + 2y(n-1) + y(n-2) = x(n), n \geq 0$.
22. **E** Determine the zero-input and the zero-state responses for the following.
- (a) $5\dot{y} + 10y = 2x, y(0) = 2, x(t) = u(t)$.
(b) $\ddot{y} + 5\dot{y} + 6y = -4x - 3\dot{x}, y(0) = -1, \dot{y}(0) = 5, x(t) = e^{-t}u(t)$.
(c) $\ddot{y} + 4y = 8x, y(0) = 1, \dot{y}(0) = 2, x(t) = u(t)$.
(d) $\ddot{y} + 2\dot{y} + 5y = \dot{x}, y(0) = 2, \dot{y}(0) = 0, x(t) = e^{-t}u(t)$.
23. **E** Show that the $[A, b, c, d]$ representation in example 13.23 is correct. Then show that the transfer function of the state-space model is the same as that of the difference equation.
24. **T** Consider the circuit of figure 13.5. The input is the voltage x , the output is the capacitor voltage v . The inductor current is called i .
- (a) Derive the $[A, b, c, d]$ representation for this system using $s(t) = [i(t), v(t)]^T$ as the state.
(b) Obtain an $[F, g, h, k]$ representation for a discrete-time model of the same circuit by sampling at times $kT, k = 0, 1, \dots$ and using the approximation $\dot{s}(kT) = 1/T(s((k+1)T) - s(kT))$. (This is called a forward-Euler approximation.)

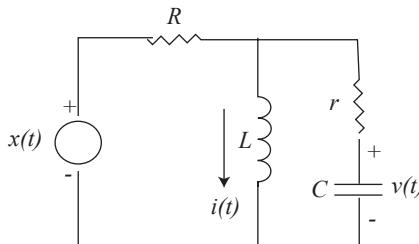


Figure 13.5: Circuit of problem 24

25. **E** For the matrix A in example 13.24, determine $e^{tA}, t \geq 0$.
26. **E** For the matrix A in example 13.26, determine $A^n, n \geq 0$.
27. **T** A continuous-time SISO system has $[A, b, c, d]$ representation with
- $$A = \begin{bmatrix} a & b \\ -b & a \end{bmatrix},$$
- in which a, b are real constants.
- (a) Find the eigenvalues of A .
- (b) For what values of a, b is the SISO system stable?
- (c) Calculate $e^{tA}, t \geq 0$.
- (d) Suppose $b = c = [1 \ 0]^T$, and $d = 0$. Find the transfer function.
28. **T** Let A be an $N \times N$ matrix. Let p be an eigenvalue of A . An N -dimensional (column) vector e , possibly complex-valued, is said to be an **eigenvector** of A corresponding to p if $e \neq 0$ and $Ae = pe$. Note that an eigenvector always exists since $\det[pI - A] = 0$. Find eigenvectors for each of the two eigenvalues of the matrices in examples 13.24 and 13.26.
29. **E** Let A be a square matrix with eigenvalue p and corresponding eigenvector e . Determine the response of the following.
- (a) $s(k+1) = As(k), k \geq 0; s(0) = e$.
- (b) $s(t) = As(t), t \geq 0; s(0) = e$.

Hint. Show that $A^n e = p^n e$ and $e^{tA} e = e^{pt} e$.

30. T Verify (13.49). Hint. First show that

$$[sI - A]^{-1}b = \frac{1}{s^N + a_{N-1}s^{N-1} + \cdots + a_0} \begin{bmatrix} 1 \\ s \\ \vdots \\ s^{N-1} \end{bmatrix},$$

by multiplying both sides by $[sI - A]$. Then check (13.49).

14

Composition and Feedback Control

Contents

14.1 Cascade composition	613
14.1.1 Stabilization	613
14.1.2 Equalization	614
14.2 Parallel composition	620
14.2.1 Stabilization	621
14.2.2 Noise cancellation	622
14.3 Feedback composition	626
14.3.1 Proportional controllers	628
14.4 PID controllers	639
14.5 Summary	647
Exercises	648

A major theme of this book is that interesting systems are often compositions of simpler systems. Systems are functions, so their composition is function composition, as discussed in section 2.1.5. However, systems are often not directly described as functions, so function composition is not the easiest tool to use to understand the composition. We have seen systems described as state machines, frequency responses, and transfer functions. In chapter 4 we obtained the state machine of the composite system from its component state machines. In section 8.5 we obtained the frequency response of the composite

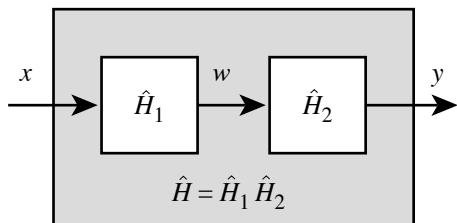


Figure 14.1: Cascade composition of two LTI systems with transfer functions H_1 and H_2 .

system from the frequency response of its component linear time-invariant (LTI) systems. We extend the latter study in this chapter to the composition of LTI systems described by their transfer functions. This important extension allows us to consider unstable systems whose impulse response has a Z or Laplace transform, but not a Fourier transform.

As before, feedback systems prove challenging. A particularly interesting issue is how to maintain stability, and how to construct stable systems out of unstable ones. We will find that some feedback compositions of stable systems result in unstable systems, and conversely, some compositions of unstable systems result in stable systems. For example, we can stabilize the helicopter in example 12.2 using feedback, in fact we can precisely control its orientation, despite the intrinsic instability. The family of techniques for doing this is known as **feedback control**. This chapter serves as an introduction to that topic. Feedback control can also be used to drive stable systems, in which case it serves to improve their response. For example, feedback can result in faster or more precise responses, and can also prevent overshoot, where a system overreacts to a command.

We will consider three styles of composition, **cascade composition**, **parallel composition**, and **feedback composition**. In each case, two LTI systems with transfer functions \hat{H}_1 and \hat{H}_2 are combined to get a new system. The transfer functions \hat{H}_1 and \hat{H}_2 are the (Z or Laplace) transforms of the respective impulse responses, h_1 and h_2 . Much of our discussion applies equally well whether the system is a continuous-time system or a discrete-time system, so in many cases we leave this unspecified.

14.1 Cascade composition

Consider the **cascade composition** shown in figure 14.1. The composition is the grey box, and it has transfer function

$$\hat{H} = \hat{H}_1 \hat{H}_2.$$

Notice that because of this simple form, if we know the pole and zero locations of the component systems, then it is easy to determine the pole and zero locations of the composition. Unless a pole of one is cancelled by a zero of the other, the poles and zeros of the composition are simply the aggregate of the poles and zeros of the components. Moreover, any pole of \hat{H} must be a pole of either \hat{H}_1 or \hat{H}_2 , so if \hat{H}_1 and \hat{H}_2 are both stable, then so is \hat{H} .

14.1.1 Stabilization

The possibility for pole-zero cancellation suggests that cascade composition might be used to stabilize an unstable system.

Example 14.1: Consider a discrete-time system with transfer function

$$\forall z \in \{z \mid |z| > |1.1|\}, \quad \hat{H}_1(z) = \frac{z}{z - 1.1}.$$

This is a proper rational polynomial with a region of convergence of the form for a causal signal, so it must be a causal system. However, it is not stable, because the region of convergence does not include the unit circle.

To stabilize this system, we might consider putting it in cascade with

$$\forall z \in \mathbb{C}, \quad \hat{H}_2(z) = \frac{z - 1.1}{z}.$$

This is a causal and stable system. The transfer function of the cascade composition is

$$\hat{H}(z) = \frac{z}{z - 1.1} \cdot \frac{z - 1.1}{z} = 1.$$

The pole at $z = 1.1$ has been cancelled, and the resulting region of convergence is the entire complex plane. Thus, the cascade composition is a causal and stable system, and we can recognize from table 13.1 that the impulse response is $h(n) = \delta(n)$.

Stabilizing systems by cancelling their poles in a cascade composition, however, is almost never a good idea. If the pole is not precisely cancelled, then no matter how small the error, the resulting system is still unstable.

Example 14.2: Suppose that in the previous example the pole location is not known precisely, and turns out to be at $z = 1.1001$ instead of $z = 1.1$. Then the cascade composition has transfer function

$$\hat{H}(z) = \frac{z}{z - 1.1001} \cdot \frac{z - 1.1}{z} = \frac{z - 1.1}{z - 1.1001},$$

which is unstable.

14.1.2 Equalization

While cascade compositions do not usually work well for stabilization, they do often work well for **equalization**. An **equalizer** is a **compensator** that reverses **distortion**. The source of the distortion, which is often called a **channel**, must be an LTI system, and the equalizer is composed in cascade with it. At first sight this is easy to do. If the channel has transfer function \hat{H}_1 , then the equalizer could have transfer function

$$\hat{H}_2 = \hat{H}_1^{-1},$$

in which case the cascade composition will have transfer function

$$\hat{H} = \hat{H}_1 \hat{H}_2 = 1,$$

which is certainly distortion-free.

Example 14.3: Some acoustic environments for audio have **resonances**, where certain frequencies are enhanced as the sound propagates through the environment. This will typically occur if the physics of the acoustic environment results in a transfer function with poles near the unit circle (for a discrete-time model) or near the imaginary axis (for a continuous-time model). Suppose for example that the

acoustic environment is well modeled by a discrete-time LTI system with transfer function

$$\forall z \in \{z \mid |z| > 0.95\}, \quad \hat{H}_1(z) = \frac{z^2}{(z-a)(z-a^*)},$$

where $a = 0.95e^{i\omega_1}$ for some frequency ω_1 . Using the methods of Section 13.2, we can infer that the magnitude response will have a strong peak at frequencies ω_1 and $-\omega_1$, because the positions on the unit circle $e^{i\omega_1}$ and $e^{-i\omega_1}$ are very close to the poles. This will result in distortion of the audio signal, where frequencies near ω_1 will be amplified.

An equalizer that will compensate for this distortion has transfer function

$$\hat{H}_2(z) = [\hat{H}_1(z)]^{-1} = \frac{(z-a)(z-a^*)}{z^2} = \frac{z^2 - 2\operatorname{Re}\{a\}z + |a|^2}{z^2}.$$

As in example 13.2, we can recognize this as the Z transform of an FIR filter with impulse response

$$\forall n \in \mathbb{Z}, \quad h_2(n) = \delta(n) - 2\operatorname{Re}\{a\}\delta(n-1) + |a|^2\delta(n-2).$$

This filter is causal and stable, and hence can serve as an effective equalizer.

There are a number of potential problems with this approach, however. First, the transfer function of the channel is probably not known, or at least not known precisely. Second, the channel may not have a stable and causal inverse.

Let us first examine the first difficulty, that the channel may not be known (precisely). If the channel model \hat{H}_1 and its inverse \hat{H}_2 are both stable, then the cascade composition is at least assured of being stable, even if the channel has been misconstrued. Moreover, if the equalizer is close to the inverse of the true channel, then often the distortion is significantly reduced despite the errors (see exercise 1).

This difficulty can sometimes be dealt with by adaptively varying the equalizer based on measurements of the distortion. One way to measure the distortion is to send through the channel a known sequence called a **training sequence** and observe the output of the channel. Suppose that the training sequence is a signal x with Z transform \hat{X} , and that the channel \hat{H}_1 is unknown. If we can observe the output y of the channel, and calculate its Z

transform \hat{Y} , then the channel transfer function is simply

$$\forall z \in \text{RoC}(h_1), \quad \hat{H}_1(z) = \frac{\hat{Y}(z)}{\hat{X}(z)},$$

where $\text{RoC}(h_1)$ is determined by identifying the poles and zeros of the rational polynomial $\hat{Y}(z)/\hat{X}(z)$ and finding the one ring-shaped region that includes the unit circle and is bordered by poles. This results in a stable channel model.

Training sequences are commonly used in digital communication systems, where, for example, a radio channel introduces distortion. However, it is also common for such channels to change over time. Radio channels, for example, change if either the transmitter or receiver moves, or if the weather changes, or if obstacles appear or disappear. Repeatedly transmitting training sequences is an expensive waste of radio bandwidth, and fortunately, is not usually necessary, as illustrated in the following example.

Example 14.4: Consider a digital communication system where the channel is modeled as a discrete-time LTI system with transfer function \hat{H}_1 , representing for example a radio transmission subsystem. Suppose that this digital communication system transmits a bit sequence represented as a discrete-time signal x of form

$$x: \mathbb{Z} \rightarrow \{0, 1\}.$$

Suppose further that we use a training sequence to obtain an initial estimate \hat{H}_2 of the inverse of the channel. But over time, the channel drifts, so that \hat{H}_2 is no longer the inverse of \hat{H}_1 . Assuming the drift is relatively slow, then after a short time, \hat{H}_2 is still close to the inverse of \hat{H}_1 , in that the cascade $\hat{H}_1\hat{H}_2$ yields only mild distortion. That is, if $x(n) = 0$ for some n , then $y(n) \approx 0$. Similarly, if $x(n) = 1$ for some n , then $y(n) \approx 1$. Thus, we can quantize y , getting an accurate estimate x without it having to be a known training sequence. That is, when $y(n) \approx 0$, we assume that $x(n) = 0$, and when $y(n) \approx 1$, we assume that $x(n) = 1$. These assumptions are called **decisions**, and in fact, such decisions must be made anyway for digital communication to occur. We have to decide whether a 1 or a 0 was transmitted, and closeness to 1 or 0 seems like an eminently reasonable basis on which to make such a decision.

Assuming there are no errors in these decisions, we can infer that

$$\hat{H}_1\hat{H}_2\hat{X}_d = \hat{Y},$$

where \hat{X}_d is the Z transform of the decision sequence. So, without using another training sequence, we can revise our estimate of the channel transfer function as follows,

$$\hat{H}_1 = \frac{\hat{Y}}{\hat{H}_2 \hat{X}_d}.$$

We replace our equalizer \hat{H}_2 with

$$\hat{H}'_2 = [\hat{H}_1]^{-1} = \frac{\hat{H}_2 \hat{X}_d}{\hat{Y}}.$$

Of course, we now start using \hat{H}'_2 , which will come closer to correcting the channel distortion, which will make our decisions more reliable for the next update.

Example 14.4 outlines a widely used technique called **decision-directed adaptive equalization**. It is so widely used, in fact, that it may be found in every digital cellular telephone and almost every modem, including voiceband data modems, radio modems, cable modems, DSL modems, etc. The algorithms used in practice to update the transfer function of the equalizer are not exactly as shown in the example, and their details are beyond the scope of this text, but they follow the general principle in the example.

Let us now turn our attention to the second difficulty with equalization, that the channel may not have a stable and causal inverse. We begin with an example.

Example 14.5: Suppose that, similar to example 14.3, a channel has transfer function

$$\forall z \text{ in } \{z \mid |z| > 0.95\}, \quad \hat{H}_1(z) = \frac{z}{(z-a)(z-a^*)},$$

where $a = 0.95e^{j\omega_1}$ for some frequency ω_1 . The inverse is

$$[\hat{H}_1(z)]^{-1} = \frac{(z-a)(z-a^*)}{z} = \frac{z^2 - 2\operatorname{Re}\{a\}z + |a|^2}{z},$$

which is not a proper rational polynomial. Thus, this cannot be the Z transform of a causal signal. Implementing a non-causal equalizer will usually be impossible, since it will require knowing future inputs. However, suppose we simply force the

equalizer have a proper rational polynomial transfer function by dividing by a high enough power M of z to make $[\hat{H}_1(z)]^{-1}/z^M$ proper. In this example, $M = 1$ is sufficient, so we define the equalizer to be

$$\hat{H}_2(z) = \frac{[\hat{H}_1(z)]^{-1}}{z} = \frac{z^2 - 2\operatorname{Re}\{a\}z + |a|^2}{z^2},$$

which we again recognize as the Z transform of an FIR filter with impulse response

$$\forall n \in \mathbb{Z}, \quad h_2(n) = \delta(n) - 2\operatorname{Re}\{a\}\delta(n-1) + |a|^2\delta(n-2).$$

This filter is causal and stable, but does it serve as an effective equalizer? Consider now the cascade,

$$\hat{H}(z) = \hat{H}_1(z)\hat{H}_2(z) = \frac{1}{z}.$$

From Section 13.1.2 we recognize this as the transfer function of the unit delay system. That is, the equalizer completely compensates for the distortion, but at the expense of introducing a one sample delay. This is usually a perfectly acceptable cost.

Example 14.5 demonstrates that when the channel inverse is not a proper rational polynomial, then introducing a delay may enable construction of a stable and causal equalizer. Not all equalization stories have such a happy ending, however. Consider the following example.

Example 14.6: Consider a channel with the following transfer function,

$$\forall z \in \{z \in \mathbb{C} \mid z \neq 0\}, \quad \hat{H}_1(z) = \frac{z-2}{z}.$$

This is a stable and causal channel. Its inverse is

$$[\hat{H}_1(z)]^{-1} = \frac{z}{z-2}.$$

This has a pole at $z = 2$, so in order to be stable, it would have to be anti-causal (so that the region of convergence can include the unit circle). Implementing an anti-causal equalizer is usually not possible.

Example 14.6 shows that not all channels can be inverted by an equalizer. All is not lost, however. Given a channel $\hat{H}_1(z)$ that has a rational Z transform, we can usually find a transfer function $\hat{H}_2(z)$ that compensates for the magnitude response part of the distortion. That is, we can find a transfer function $\hat{H}_2(z)$ that is stable and causal such that the magnitude response of the composite satisfies

$$|H_1(\omega)H_2(\omega)| = |\hat{H}_1(e^{i\omega})\hat{H}_2(e^{i\omega})| = 1.$$

For some applications, this is sufficient. In audio equalization, for example, this is almost always sufficient, because the human ear is not very sensitive to the phase of audio signals. It hears only the magnitude of the frequency components.

Example 14.7: Continuing example 14.6, let \hat{H}_2 be given by

$$\hat{H}_2 = \frac{z}{1-2z} = \frac{-0.5z}{z-0.5}.$$

This has a pole at $z = 0.5$, and is a proper rational polynomial, so it can be the transfer function of a causal and stable filter. Consider the cascade composition,

$$\hat{H}(z) = \hat{H}_1(z)\hat{H}_2(z) = \frac{z-2}{z} \cdot \frac{-0.5z}{z-0.5} = \frac{1-0.5z}{z-0.5}.$$

This hardly looks like what we want, but if we rewrite it slightly, it is easy to show that the magnitude frequency response has value one for all ω ,

$$\hat{H}(z) = \frac{1-0.5z}{z-0.5} = z \frac{z^{-1}-0.5}{z-0.5}.$$

The magnitude frequency response is

$$|H(\omega)| = |\hat{H}(e^{i\omega})| = |e^{i\omega}| \cdot \frac{|e^{-i\omega} - 0.5|}{|e^{i\omega} - 0.5|} = 1.$$

This magnitude is equal to 1 because the numerator, $e^{-i\omega} - 0.5$, is the complex conjugate of the denominator, $e^{i\omega} - 0.5$, so they have the same magnitude.

The method in example 14.7 can be generalized so that for most channels it is possible to cancel any magnitude distortion. The key is that if the channel transfer function has a

zero outside the unit circle, say at $z = a$, then its inverse has a pole at the same location, $z = a$. A pole outside the unit circle makes it impossible to have a stable and causal filter. So the trick is to place a pole instead at $z = 1/a^*$. This pole will cancel the effect on the magnitude (but not the phase) of the zero at $z = a$.

There are still channels for which this method will not work.

Example 14.8: Consider a channel given by

$$\forall z \in \{z \in \mathbb{C} \mid z \neq 0\}, \quad \hat{H}_1(z) = \frac{z-1}{z}.$$

This has a pole at $z = 0$ and a zero at $z = 1$. Its inverse cannot be stable because it will have a pole at $z = 1$. In fact, no equalization is possible. This is intuitive because the frequency response is zero at $\omega = 0$, and no stable equalizer in cascade with this channel can reconstruct the original component at $\omega = 0$. It would have to have infinite gain at $\omega = 0$, which would make it unstable.

14.2 Parallel composition

Consider the **parallel composition** shown in figure 14.2. The transfer function of the composition system is

$$\hat{H} = \hat{H}_1 + \hat{H}_2.$$

This is valid whether these are Laplace transforms or Z transforms. Once again, notice that a pole of \hat{H} must be a pole of either \hat{H}_1 or \hat{H}_2 , so if \hat{H}_1 and \hat{H}_2 are stable, then so is \hat{H} . At the poles of \hat{H}_1 , $\hat{H}_1(z)$ is infinite, so very likely a pole of \hat{H}_1 will also be a pole of \hat{H} . However, just as in the cascade composition, this pole may be cancelled by a zero.

Determining the location of the zeros of the composition, however, is slightly more complicated than for cascade composition. The sum has to be put into rational polynomial form, and the polynomials then need to be factored.

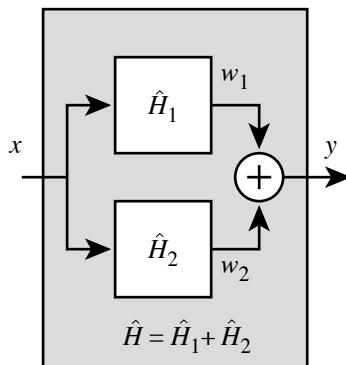


Figure 14.2: Parallel composition of two LTI systems with transfer functions H_1 and H_2 .

14.2.1 Stabilization

Just as with cascade composition, stabilizing systems by cancelling their poles in a parallel composition is possible, but is almost never a good idea.

Example 14.9: Consider a discrete-time system with transfer function

$$\forall z \in \{z \mid |z| > |1.1|\}, \quad \hat{H}_1(z) = \frac{z}{z - 1.1} .$$

This describes a causal but unstable system. Suppose we combine this in parallel with a system with transfer function

$$\forall z \in \{z \mid |z| > |1.1|\}, \quad \hat{H}_2(z) = \frac{-1.1}{z - 1.1} .$$

This is again causal and unstable. The transfer function of the parallel composition is

$$\hat{H}(z) = \frac{z}{z - 1.1} + \frac{-1.1}{z - 1.1} = \frac{z - 1.1}{z - 1.1} = 1 .$$

The pole at $z = 1.1$ has been cancelled, and the resulting region of convergence is the entire complex plane. Thus, the parallel composition is a causal and stable system with impulse response $h(n) = \delta(n)$.

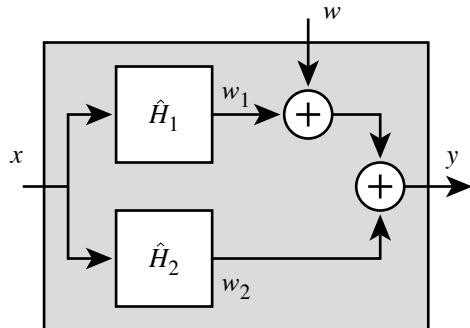


Figure 14.3: Structure of a noise canceller.

However, if the pole is not precisely cancelled, then no matter how small the error, the resulting system is still unstable.

Example 14.10: Suppose that in the previous example the pole location is not known precisely, and turns out to be at $z = 1.1001$ instead of $z = 1.1$. Then the parallel composition has transfer function

$$\hat{H}(z) = \frac{z}{z - 1.1001} + \frac{-1.1}{z - 1.1} = \frac{z^2 - 2.2z + 1.21001}{(z - 1.1001)(z - 1.1)},$$

which is unstable.

14.2.2 Noise cancellation

While parallel compositions do not usually work well for stabilization, with a small modification they do often work well for **noise cancellation**. A **noise canceller** is a compensator that removes an unwanted component from a signal. The unwanted component is called **noise**.

The pattern of a noise cancellation problem is shown in figure 14.3. The signal x is a noise source. This signal is filtered by \hat{H}_1 and added to the **desired signal** w . The result is a

noisy signal. To cancel the noise, the signal from the noise source is filtered by a noise cancelling filter \hat{H}_2 and the result is added to the noisy signal. If x has (Laplace or Z) transform \hat{X} , w has transform \hat{W} , and y has transform \hat{Y} , then

$$\hat{Y} = \hat{W} + (\hat{H}_1 + \hat{H}_2)\hat{X}.$$

From this it is evident that if we choose

$$\hat{H}_2 = -\hat{H}_1,$$

then y will be a clean (noise-free) signal, equal to w . The following examples describe real-world applications of this pattern.

Example 14.11: A connection to the telephone network uses two wires (called a **twisted pair**, consisting of **tip and ring**) to connect a telephone to a central office. The central office may be, perhaps, 4 kilometers away. The two wires carry voice signals to and from the customer premises, representing the voice signals as a voltage difference across the two wires. Since two wires can only have one voltage difference across them, the incoming voice signal and the outgoing voice signal share the same twisted pair.

The central office needs to separate the voice signal from the local customer premises (called the **near-end signal**) from the voice signal that comes from the other end of the connection (called the **far-end signal**). The near end signal is typically digitized (sampled and quantized), and a discrete-time representation of the voice signal is transmitted over the network to the far end. The network itself consists of circuits that can carry voice signals in one direction at a time. Thus, in the network, four wires (or equivalent) are required for a telephone connection, one wire pair for each direction.

As indicated in figure 14.4, the conversion from a two-wire to a four-wire connection is done by a device called a **hybrid**. A hybrid is a Wheatstone bridge, a circuit that can separate two signals based on the electrical impedance looking into the local twisted pair and the electrical impedance looking into the network. The design of this circuit is a suitable topic for a text on electrical circuits.

A connection between subscribers A and B involves two hybrids, one in each subscriber's central office. The hybrid in B 's central office ideally will pass all of the

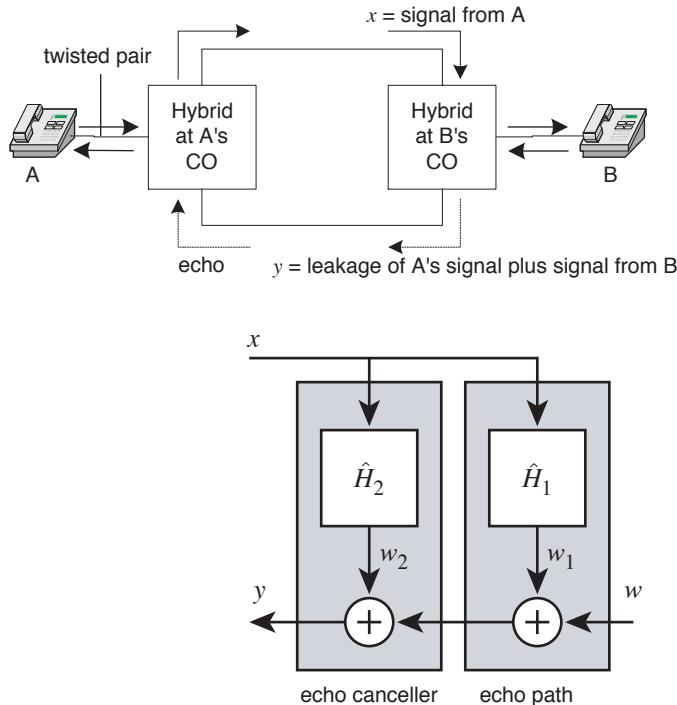


Figure 14.4: A telephone central office converts the two-wire connection with a customer telephone into a four-wire connection with the telephone network using a device called a hybrid. An imperfect hybrid leaks, causing echo. An echo canceller removes the leaked signal.

incoming signal x to B 's two-wire circuit, and none back into the network. However, the hybrid is not perfect, and some of the incoming signal x leaks through the hybrid into the return path back to A . The signal y in the figure is the sum of the signal from B and the leaked signal from A . A hears the leaked signal as an echo, since it is A 's own signal, delayed by propagation through the telephone network.

If the telephone connection includes a satellite link, then the delay from one end of the connection to the other is about 300ms. This is the time it takes for a radio signal to propagate to a geosynchronous satellite and back. The echo traverses this link twice: once going from A to B , and the second time coming back. Thus, the echo is A 's own signal delayed by about 600ms. For voice signals, 600ms of delay is enough to create a very annoying echo that can make it difficult to speak. Humans have difficulty speaking when they hear their own voices 600ms later. Consequently, the designers of the telephone network have put echo cancellers in to prevent the echo from occurring.

Let \hat{H}_1 be the transfer function of the hybrid leakage path. The echo canceller is the filter \hat{H}_2 placed in parallel composition with the hybrid, as shown in the figure. The output w_2 of this filter is added to the output $w_1 + w$ of the hybrid, so the signal that actually goes back is $y = w_2 + w_1 + w$. If

$$\hat{H}_2 = -\hat{H}_1,$$

then $y = w$ and the echo is cancelled perfectly. Moreover, note that as long as \hat{H}_1 is stable and causal, so will be the echo canceller \hat{H}_2 .

However, \hat{H}_1 is not usually known in advance, and also it changes over time. So either a fixed \hat{H}_2 is designed to match a ‘typical’ \hat{H}_1 , or an adaptive echo canceller is designed that estimates the characteristics of the echo path (\hat{H}_1) and changes \hat{H}_2 accordingly. Adaptive echo cancellers are common in the telephone network today.

The following example combines cascade and parallel composition to achieve noise cancellation.

Example 14.12: Consider a microphone in a noisy environment. For example, a traffic helicopter might be used to deliver live traffic reports over the radio, but the (considerable) background noise of the helicopter would be highly undesirable

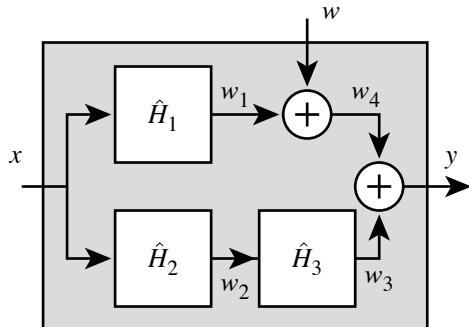


Figure 14.5: Traffic helicopter noise cancellation/equalization problem.

on the radio. Fortunately, the background noise can be cancelled. Referring to Figure 14.5, suppose that w is the announcer's voice, x is the engine noise, and \hat{H}_1 represents the acoustic path from the engine noise to the microphone. The microphone picks up both the engine noise and the announcer's voice, producing the noisy signal w_4 . We can place a second microphone somewhere far enough from the announcer so as to not pick up much of his or her voice. Since this microphone is in a different place, say on the back of the announcer's helmet, the acoustic path is different, so we model that path with another transfer function \hat{H}_2 . To cancel the noise, we design a filter \hat{H}_3 . This filter needs to equalize (invert) \hat{H}_2 and cancel \hat{H}_1 . That is, its ideal value is

$$\hat{H}_3 = -\hat{H}_1/\hat{H}_2.$$

Of course, as with the equalization scenario, we have to ensure that this filter remains stable. Once again, in practice, it is necessary to make the filter adaptive.

14.3 Feedback composition

Consider the **feedback composition** in figure 14.6. It is a composition of two systems with transfer functions \hat{H}_1 and \hat{H}_2 . We assume that these systems are causal and that \hat{H}_1 and \hat{H}_2 are proper rational polynomials in z or s . The regions of convergence of these two transfer functions are those suitable for causal systems (the region outside the largest

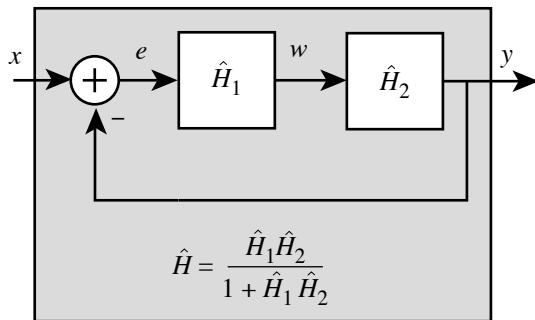


Figure 14.6: Negative feedback composition of two LTI systems with transfer functions H_1 and H_2 .

circle passing through a pole, for discrete time, and the region to the right of the pole with the largest real part, for continuous-time).

In terms of Laplace or Z transforms, the signals in the figure are related by

$$\hat{Y} = \hat{H}_2 \hat{H}_1 \hat{E},$$

and

$$\hat{E} = \hat{X} - \hat{Y}.$$

Notice that, by convention, the feedback term is subtracted, as indicated by the minus sign adjacent to the adder (for this reason, this composition is called **negative feedback**). Combining these two equations to eliminate \hat{E} , we get

$$\hat{Y} = \hat{H}_1 \hat{H}_2 (\hat{X} - \hat{Y}),$$

which we can solve for the transfer function of the composition,

$$\hat{H} = \frac{\hat{Y}}{\hat{X}} = \frac{\hat{H}_1 \hat{H}_2}{1 + \hat{H}_1 \hat{H}_2}. \quad (14.1)$$

This is often called the **closed-loop transfer function**, to contrast it with the **open-loop transfer function**, which is simply $\hat{H}_1 \hat{H}_2$. We will assume that this resulting system is causal, and that the region of convergence of this transfer function is therefore determined by the roots of the denominator polynomial, $1 + \hat{H}_1 \hat{H}_2$.

The closed-loop transfer function is valid as long as the denominator $1 + \hat{H}_1\hat{H}_2$ is not identically zero (that is, it is not zero for *all* s or z in \mathbb{C} – it may be zero *some* s or z in \mathbb{C}). This is sufficient for the feedback loop to be well-formed, although in general, this fact is not trivial to demonstrate (Exercise 8 considers the easier case where $\hat{H}_1\hat{H}_2$ is causal and strictly proper, in which case the system $\hat{H}_1\hat{H}_2$ has state-determined output). We will assume henceforth, without comment, that the denominator is not identically zero.

Feedback composition is useful for stabilizing unstable systems. In the case of cascade and parallel composition, a pole of the composite must be a pole of one of the components. The only way to remove or alter a pole of the components is to cancel it with a zero. For this reason, cascade and parallel composition are *not* effective for stabilizing unstable systems. Any error in the specification of the unstable pole location results in a failed cancellation, which results in an unstable composition.

In contrast, the poles of the feedback composition are the roots of the denominator $1 + \hat{H}_1\hat{H}_2$, which are generally quite different from the poles of \hat{H}_1 and \hat{H}_2 . This leads to the following important conclusion:

The poles of a feedback composition can be different from the poles of its component subsystems. Consequently, unstable system can be effectively and robustly stabilized by feedback.

The stabilization is **robust** in that small changes in the pole or zero locations do not result in the composition going unstable. We will be able to quantify this robustness.

14.3.1 Proportional controllers

In control applications, one of the two systems being composed, say \hat{H}_2 , is called the **plant**. This is a physical system that is given to us to control. Its transfer function is determined by its physics. The second system being composed, say \hat{H}_1 , is the **controller**. We design this system to get the plant to do what we want. The following example illustrates a simple strategy called a **proportional controller** or **P controller**.

Example 14.13: For this example we take as the plant the simplified continuous-time helicopter model of example 12.2,

$$\dot{y}(t) = \frac{1}{M}w(t).$$

Here $y(t)$ is the angular velocity at time t and $w(t)$ is the torque. M is the moment of inertia.

We have renamed the input w (instead of x) because we wish to control the helicopter, and the control input signal will not be the torque. Instead, let's define the input x to be the desired angular velocity. So, to get the helicopter to not rotate, we provide input $x(t) = 0$.

Let us call the impulse response of the plant h_2 , to conform with the notation in Figure 14.6; it is given by

$$\forall t \in \mathbb{R}, \quad h_2(t) = u(t)/M,$$

where u is the unit step. The transfer function is

$$\hat{H}_2(s) = 1/(Ms),$$

with

$$RoC(h) = \{s \in \mathbb{C} \mid Re(s) > 0\}.$$

\hat{H}_2 has a pole at $s = 0$, so this is an unstable system.

As a compensator we can simply place a gain K in a negative feedback composition, as shown in Figure 14.7. The intuition is as follows. Suppose we wish to keep the helicopter from rotating. That is, we would like the output angular velocity to be zero, $y(t) = 0$. Then we should apply an input of zero, $x(t) = 0$. However, the plant is unstable, so even with a zero input, the output diverges (even the smallest non-zero initial condition or the smallest input disturbance will cause it to diverge). With the feedback arrangement in Figure 14.7, if the output angular velocity rises above zero, then the input is modified downwards (the feedback is negative), which will result in a negative torque being applied to the plant, which will counter the rising velocity. If the output angular velocity drops below zero, then the torque will be modified upwards, which again will tend to counter the dropping velocity. The output velocity will stabilize at zero.

To get the helicopter to rotate, for example to execute a turn, we simply apply a non-zero input. The feedback system will again compensate so that the helicopter will rotate at the angular velocity specified by the input.

The signal e is the difference between the input x , which is the desired angular velocity, and the output y , which is the actual angular velocity. It is called the **error signal**. Intuitively, this signal is zero when everything is as desired, when the output angular velocity matches the input.

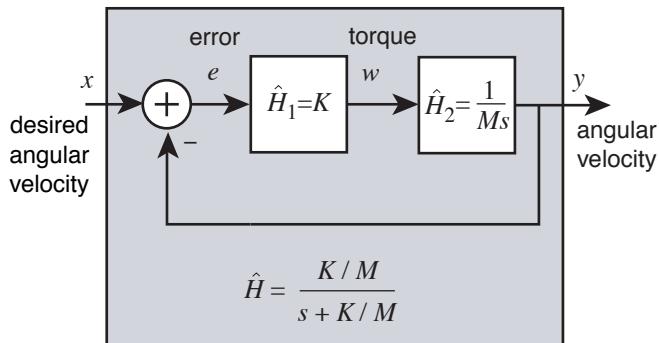
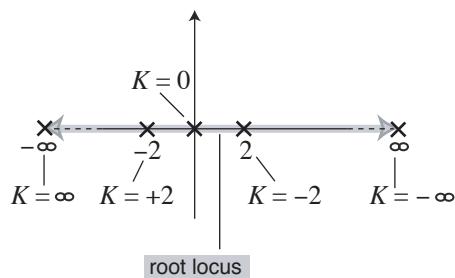
Figure 14.7: A negative feedback proportional controller with gain K .

Figure 14.8: Root locus of the helicopter P controller.

A compensator like that in example 14.13 and Figure 14.7 is called a **proportional controller** or **P controller**. The input w to the plant is proportional to the error e . The objective of the control system is to have the output y of the plant track the input x as closely as possible. I.e., the error e needs to be small. We can use (14.1) to find the transfer function of the closed-loop system.

Example 14.14: Continuing with the helicopter of example 14.13, the closed loop system transfer function is

$$\hat{G}(s) = \frac{K\hat{H}(s)}{1 + K\hat{H}(s)} = \frac{K/M}{s + K/M}. \quad (14.2)$$

which has a pole at $s = -K/M$. If $K > 0$, the closed loop system is stable, and if $K < 0$, it is unstable. Thus, we have considerable freedom to choose K . How should we choose its value?

As K increases from 0 to ∞ , the pole at $s = -K/M$ moves left from 0 to $-\infty$. As K decreases from 0 to $-\infty$, the pole moves to the right from 0 to ∞ . The locus of the pole as K varies is called the **root locus**, since the pole is a root of the denominator polynomial.

Figure 14.8 shows the root locus as a thick gray line, on which are marked the locations of the pole for $K = 0, \pm 2, \pm \infty$. Since there is only one pole, the root locus comprises only one ‘branch’. In general the root locus has as many branches as the number of poles, with each branch showing by the movement of one pole as K varies.

Note that in principle, the same transfer function as the closed-loop transfer function can be achieved by a cascade composition. But as in example 14.1, the resulting system is not robust, in that even the smallest change in the pole location of the plant can cause the system to go unstable (see problem 6). The feedback system, however, is robust, as shown in the following example

Example 14.15: Continuing with the P controller for the helicopter, suppose that our model of the plant is not perfect, and its actual transfer function is

$$\hat{H}_2(s) = \frac{1}{M(s - \varepsilon)} ,$$

for some small value of $\varepsilon > 0$. In that case, the closed loop transfer function is

$$\hat{H}(s) = \frac{K/M}{s - \varepsilon + K/M} ,$$

which has a pole at $s = \varepsilon - K/M$. So the feedback system remains stable so long as

$$\varepsilon < K/M.$$

In practice, when designing feedback controllers, we first quantify our uncertainty about the plant, and then determine the controller parameters so that under all possible plant transfer functions, the closed-loop system is stable.

Example 14.16: Continuing the helicopter example, we might say that $\epsilon < 0.5$. In that case, if we choose K so that $K/M > 0.5$, we would guarantee stability for all values of $\epsilon < 0.5$. We then say that the proportional feedback controller is **robust** for all plants with $\epsilon < 0.5$.

We still have a large number of choices for K . How do we select one? To understand the implications of different choices of K we need to study the behavior of the output y (or the error signal e) for different choices of K . In the following examples we use the closed-loop transfer function to analyze the response of a proportional controller system to various inputs. The first example studies the response to a step function input.

Example 14.17: Continuing the helicopter example, suppose that the input is a step function, $\forall t, x(t) = au(t)$ where a is a constant and u is the unit step. This input declares that at time $t = 0$, we wish for the helicopter to begin rotating with angular velocity a . The closed-loop transfer function is given by (14.2), and the Laplace transform of x is $\hat{X}(s) = a/s$, from table 13.3, so the Laplace transform of the output is

$$\hat{Y}(s) = \hat{G}(s)\hat{X}(s) = \frac{K/M}{s + K/M} \cdot \frac{a}{s}$$

Carrying out the partial fraction expansion, this becomes

$$\hat{Y}(s) = \frac{-a}{s + K/M} + \frac{a}{s} .$$

We can use this to find the inverse Laplace transform,

$$\forall t, \quad y(t) = -ae^{-Kt/M}u(t) + au(t).$$

The second term is the **steady-state response** y_{ss} , which in this case equals the input. So the first term is the **tracking error** y_{tr} , which goes to zero faster for larger K . Hence for step inputs, the larger the gain K , the smaller the tracking error.

In the previous example, we find that the error goes to zero when the input is a step function. Moreover, the error goes to zero faster if the gain K is larger than if it is smaller. In the following example, we find that if the input is sinusoidal, then larger gain K results in an ability to track higher frequency inputs.

Example 14.18: Suppose the input to the P controller helicopter system is a sinusoid of amplitude A and frequency ω_0 ,

$$\forall t \in \mathbb{R}, \quad x(t) = A(\cos \omega_0 t)u(t).$$

We know that the response can be decomposed as $y = y_{tr} + y_{ss}$. The transient response y_{tr} is due to the pole at $s = -K/M$, and so it is of the form

$$\forall t \in \mathbb{R}, \quad y_{tr}(t) = Re^{-Kt/M},$$

for some constant R . The steady-state response is determined by the frequency response at ω_0 . The frequency response is

$$\forall \omega \in \mathbb{R}, \quad H(\omega) = \hat{H}(i\omega) = \frac{K/M}{i\omega + K/M},$$

with magnitude and phase given by

$$|H(\omega)| = \frac{K/M}{[\omega^2 + (K/M)^2]^{1/2}}, \quad \angle H(\omega) = -\tan^{-1} \frac{\omega M}{K}.$$

So the steady-state response is

$$\forall t, \quad y_{ss}(t) = |H(\omega_0)|A \cos(\omega_0 t + \angle H(\omega_0)).$$

Thus the steady-state output is a sinusoid of the same frequency as the input but with a smaller amplitude (unless $\omega_0 = 0$). The larger ω_0 is, the smaller the output amplitude. Hence, the ability of the closed-loop system to track a sinusoidal input decreases as the frequency of the sinusoidal input increases. However, increasing K reduces this effect. Thus, larger gain in the feedback loop improves its ability to track higher frequency sinusoidal inputs.

In addition to the reduction in amplitude, the output has a phase difference. Again, if $\omega_0 = 0$, there is no phase error, because $\tan^{-1}(0) = 0$. As ω_0 increases, the phase lag increases (the phase angle decreases). Once again, however, increasing the gain K reduces the effect.

The previous two examples suggest that large gain in the feedback loop is always better. For a step function input, it causes the transient error to die out faster. For a sinusoidal input, it improves the ability to track higher frequency inputs, and it reduces the phase error in the tracking. A large gain is not always a good idea, however, as seen in the next example, a DC motor.

Example 14.19: The angular position y of a DC motor is determined by the input voltage w according to the differential equation

$$M\ddot{y}(t) + D\dot{y}(t) = Lw(t),$$

where M is the moment of inertia of the rotor and attached load, $D\dot{y}$ is the damping force, and the torque Lw is proportional to the voltage. The transfer function is

$$\hat{H}_2(s) = \frac{L}{Ms^2 + Ds} = \frac{L/M}{s(s + D/M)}.$$

which has one pole at $s = 0$ and one pole at $s = -D/M$. By itself the DC motor is unstable because of the pole at $s = 0$. The transfer function of the feedback composition with proportional gain K is

$$\hat{H}(s) = \frac{K\hat{H}_2(s)}{1 + K\hat{H}_2(s)} = \frac{KL}{Ms^2 + Ds + KL}.$$

There are two closed loop poles—the roots of $Ms^2 + Ds + KL$ —located at

$$s = -\frac{D}{2M} \pm \sqrt{\frac{D^2}{4M^2} - \frac{KL}{M}}.$$

The closed loop system is stable if both poles have negative real parts, which is the case if $K > 0$. If $K < D^2/(4ML)$ both poles are real. But if $K > D^2/(4ML)$, the two poles form a complex conjugate pair located at

$$s = -\frac{D}{2M} \pm i\sqrt{\frac{KL}{M} - \frac{D^2}{4M^2}}.$$

The real part is fixed at $D/2M$, but the imaginary part increases with K . We investigate performance for the parameter values $L/M = 10, D/M = 0.1$. The transfer function is

$$\hat{H}(s) = \frac{10K}{s^2 + 0.1s + 10K}.$$

Because there are two poles, the root locus has two branches, as shown in Figure 14.9. For $K = 0$, the two poles are located at 0 and -0.1, as illustrated by crosses in the figure. As K increases the two poles move towards each other, coinciding at -0.05 when $K = 0.00025$. For larger values of K , the two branches split into a pair of complex conjugate poles.

To appreciate what values of $K > 0$ to select for good tracking, we consider the response to a step input $x = u(t)$ for two different values of K . For $K = 0.00025$, the Laplace transform of the output y is

$$\begin{aligned}\hat{Y}(s) &= \frac{10K}{s^2 + 0.1s + 10K} \frac{1}{s} \\ &= \frac{0.0025}{(s + 0.05)^2} \frac{1}{s} \\ &= -\frac{1}{s + 0.05} - \frac{0.05}{(s + 0.05)^2} + \frac{1}{s}.\end{aligned}$$

So the time domain response is

$$\forall t, \quad y(t) = \{-e^{-0.05t} - 0.05te^{-0.05t}\}u(t) + u(t). \quad (14.3)$$

For $K = 0.0025$, the Laplace transform of the output y is

$$\begin{aligned}\hat{Y}(s) &= \frac{0.025}{s^2 + 0.1s + 0.025} \frac{1}{s} \\ &\approx \frac{-0.5 + i0.17}{s + 0.05 - i0.15} + \frac{-0.5 - i0.17}{s + 0.05 + i0.15} + \frac{1}{s}.\end{aligned}$$

So

$$\begin{aligned}\forall t, \quad y(t) &= e^{-0.5t}[0.527e^{i(0.15t+2.82)} + 0.527e^{-i(0.15t+2.82)}]u(t) \\ &\quad + u(t) \\ &= 0.527e^{-0.5t} \times 2\cos(0.15t + 2.82)u(t) + u(t).\end{aligned} \quad (14.4)$$

The right-hand panel in Figure 14.9 shows plots of the responses (14.3) and (14.4) that illustrate the design tradeoffs. In both cases, the output approaches the input as $t \rightarrow \infty$, so the asymptotic tracking error is zero. The response for the higher gain is faster but it overshoots the asymptotic value. The response for the lower gain is slower but there is no overshoot. In this example, K must be selected to balance speed of response versus the magnitude of the overshoot. In some applications, overshoot may be completely unacceptable.

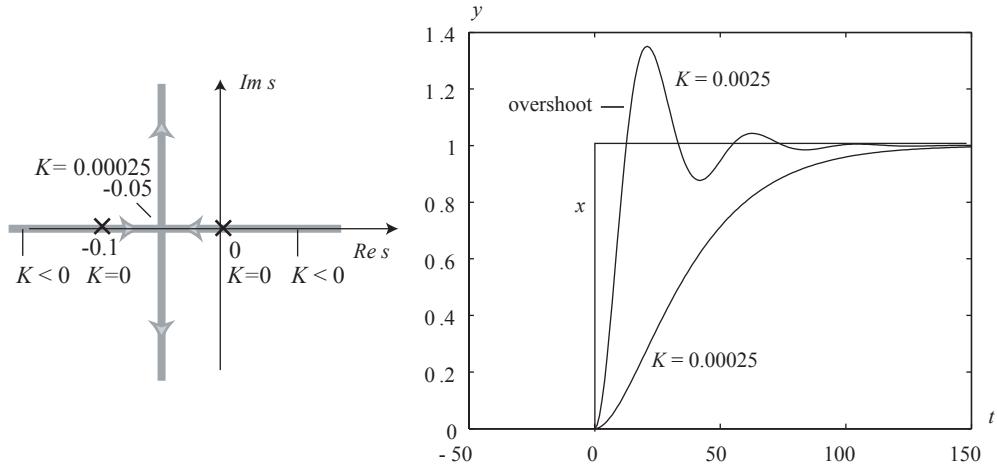


Figure 14.9: The root locus and step response for two values of K of a DC motor with proportional feedback.

We can now investigate the proportional feedback control in a general setting. Suppose the plant transfer function is a proper rational polynomial

$$\hat{H}_2(s) = \frac{\hat{A}(s)}{\hat{B}(s)},$$

where \hat{A} has degree M , \hat{B} has degree N , and $M \leq N$ (\hat{H}_2 is proper). The closed loop transfer function is

$$\hat{H}(s) = \frac{K\hat{H}_2(s)}{1 + K\hat{H}_2(s)} = \frac{K\hat{A}(s)}{\hat{B}(s) + K\hat{A}(s)}. \quad (14.5)$$

The closed loop poles are the N roots of the equation $\hat{B}(s) + K\hat{A}(s) = 0$. These roots will depend on K , so we denote them $p_1(K), \dots, p_n(K)$. As K varies, these roots will trace out the N branches of the root locus. At $K = 0$, the poles are the roots of $\hat{B}(s) = 0$, which are the poles of the plant transfer function $\hat{A}(s)/\hat{B}(s)$. The stability of the closed loop plant requires that K must be such that

$$\operatorname{Re}\{p_1(K)\} < 0, \dots, \operatorname{Re}\{p_n(K)\} < 0. \quad (14.6)$$

Within those values of K that satisfy (14.6) we must select K to get a good response.

The following example shows that a proportional compensator may be unable to guarantee closed loop stability.

Example 14.20: Consider a plant transfer function given by

$$\hat{H}_2(s) = \frac{\hat{A}(s)}{\hat{B}(s)} = \frac{s+1}{(s-1)(s^2 + 0.5s + 1.25)}.$$

There is one zero at $s = -1$, one pole at $s = 1$ and a pair of complex conjugate poles at $s = -0.5 \pm i1.09$. The plant is unstable because of the pole at $s = 1$. The closed loop poles are the roots of the polynomial

$$P(K, s) = K\hat{A}(s) + \hat{B}(s) = K(s+1) + (s-1)((s+0.25)^2 + 1.188).$$

Figure 14.10 shows the three branches of the root locus plot for $K > 0$. As K increases, the unstable pole moves towards the zero, while the complex conjugate poles move into the right-half plane. We need to find the values of K that satisfy the stability condition (14.6). The value of K for which the pole at $s = 1$ moves to $s = 0$ is obtained from the condition $P(K, 0) = 0$, which gives $K - (0.5^2 + 1) = 0$ or $K = 1.25$. So one condition for stability is $K > 1.25$. The complex conjugate poles cross the imaginary axis at $s = \pm i1.15$ for $K = 0.6$. So the second condition for stability is $K < 0.6$. The two conditions $K > 1.25$ and $K < 0.6$ are inconsistent, so no proportional compensator can stabilize this system.

We return to the general discussion. Suppose the stability condition (14.6) can be met. Among the values of K that achieve stability, we select that value for which the output y closely tracks a step input, $x = u$. In this case, the Laplace transform of the input is $1/s$, so the Laplace transform of y is, from (14.5),

$$\hat{Y}(s) = \hat{H}(s) \frac{1}{s} = \frac{K\hat{A}(s)}{\hat{B}(s) + K\hat{A}(s)} \frac{1}{s}. \quad (14.7)$$

Assuming for simplicity that all the poles $p_1(K), \dots, p_n(K)$ have multiplicity 1, \hat{Y} has the partial fraction expansion

$$\hat{Y}(s) = \sum_{i=1}^n \frac{R_i}{s - p_i(K)} + \frac{R_0}{s},$$

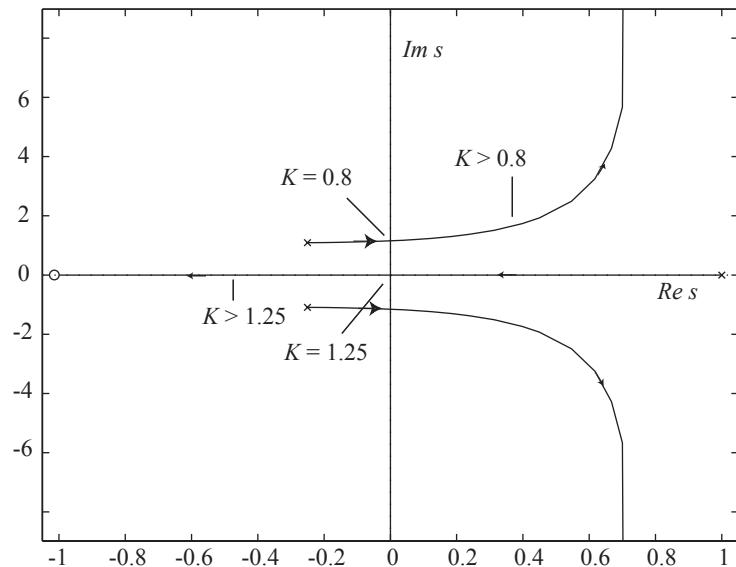


Figure 14.10: Root locus for example 14.20. Stability requires $K > 1.25$ and $K < 0.6$. Therefore, there is no stabilizing proportional compensator.

and hence the time-domain behavior of

$$\forall t, \quad y(t) = \left[\sum_{i=1}^n R_i e^{p_i(K)t} \right] u(t) + R_0 u(t).$$

The first term is the transient response, y_{tr} , and the second term is the steady-state response $y_{ss} = R_0 u$. The transient response goes to zero, since from (14.6), $\text{Re}\{p_i(K)\} < 0$ for all i . The input is the unit step, $x = u$. So the steady-state tracking error is $|R_0 - 1|$, which depends on R_0 . It is easy to find the residue R_0 . We simply multiply both sides of (14.7) by s and evaluate both sides at $s = 0$, to get

$$R_0 = \hat{G}(0) = \frac{K\hat{H}_2(0)}{1 + K\hat{H}_2(0)}.$$

To have zero steady-state error, we want $R_0 = 1$, which can only happen if $\hat{H}_2(0) = \infty$. But this means $s = 0$ must be a pole of the plant transfer function \hat{H}_2 . (This is the case in the examples of the helicopter and the DC motor.) If the plant does not have a pole at $s = 0$, the steady-state error will be

$$\left| 1 - \frac{K\hat{H}_2(0)}{1 + K\hat{H}_2(0)} \right|.$$

This error is smaller the larger the gain K . So to minimize the steady-state error we should choose as large a gain as possible, subject to the stability requirement (14.6).

However, a large value of K may lead to poor transient behavior by causing overshoots, as happened in the DC motor example in Figure 14.9 for the larger gain $K = 0.0025$. To decide the appropriate K is a matter of trial and error. One studies the transient response for different (stabilizing) values of K (as we did for the DC motor) and selects K that gives a satisfactory transient behavior.

14.4 PID controllers

The P controller discussed in the previous section achieves zero steady-state error if the plant has a pole at $s = 0$. This means that the plant includes an integrator, since the transfer function of an integrator is $1/s$, which has a pole at $s = 0$. If the plant does not have a pole at $s = 0$, however, a non-zero error results. While this error can be reduced by choosing a large gain K in the controller, this results in poor transient behavior.

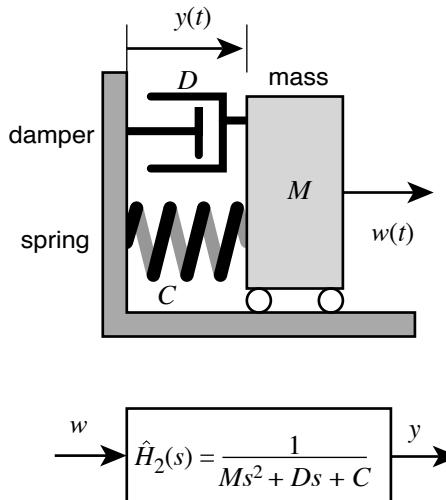


Figure 14.11: A mass-spring-damper system.

In this section, we develop the well-known **PID controller**, which includes an integrator in the controller. It can achieve zero steady-state error even if the plant does not have a pole at $s = 0$, and still achieve reasonable transient behavior. The PID controller is a generalization of the P controller, in that with certain choices of parameters, it becomes a P controller.

We begin with an example that has rich enough dynamics to demonstrate the strengths of the PID controller. This example describes a mechanical system, but just about any physical system that is modeled by a linear second-order differential equation is subject to similar analysis. This includes, for example, electrical circuits having resistors, capacitors, and inductors.

Example 14.21: A basic **mass-spring-damper system** is illustrated in Figure 14.11. This system has a mass M that slides on a frictionless surface, a spring that attaches the mass to a fixed physical object, and a damper, which absorbs mechanical energy. A damper might be, for example, a dashpot, which is a cylinder filled with oil plus a piston. A familiar example of such a damper is a shock absorber in the suspension system of a car.

Suppose that an external force w is applied to the mass, where w is a continuous-time signal. The differential equation governing the system is obtained by setting the sum of all forces to zero,

$$M\ddot{y}(t) + D\dot{y}(t) + Cy(t) = w(t).$$

The output $y(t)$ is the position of the mass at time t , $M\ddot{y}(t)$ is the inertial force, $D\dot{y}(t)$ is the damping force due to the damper, $Cy(t)$ is the restoring force of the spring, and $w(t)$ is the externally applied force. We assume that $y(t) = 0$ when the spring is in its equilibrium position (neither extended nor compressed). M , D , and C are constants. Taking the Laplace transform, using the differentiation property from table 13.4, gives

$$s^2\hat{Y}(s) + Ds\hat{Y}(s) + CY(s) = W(s),$$

so the plant or open loop transfer function is

$$\hat{H}_2(s) = \frac{\hat{Y}(s)}{\hat{W}(s)} = \frac{1}{Ms^2 + Ds + C}.$$

Suppose for example that the constants have values $M = 1$, $D = 1$, and $C = 1.25$. Then

$$\hat{H}_2(s) = \frac{1}{s^2 + s + 1.25}. \quad (14.8)$$

In this case, the transfer function has a pair of complex poles at $s = -0.5 \pm i$. Since their real part is strictly negative, the system is stable.

Suppose we wish to drive the system to move the mass to the right one unit of distance at time $t = 0$. We can apply an input force that is a unit step, scaled so that the steady-state response places the mass at position $y(t) = 1$. The final steady-state output is determined by the DC gain, which is $\hat{H}_2(0) = 1/1.25 = 0.8$, so we can apply an input given by

$$\forall t, \quad , w(t) = \frac{1}{0.8}u(t) = 1.25u(t),$$

where u is the unit step signal. The resulting response y_O has Laplace transform

$$\hat{Y}_O(s) = \frac{1}{s^2 + s + 1.25} \cdot \frac{1.25}{s} = \frac{-0.5 + 0.25i}{s + 0.5 - i} + \frac{-0.5 - 0.25i}{s + 0.5 + i} + \frac{1}{s}.$$

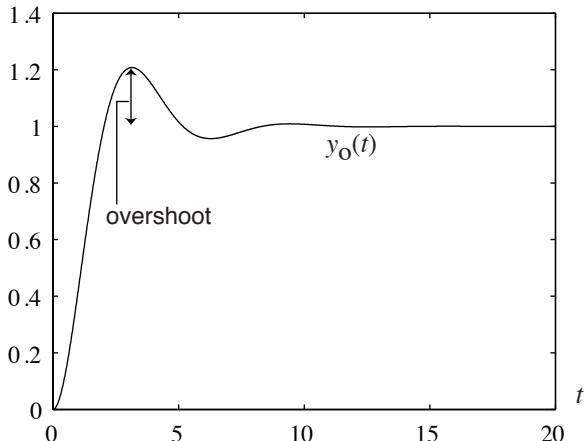


Figure 14.12: The open loop step response y_O of the mass-spring-damper system.

We call this the open-loop step response, because there is no control loop (yet).

Taking the inverse transform gives the open-loop step response

$$\forall t, \quad y_O(t) = e^{-0.5t} [(-0.5 + 0.25i)e^{it} + (-0.5 - 0.25i)e^{-it}]u(t) + u(t).$$

By combining the complex conjugate terms, this can be expressed as

$$\forall t, \quad y_O(t) = Re^{-0.5t} \cos(t + \theta)u(t) + u(t),$$

where $R = 1.12$ and $\theta = 2.68$. Figure 14.12 displays a plot of this open-loop step response y_O . Notice that the mass settles to position $y(t) = 1$ for large t .

This system in the previous example is stable, and therefore does not need a feedback control loop to stabilize it. However, there are two difficulties with its open-loop response, shown in Figure 14.12, that can be corrected using a controller. First, it takes approximately 10 units of time for the transient to disappear, which may be too slow for some applications. Moreover, there is an overshoot of 20 percent beyond the final steady-state value, which may be too much.

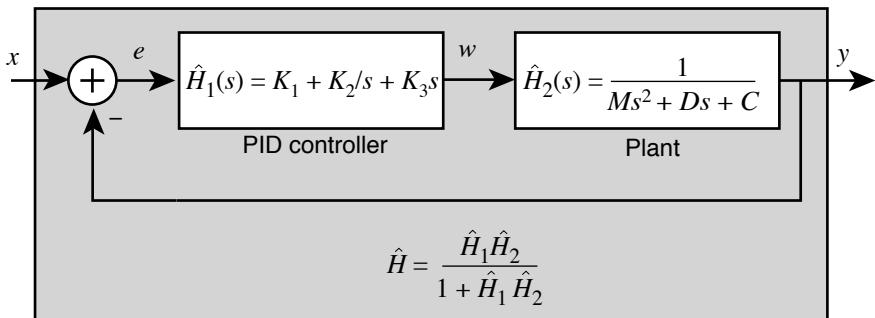


Figure 14.13: The mass-spring-damper system composed with a PID controller in a feedback composition.

We can correct for the slow response and the large overshoot, using a **PID controller**. The term ‘PID’ stands for proportional plus integral plus derivative. A PID controller generalizes the P controller of the previous section by adding an integral and derivative term.

The general form of the transfer function of a PID controller is

$$\hat{H}_1(s) = K_1 + \frac{K_2}{s} + K_3 s = \frac{K_3 s^2 + K_1 s + K_2}{s}. \quad (14.9)$$

We will compose this with the plant in a feedback loop, as shown in Figure 14.13. Here K_1, K_2, K_3 are constants to be selected by the designer. If $K_2 = K_3 = 0$, then we have a P controller. If $K_1 = K_3 = 0$, $\hat{H}_1(s) = K_2/s$, we have an **integral controller**, so called because $1/s$ is the transfer function of an integrator. That is, if the input to the integral controller is e , and the output is w , then

$$\forall t, \quad w(t) = K_2 \int_{-\infty}^t e(\tau) d\tau.$$

If $K_1 = K_2 = 0$, $\hat{H}_1(s) = K_3 s$, then we have a **derivative controller**, so called because s is the transfer function of a differentiator. That is, if the input to the derivative controller is e , and the output is w , then

$$\forall t, \quad w(t) = K_3 \dot{e}(t).$$

The following table offers guidelines for selecting the parameters of a PID controller. Of course, these are guidelines only—the actual performance of the closed loop system depends on the plant transfer function and must be checked in detail.

Parameter	Response speed	Overshoot	Steady-state error
K_1	Faster	Larger	Decreases
K_2	Faster	Larger	Zero
K_3	Minor change	Smaller	Minor change

Example 14.22: We now evaluate a PID controller for the mass-spring-damper system of Figure 14.11, using the feedback composition of Figure 14.6. We assume the parameters values $M = 1$, $D = 1$, and $C = 1.25$, as in example 14.21. The closed-loop transfer function with the PID controller is

$$\hat{H}(s) = \frac{\hat{H}_1(s)\hat{H}_2(s)}{1 + \hat{H}_1(s)\hat{H}_2(s)} = \frac{K_3 s^2 + K_1 s + K_2}{s^3 + (1 + K_3)s^2 + (1.25 + K_1)s + K_2}.$$

Suppose we provide as input a unit step. This means that we wish to move the mass to the right one unit of distance, starting at time $t = 0$. The controller will attempt to track this input. The response to a unit step input has Laplace transform

$$\hat{Y}_{pid}(s) = \hat{H}(s) \cdot \frac{1}{s} = \frac{K_3 s^2 + K_1 s + K_2}{s^3 + (1 + K_3)s^2 + (1.25 + K_1)s + K_2} \cdot \frac{1}{s}. \quad (14.10)$$

We now need to select the values for the parameters of the PID controller, K_1 , K_2 , and K_3 . We first try proportional control with $K_1 = 10$, and $K_2 = K_3 = 0$. In this case, the step response has the Laplace transform

$$\hat{Y}_p(s) = \frac{10}{s^2 + s + 11.25} \cdot \frac{1}{s}.$$

The inverse Laplace transform gives the time response y_p , which is plotted in Figure 14.14. The steady-state value is determined by the DC gain of the closed loop transfer function,

$$\left. \frac{10}{s^2 + s + 11.25} \right|_{s=0} = \frac{10}{11.25} \approx 0.89.$$

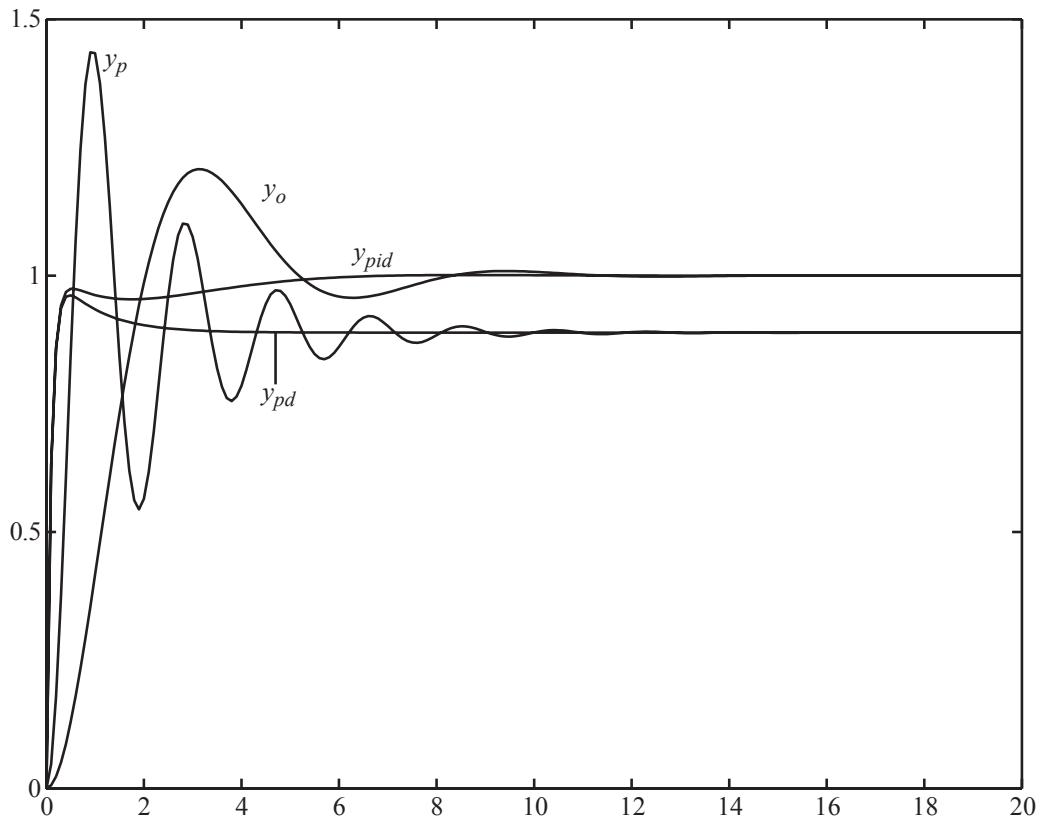


Figure 14.14: The step response for open loop, y_o , with P-control, y_p , PD-control, y_{pd} , and PID-control, y_{pid} .

This yields an error of 11 percent, and the overshoot of 50 percent is much worse than that of the open-loop response y_o , also shown in the figure. Thus, a P controller with gain $K = 10$ is useless for this application.

Following the guidelines in the table above, we add derivative control to reduce the overshoot. The result is a so-called **PD controller**, because it adds a proportional and a derivative term. For the PD controller we choose $K_1 = 10$ and $K_3 = 10$. Substitution in (14.10) gives the Laplace transform of the step response,

$$\hat{Y}_{pd}(s) = \frac{10s + 10}{s^2 + 11s + 11.25} \cdot \frac{1}{s}.$$

The steady-state value is given by the DC gain of the closed loop transfer function,

$$\left. \frac{10s + 10}{s^2 + 11s + 11.25} \right|_{s=0} \approx 0.89,$$

which is the same as the steady-state value for the P controller. The inverse Laplace transform gives the time response y_{pd} , which is plotted in Figure 14.14. The overshoot is reduced to 10 percent—a large improvement. Also, the response is quicker—the transient disappears in about 4 time units.

Finally, to eliminate the steady-state error we add integral control. For the PID controller we choose $K_1 = 10, K_2 = 5, K_3 = 10$. Substitution in (14.10) gives the Laplace transform of the step response

$$\hat{Y}_{pid}(s) = \frac{10s^2 + 10s + 5}{s^3 + 11s^2 + 11.25s + 5} \cdot \frac{1}{s}.$$

The steady-state value is again given by the DC gain of the closed loop transfer function,

$$\left. \frac{10s^2 + 10s + 5}{s^3 + 11s^2 + 11.25s + 5} \right|_{s=0} = 1.$$

So the steady-state error is eliminated, as expected. The time response y_{pid} is plotted in Figure 14.14. It shows significant improvement over the other responses. There is no overshoot, and the transient disappears in about 4 time units. Further tuning of the parameters K_1, K_2, K_3 could yield small improvements.

14.5 Summary

This chapter considers cascade, parallel, and feedback compositions of LTI systems described by Z or Laplace transforms. Cascade composition is applied to equalization, parallel composition is applied to noise cancellation, and feedback composition is applied to control.

Because we are using Z and Laplace transforms rather than Fourier transforms, we are able to consider unstable systems. In particular, we find that while, in principle, cascade and parallel compositions can be used to stabilize unstable systems, the result is not robust. Small changes in parameter values can result in the system being once again unstable. Feedback composition, on the other hand, can be used to robustly stabilize unstable systems. We illustrate this first with a simple helicopter example. The second example, a DC motor, benefits from more sophisticated controllers. The third example, a mass-spring-damper system, motivates the development of the well-known PID controller structure. PID controllers can be used to stabilize unstable systems and to improve the response time, precision, and overshoot of stable systems.

Exercises

Each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **E** This exercise studies equalization when the channel is only known approximately.

Consider the cascade composition of figure 14.1, where \hat{H}_1 is the channel to be equalized, and \hat{H}_2 is the equalizer. If the equalizer is working perfectly, then $x = y$. For example, if

$$\hat{H}_1(z) = \frac{z}{z - 0.5} \quad \text{and} \quad \hat{H}_2(z) = \frac{z - 0.5}{z} ,$$

then $x = y$ because $\hat{H}_1(z)\hat{H}_2(z) = 1$.

- (a) Suppose that $\hat{H}_2(z)$ is as given above, but the plant is a bit different,

$$\hat{H}_1(z) = \frac{z}{z - 0.5 - \varepsilon} .$$

Suppose that $x = \delta$, the Kronecker delta function. Plot $y - x$ for $\varepsilon = 0.1$ and $\varepsilon = -0.1$.

- (b) Now suppose that the equalizer is

$$\hat{H}_2(z) = \frac{z - 2}{z} ,$$

and the channel is

$$\hat{H}_1(z) = \frac{z}{z - 2 - \varepsilon} .$$

Again suppose that $x = \delta$, the Kronecker delta function. Plot $y - x$ for $\varepsilon = 0.1, -0.1$.

- (c) For part (b), show that equalization error $y - x$ grows without bound whenever $\varepsilon \neq 0, |\varepsilon| < 1$.

2. **E** This exercise studies equalization for continuous-time channels. Consider the cascade composition of figure 14.1, where \hat{H}_1 is the channel to be equalized, and \hat{H}_2 is the equalizer. Both are causal. If

$$\hat{H}_1(s) = \frac{s + 1}{s + 2} \quad \text{and} \quad \hat{H}_2(s) = \frac{s + 2}{s + 1} ,$$

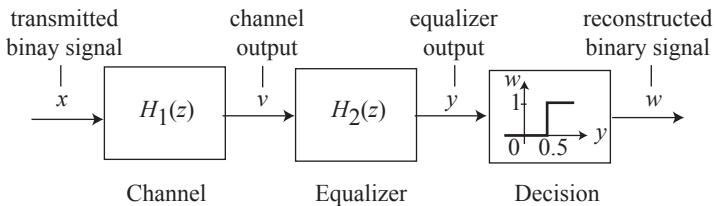


Figure 14.15: Arrangement of decision-directed equalization of Exercise 3.

then $x = y$ because $\hat{H}_1(s)\hat{H}_2(s) = 1$.

(a) Suppose \hat{H}_2 is as above but

$$\hat{H}_1(s) = \frac{s+1}{s+2+\epsilon} .$$

Suppose $x = u$, the unit step. Plot $y - x$ for $\epsilon = 0.1$ and $\epsilon = -0.1$, and calculate the steady state error.

(b) Now suppose the equalizer is

$$\hat{H}_2(s) = \frac{s-1}{s+2} ,$$

and the channel is

$$\hat{H}_1(s) = \frac{s+2}{s-1-\epsilon} .$$

Again suppose that $x = u$. Plot $y - x$ for $\epsilon = 0.1, -0.1$.

(c) For part (b) show that the error $y - x$ grows without bound for any $\epsilon \neq 0$, $|\epsilon| < 1$.

3. T This exercise explores decision-directed equalization. The arrangement is shown in Figure 14.15. The transmitted signal is a binary sequence $x : \mathbb{Z} \rightarrow \{0, 1\}$. The causal channel transfer function is \hat{H}_1 and the equalizer transfer function is \hat{H}_2 . The channel output is the real-valued signal $v : \mathbb{Z} \rightarrow \mathbb{R}$. The equalizer output is the real-valued signal $y : \mathbb{Z} \rightarrow \mathbb{R}$. This signal is fed to a decision unit whose binary output at time n , $w(n) = 0$ if $y(n) < 0.5$ and $w(n) = 1$ if $y(n) \geq 0.5$. Thus the decision unit is a (nonlinear) memoryless system,

$$\text{Decision} : [\mathbb{Z} \rightarrow \mathbb{R}] \rightarrow [\mathbb{Z} \rightarrow \{0, 1\}],$$

defined by a threshold rule

$$\forall n, \quad (\text{Decision}(y))(n) = \begin{cases} 0, & y(n) < 0.5, \\ 1, & y(n) \geq 0.5 \end{cases}$$

At each point in time, the receiver has an estimate \hat{H}_1^e of the true channel transfer function, \hat{H}_1 . The equalizer is set at

$$\hat{H}_2(z) = [\hat{H}_1^e(z)]^{-1}. \quad (14.11)$$

- (a) Suppose that initially $\hat{H}_1(z) = \frac{z}{z-0.2}$, and the estimate is perfect, $\hat{H}_1^e = \hat{H}_1$. (This perfect estimate is achieved using a known training sequence for x .) Determine the respective impulse responses h_1 and h_2 .

Now suppose the signal x is

$$\forall n, \quad x(n) = \begin{cases} 0, & n < 0 \\ 1, & n \geq 0, n \text{ even} \\ 0, & n \geq 0, n \text{ odd} \end{cases} \quad (14.12)$$

Calculate the channel output $v(n) = (h_1 * x)(n), n \leq 3$. Then calculate the equalizer output $y(n) = (h_2 * v)(n), n \leq 3$, and check that $y(n) = x(n), n \leq 3$. Also check that $w(n) = x(n), n \leq 3$.

- (b) Now suppose the channel transfer function has changed to

$$\hat{H}_1(z) = \frac{z}{z-0.3},$$

but the receiver's estimate hasn't changed, i.e.

$$\hat{H}_1^e(z) = \frac{z}{z-0.2},$$

so the equalizer (14.11) hasn't changed either. For the same input signal again calculate the channel and equalizer outputs $v(n)$ and $y(n)$ for $n \leq 3$. Check that $y(n) \neq x(n)$ for $n > 0$. But show that the decision $w(n) = x(n)$ for $n \leq 3$. So the equalizer correctly determines x .

- (c) Since the receiver's decision $w = x$, it can make a new estimate of the channel using the fact that $\hat{Y} = \hat{H}_1 \hat{H}_2 \hat{X} = \hat{H}_1 \hat{H}_2 \hat{W}$. The new estimate is

$$\hat{H}_1^e = \frac{\hat{Y}}{\hat{H}_2 \hat{W}}. \quad (14.13)$$

Suppose time is 3, and the receiver has observed $y(n), w(n), n \leq 3$. Since the Z transforms \hat{Y} and \hat{W} also depend on values of $y(n), w(n)$ for $n > 3$, these Z transforms can *not* be calculated at time $n = 3$, and so the estimator (14.13) cannot be used. The following approach will work, however.

Suppose the receiver knows that the unknown channel transfer function is of the form

$$\hat{H}_1(z) = \frac{z}{z-a},$$

so that only the parameter a has to be estimated. Using this information, we have

$$\hat{Y}(z) = \frac{z}{z-a} \frac{z-0.2}{z} \hat{W}(z) = \frac{z-0.2}{z-a} W(z).$$

Now take the inverse Z transform and express the time-domain relation between y and w . Show that you can estimate a knowing $y(0), y(1), w(0), w(1)$.

4. E This continues Exercise 3. It shows that if the channel estimate \hat{H}_1^e is not sufficiently close to the true channel \hat{H}_1 , the decision may become incorrect. Suppose the true channel is $\hat{H}_1(z) = \frac{z}{z-a}$, the estimate is $\hat{H}_1^e(z) = \frac{z}{z-0.2}$, the equalizer is $\hat{H}_2(z) = [\hat{H}_1^e(z)]^{-1} = \frac{z-0.2}{z}$, and the decision is as in Figure 14.15. Assume the input signal x to be the same as in (14.12). Show that if $a = 0.6$ then $w(0) = x(0), w(1) = x(1), w(2) = x(2)$, but $w(3) \neq x(3)$.
5. E This exercise continues the discussion in examples 14.5, 14.6 for the continuous-time, causal and stable channel with impulse response h_1 and transfer function

$$\forall s \in \text{RoC}(h_1) = \{s \mid \text{Re}\{s\} > -1\}, \quad \hat{H}_1(s) = \frac{s-2}{s+1}.$$

- (a) Calculate h_1 and sketch it. (Observe how the zero in the right-half plane at $s = 2$ accounts for the negative values.)

- (b) The inverse of \hat{H}_1 ,

$$\hat{H}_2(s) = \frac{s+1}{s-2},$$

has a pole at $s = 2$. So as a causal system, the inverse is unstable. But as a non-causal system, it is stable with $\text{RoC} = \{s \mid \text{Re}\{s\} < 2\}$ which includes the imaginary axis. Evaluate the impulse response h_2 of \hat{H}_2 as an anti-causal system, and give a sketch.

- (c) The impulse response h_2 calculated in (a) is non-zero for $t \leq 0$. Consider the finite-duration, anti-causal impulse response h_3 obtained by truncating h_2 before time -5,

$$\forall t \in \mathbb{R}, \quad h_3(t) = \begin{cases} h_2(t), & t \geq -5 \\ 0, & t < -5 \end{cases}$$

and sketch h_3 . Calculate the transfer function \hat{H}_3 , including its *RoC*, by using the definition of the Laplace transform.

- (d) Obtain the causal impulse response h_4 by delaying h_3 by time T , i.e.

$$\forall t \in \mathbb{R}, \quad h_4(t) = h_3(t + T).$$

Sketch h_4 and find its transfer function, \hat{H}_4 . Then \hat{H}_4 is an approximate inverse of \hat{H}_1 with a delay of 5 time units. (**Note:** h_3 has a delta function at 0.)

6. **T** The proportional controller of Figure 14.7 stabilizes the plant for $K > 1$. In this exercise, we try to achieve the same effect by the cascade compensator of figure 14.1.

- (a) Assume that the plant \hat{H}_2 is as given in Figure 14.7. Design \hat{H}_1 for the cascade composition of figure 14.1 so that $\hat{H}_2\hat{H}_1$ is the same as the closed-loop transfer function achieved in Figure 14.7.
- (b) Now suppose that the model of the plant is not perfect, and the plant's real transfer function is

$$\hat{H}_2(s) = \frac{1}{M(s - \varepsilon)},$$

for some small value of $\varepsilon > 0$. Using the same \hat{H}_1 that you designed in part (a), what is the transfer function of the cascade composition? Is it stable?

7. **T** Consider a discrete-time causal plant with transfer function

$$\hat{H}_2(z) = \frac{z}{z - 2}.$$

- (a) Where are the poles and zeros? Is the plant stable?
- (b) Find the impulse response of the plant. Is it bounded?
- (c) Give the closed-loop transfer function for the P controller for this plant.
- (d) Sketch the root locus for the P controller for this plant.

- (e) For what values of K is the closed-loop system stable?
- (f) Find the step response of the closed-loop system. Identify the transient and steady-state responses. For $K = 10$, what is the steady-state tracking error?
- (g) Suppose that the plant is instead given by

$$\hat{H}_2 = \frac{z}{z - 2 - \epsilon},$$

for some real $\epsilon \geq 0$. For what values of K is the P controller robust for plants with $|\epsilon| < 0.5$?

8. T Consider the feedback composition in Figure 14.6. Suppose that $\hat{H}_1\hat{H}_2$ is causal and **strictly proper**, meaning that the order of the numerator is greater than the order of the denominator.

- (a) Show that if $\hat{H}_1\hat{H}_2$ is causal and strictly proper, then so is \hat{H} , the transfer function of the feedback composition given by (14.1).
- (b) For the discrete-time case, show that we can write

$$\hat{H}_1(z)\hat{H}_2(z) = z^{-1}\hat{G}(z), \quad (14.14)$$

where $G(z)$ is proper, and is the transfer function of a causal system. Intuitively, this means that there must be a net unit delay in the feedback loop, because z^{-1} is the transfer function of a unit delay.

- (c) Use the result of part (a) to demonstrate that the system $\hat{H}_1\hat{H}_2$ has state-determined output.
- (d) For the continuous-time case, show that we can write

$$\hat{H}_1(s)\hat{H}_2(s) = s^{-1}\hat{G}(s), \quad (14.15)$$

where $G(s)$ is proper, and is the transfer function of a causal system. Intuitively, this means that there must be an integration in the feedback loop, because s^{-1} is the transfer function of an integrator.

- (e) Use the result of part (c) to demonstrate that the system $\hat{H}_1\hat{H}_2$ has state-determined output, assuming that the input is bounded and piecewise continuous.

9. E Consider the m th order polynomial $s^N + a_{m-1}s^{m-1} + \dots + a_1s + a_0$. Suppose all its roots have negative real parts. Show that all coefficients of the polynomial

must be positive, i.e., $a_{m-1} > 0, \dots, a_0 > 0$. Hint. Express the polynomial as $(s - p_1) \cdots (s - p_m)$ with $\operatorname{Re}\{p_i\} > 0$. Note that complex roots must occur in complex conjugate pairs. (The positiveness of all coefficients is a necessary condition. A sufficient condition is given by the **Routh-Hurwitz** criterion, described in control theory texts.)

10. **T** Consider the feedback composition in figure 14.6. The plant's transfer function is $\hat{H}_2(s) = 1/s^2$.
 - (a) Show that no PI controller in the form $\hat{H}_1(s) = K_1 + K_2/s$ can stabilize the closed loop system for any values of K_1, K_2 . Hint. Use the result of problem 9.
 - (b) Show that by the proper choice of the coefficients K_1, K_2 of a PD controller in the form $\hat{H}_1(s) = K_1 + K_2 s$, you can place the closed-loop poles at any locations p_1, p_2 (these must be complex conjugate if they are complex).
11. **T** Consider the feedback composition in figure 14.6. The plant's transfer function is $\hat{H}_2(s) = 1/(s^2 + 2s + 1)$. The PI controller is $\hat{H}_1(s) = K_1 + K_2/s$.
 - (a) Take $K_2 = 0$, and plot the root locus as K_1 varies. For what values of K_1 is the closed loop system stable? What is the steady state error to a step input as a function of K_1 ?
 - (b) Select K_1, K_2 such that the closed loop system is stable and has zero-steady state error.



Sets and Functions

Contents

A.1 Sets	656
A.1.1 Assignment and assertion	657
A.1.2 Sets of sets	658
A.1.3 Variables and predicates	659
A.1.4 Quantification over sets	660
<i>Probing Further: Predicates in Matlab</i>	661
A.1.5 Some useful sets	662
A.1.6 Set operations: union, intersection, complement	663
A.1.7 Predicate operations	664
A.1.8 Permutations and combinations	665
A.1.9 Product sets	666
<i>Basics: Tuples, strings, and sequences</i>	667
A.1.10 Evaluating an expression	672
A.2 Functions	677
A.2.1 Defining functions	679
A.2.2 Tuples and sequences as functions	679
A.2.3 Function properties	680
A.3 Summary	680
<i>Probing Further: Infinite sets</i>	681
<i>Probing Further: Even bigger sets</i>	683
Exercises	684

This appendix establishes the notation of sets and functions as used in the book. We review the use of this mathematical language to describe sets in a variety of ways, to combine sets using the operations of union, intersection, and product, and to derive logical consequences. We also review how to formulate and understand predicates, and we define certain sets that occur frequently in the study of signals and systems. Finally, we review functions.

A.1 Sets

A **set** is a collection of **elements**. The set of **natural numbers**, for example, is the collection of all positive integers. This set is so commonly used that it is denoted by the special symbol \mathbb{N} ,

$$\mathbb{N} = \{1, 2, 3, \dots\}. \quad (\text{A.1})$$

In (A.1) the left hand side is the name of the set and the right hand side is an enumeration or list of all the elements of the set, enclosed by curly braces. We read (A.1) as ‘ \mathbb{N} is the set consisting of the numbers 1, 2, 3, and so on.’ The **ellipsis** ‘ \dots ’ means ‘and so on’. Because \mathbb{N} is an infinite set we cannot list all its elements, and so we have to use ellipsis. For a finite set, we may use ellipsis as a convenient shorthand, as in

$$A = \{1, 2, 3, \dots, 100\}, \quad (\text{A.2})$$

which defines A to be the set consisting of the first 100 natural numbers. \mathbb{N} and A are sets of numbers.

Many authors include the number zero in the set of natural numbers. For no particularly good reason, in this text, we denote the set of **non-negative integers** by a slightly different symbol,

$$\mathbb{N}_0 = \{0, 1, 2, 3, \dots\}.$$

An element of a set is also said to be a **member** of the set. The number 10 is a member of the set A defined in (A.2), but the number 110 is not a member of A . We express these two facts by the two expressions:

$$10 \in A, \quad 110 \notin A.$$

The symbol ‘ \in ’ is read ‘is a member of’ or ‘belongs to’ and the symbol ‘ \notin ’ is read ‘is not a member of’ or ‘does not belong to.’

When we define a set by enumerating or listing all its elements, we enclose the list in curly braces $\{\dots\}$. It is not always necessary to give the set a name. We can instead refer to it directly by enumerating its elements. Thus

$$\{1, 2, 3, 4, 5\}$$

is the set consisting of the numbers $1, 2, \dots, 5$.

The order in which the elements of the set appear in the list is not (usually) significant. When the order is significant, the set is called an **ordered set**.

An element is either a member of a set or it is not. It cannot be a member more than once. So, for example, $\{1, 2, 1\}$ is not a set.

Two sets are equal if and only if every element of the first set is also an element of the second set, and every element of the second set is a member of the first set. So if $B = \{1, 2, 3, 4, 5\}$ and $C = \{5, 3, 4, 1, 2\}$, then it is correct to state

$$B = C. \quad (\text{A.3})$$

Let $A = \{1, 2, \dots, 10\}$, and $B = \{1, \dots, 5\}$. B is a **subset** of A , and A is a subset of \mathbb{N} . We express these assertions as:

$$B \subset A, \quad A \subset \mathbb{N}.$$

Some texts use the symbol \subset to denote a **proper subset**, where $A \subset B$ means “ A is a subset of B and is not equal to B .” Those texts will write $A \subseteq B$ to mean “ A is a subset of B and may be equal to B .” In this text, we will not make the distinction. We will use the symbol \subset to mean subset, and if we need to refer to a proper subset, we make it clear that we are talking about a proper subset.

The **empty set** (a set with no elements) is written \emptyset . For any set A , $\emptyset \subset A$.

A.1.1 Assignment and assertion

Although the expressions (A.1) and (A.3) are both in the form of equations, the “=” in these two expressions have very different meanings. Expression (A.1) (as well as (A.2)) is an **assignment**: the set on the right-hand side is assigned to the name \mathbb{N} on the left-hand

side. Expression (A.3) is an **assertion**, which is an expression that can be true or false. In other words, an assertion is an expression that has a truth value. Thus (A.3) asserts that the two sides are equal. Since this is true, (A.3) is a true assertion. But the assertion

$$\mathbb{N} = A$$

is a false assertion. An assertion is true or false, while an assignment is a tautology (something that is trivially true because the definition makes it so). Some notation systems make a distinction between an assignment and an assertion by writing an assignment using the symbol “`:`” instead of “`=`” as in

$$\mathbb{N} := \{1, 2, 3, \dots\}.$$

Other notation systems use “`=`” for assignments and “`==`” for assertions. We will not make these notational distinctions (except in Chapter 6), since it will be clear from the context whether an expression is an assignment or an assertion.¹

Context is essential in order to disambiguate whether an expression like

$$\text{MyNumbers} = \{1, 3, 5\}$$

is an assertion or an assignment. Thus, for example, in the context,

Define the set *MyNumbers* by $\text{MyNumbers} = \{1, 3, 5\}$,

the expression is clearly an assignment, as indicated by “Define the set …”. However, in the following context,

If we define *MyNumbers* by $\text{MyNumbers} = \{1, 3, 5\}$, then
 $\text{MyNumbers} = \{3, 5, 1\}$,

the first “`=`” is an assignment, but the second is an assertion.

A.1.2 Sets of sets

Nearly anything can be an element of a set, so sets can be elements that are themselves sets. Suppose, for example, that *X* is a set. Then we can construct the set of all subsets of

¹A symbol such as “`=`” which has more than one meaning depending on the context is said to be **overloaded**. C++ uses overloaded symbols, while Java does not (Java does support overloaded methods, however). People often have difficulty reading other people’s code written in a language that permits overloading.

X , which is written $\wp(X)$ and is called the **powerset** of X .² Notice that since $\emptyset \subset X$, then $\emptyset \in \wp(X)$. (\emptyset denotes the empty set.)

The fact that elements of sets can themselves be sets leads to an interesting limitation in the notion of sets. Consider a set R defined to consist of all sets that are not members of themselves. Then is the assertion $R \in R$ true or false? If it is true, then R must not be a member of R , and if it is false, then R must be a member of R . This paradox is known as **Russell's paradox**. It demonstrates that the notion of sets is not in fact as universal as once thought. This subtlety, however, will not in any way infringe on our ability to use sets in this book, so we can safely ignore it.

A.1.3 Variables and predicates

We can refer to a particular element of a set by using its name, for example the element 55 in \mathbb{N} . We often need to refer to a general element in a set. We do this by using a **variable**. We usually use lower case letters for variable names, such as x, y, n, t . Thus $n \in \mathbb{N}$ refers to any natural number. \mathbb{N} is the set of values that the variable n can take on. We may also use a character string for a variable name such as $city \in USCities$. We say that “ n is a variable over \mathbb{N} ” and “ $city$ is a variable over $USCities$,” where $USCities$ is the set of cities in the United States.

A variable can be assigned (or substituted by) any value in its range. Thus the assignment $n = 5$ assigns the value 5 to n , and $city = Berkeley$ assigns the value Berkeley to $city$.

Once again the use of “=” in an expression like $n = 5$ is ambiguous, because the expression could be an assignment or an assertion, depending on the context. Thus, for example, in the context,

Let $n = 5, m = 6$, and $k = 2$, then $m = k + n$

the first three “=” are assignments, but the last is an assertion, which happens to be false.

We can use variables to form expressions such as $n \leq 5$. Now, when we assign a particular value to n in this expression, the expression become an assertion that evaluates to true or false. (For instance, $n \leq 5$ evaluates to true for $n = 3$ and to false for $n = 6$.) An expression such as $x \leq 5$ which evaluates to true or false when we assign the variable a specific value

²The powerset of X is sometimes written 2^X .

is called a **predicate** (in x).³ Predicates are used to define new sets from old ones, as in this example:

$$B = \{x \in \mathbb{N} \mid x \leq 5\}$$

which reads “ B is the set of all elements x in \mathbb{N} such that (the symbol ‘|’ means ‘such that’) the predicate $x \leq 5$ is true.” More generally, we use the following prototype expression to define a new set $NewSet$ from an old set Set

$$\boxed{NewSet = \{x \in Set \mid Pred(x)\}}. \quad (\text{A.4})$$

In this **prototype** expression for defining sets, $x \in Set$ means that x is a variable over the set Set , $Pred(x)$ is a predicate in x , and so $NewSet$ is the set consisting of all elements x in Set for which $Pred(x)$ evaluates to true.

The concept of predicate is very general. In essence, a predicate is a condition involving any attributes or properties of the elements of Set . Consider

$$TallStudents = \{name \in Students \mid name \text{ is more than 6 feet tall}\}.$$

Here the predicate is “ $name$ is more than 6 feet tall.”

The variable name “ x ” used in (A.4) is not significant. The sets $\{x \in \mathbb{N} \mid x \geq 5\}$ and $\{n \in \mathbb{N} \mid n \geq 5\}$ are the *same* sets even though the variable names used in the prototypes are different. This is because the predicates ‘ $n \geq 5$ ’ and ‘ $x \geq 5$ ’ both evaluate to true or both evaluate to false when the same value is assigned to n and x . We say that the variable name x used in (A.4) is a **dummy variable** since the meaning of the expression is unchanged if we substitute x with another variable name, say y . You are already familiar with the use of dummy variables in integrals. The two integrals below evaluate to the same number:

$$\int_0^1 x^2 dx = \int_0^1 y^2 dy.$$

A.1.4 Quantification over sets

Consider the set $A = \{1, 3, 4\}$. Suppose we want to make the assertion that every element of A is smaller than 7. We could do this by the three expressions

$$1 < 7, \quad 3 < 7, \quad 4 < 7,$$

³A specific value is said to **satisfy** a predicate if it evaluates to true, and **not to satisfy** the predicate if the predicate evaluates to false.

which gets to be very clumsy if A has many more elements. So mathematicians have invented a shorthand. The idea is to be able to say that $x < 7$ for every value that the variable x takes in the set A . The precise expression is

$$\forall x \in A, \quad x < 7. \quad (\text{A.5})$$

The symbol ‘ \forall ’ reads ‘**for all**’, so the expression reads, “for all values of x in A , $x < 7$.” The phrase $\forall x \in A$ is called **universal quantification**. Note that in the expression (A.5), x is again a dummy variable; the meaning of the expression is unchanged if we use another variable name. Note, also, that (A.5) is an assertion which, in this case, evaluates to true. However, the assertion

$$\forall x \in A, \quad x > 3$$

is false, since for at least one value of $x \in A$, namely $x = 1$, $x > 3$ is false.

Suppose we want to say that there is at least one element in A that is larger than 3. We can say this using **existential quantification** as in

$$\exists x \in A, \quad x > 3. \quad (\text{A.6})$$

Probing Further: Predicates in Matlab

In Matlab, “=” is always used as an assignment, while “==” is used to express an assertion. Thus the Matlab program,

```
n = 5, m = 6, k = 2, m = k+n
```

returns

```
n = 5, m = 6, k = 2, m = 7
```

because the expression $m=k+n$ assigns the value 7 to m . However, the Matlab program

```
n = 5, m = 6, k = 2, m == k+n
```

returns

```
n = 5, m = 6, k = 2, ans = 0
```

where $\text{ans} = 0$ means that the assertion $m == k+n$ evaluates to false.

The symbol ‘ \exists ’ reads ‘**there exists**’, so the expression (A.6) reads ‘there exists a value of x in A , $x > 3$ ’. Once again, any other variable name could be used in place of x , and the meaning of the assertion is unchanged.

In general, the expression,

$$\boxed{\forall x \in A, \quad Pred(x),} \quad (\text{A.7})$$

is an assertion that evaluates to true if $Pred(x)$ evaluates to true for every value of $x \in A$, and

$$\boxed{\exists x \in A, \quad Pred(x),} \quad (\text{A.8})$$

is an assertion that evaluates to true if $Pred(x)$ evaluates to true for at least one value of $x \in A$.

Conversely, the assertion (A.7) evaluates to false if $Pred(x)$ evaluates to false for at least one value of $x \in A$, and the assertion (A.8) evaluates to false if $Pred(x)$ evaluates to false for every value of $x \in A$.

We can use these two quantifiers to define sets using the prototype new set constructor (A.4). For example

$$EvenNumbers = \{n \in \mathbb{N} \mid \exists k \in \mathbb{N}, n = 2k\}$$

is the set of all even numbers, since the predicate in the variable n ,

$$\exists k \in \mathbb{N}, \quad n = 2k,$$

evaluates to true if and only if n is even.

A.1.5 Some useful sets

The following sets are frequently used in the book:

$\mathbb{N} = \{1, 2, \dots\}$	natural numbers
$\mathbb{N}_0 = \{0, 1, 2, \dots\}$	non-negative integers
$\mathbb{Z} = \{\dots, -2, -1, 0, 1, 2, \dots\}$	integers
$\mathbb{Z}_+ = \{0, 1, 2, \dots\}$	non-negative integers, same as \mathbb{N}_0
$\mathbb{R} = (-\infty, \infty)$	real numbers
$\mathbb{R}_+ = [0, \infty)$	non-negative real numbers
$\mathbb{C} = \{x + jy \mid x, y \in \mathbb{R}\}$	complex numbers , $j = \sqrt{-1}$

If α, β are real numbers, then **intervals** of real numbers are written

$[\alpha, \beta]$	$=$	$\{x \in \mathbb{R} \mid \alpha \leq x \leq \beta\}$
(α, β)	$=$	$\{x \in \mathbb{R} \mid \alpha < x < \beta\}$
$(\alpha, \beta]$	$=$	$\{x \in \mathbb{R} \mid \alpha < x \leq \beta\}$
$(-\infty, \infty)$	$=$	\mathbb{R}

Note the meaning of the difference in notation: both end-points α and β are included in $[\alpha, \beta]$, and we say that $[\alpha, \beta]$ is a **closed** interval; neither end-point is included in (α, β) , and we call this an **open** interval; the interval $(\alpha, \beta]$ is said to be half-open, half-closed. Whether an end-point is included in an interval or not is indicated by the use of square brackets $[,]$ or parentheses $(,)$.

Other useful sets are:

<i>Binary</i>	$=$	$\{0, 1\}$	the binary values
<i>Binary</i> *	$=$	$\{0, 1\}^*$	set of all finite binary strings
<i>Bools</i>	$=$	$\{\text{true}, \text{false}\}$	truth values
<i>Bools</i> *	$=$	$\{\text{true}, \text{false}\}^*$	set of finite sequences of truth values
<i>Char</i>	$=$	$\{a, b, \dots\}$	set of all alphanumeric characters
<i>Char</i> *	$=$	$\{a, b, \dots\}^*$	set of all finite character strings

A.1.6 Set operations: union, intersection, complement

If A and B are sets, then the **intersection** $A \cap B$ is the set consisting of all elements that are in both A and B . The **union** $A \cup B$ is the set consisting of all elements that are either in A or in B or in both A and B . We can express these definitions using variables as:

$$A \cap B = \{x \mid x \in A \wedge x \in B\}, \quad A \cup B = \{x \mid x \in A \vee x \in B\}$$

where \wedge is the notation for the **logical and** and \vee is the symbol for the **logical or**. The predicate “ $x \in A \wedge x \in B$ ” reads “ x is a member of A and x is a member of B ”; “ $x \in A \vee x \in B$ ” reads “ x is a member of A or x is a member of B .” The logical and of two predicates is also called their **conjunction** and their logical or is also called their **disjunction**. The symbols \wedge and \vee are called **logical connectives**.

If A, X are sets, then $X \setminus A$ is the set consisting of all elements in X that are not in A (think of it as **set subtraction**, $X - A$). When $A \subset X$, $X \setminus A$ is called the **complement** of A in X . When X is understood, we can write A^c instead of $X \setminus A$.

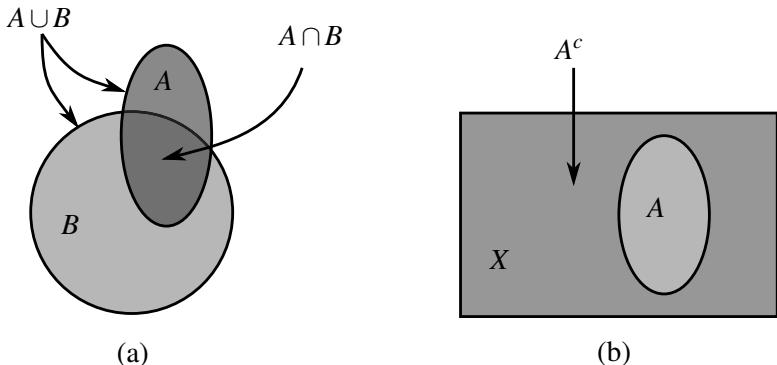


Figure A.1: (a) Union and intersection. (b) Set complement.

We gain some intuitive understanding by depicting sets and set operations using pictures. Figure A.1 illustrates union, intersection, and complement.

A.1.7 Predicate operations

Given two predicates $P(x)$ and $Q(x)$ we can form their conjunction $P(x) \wedge Q(x)$, and their disjunction $P(x) \vee Q(x)$. These predicate operations correspond to the set operations of intersection and union:

$$\begin{aligned} \{x \in X \mid P(x) \wedge Q(x)\} &= \{x \in X \mid P(x)\} \cap \{x \in X \mid Q(x)\} \\ \{x \in X \mid P(x) \vee Q(x)\} &= \{x \in X \mid P(x)\} \cup \{x \in X \mid Q(x)\}. \end{aligned} \quad (\text{A.9})$$

There is a helpful visual similarity between \wedge and \cap , and between \vee and \cup .

The counterpart of the complement of a set is the **negation** of a predicate. We denote by $\neg Pred(x)$ the predicate that evaluates to false for any value of x for which $Pred(x)$ evaluates to true, and that evaluates to true for any value of x for which $Pred(x)$ evaluates to false. We read “ $\neg Pred(x)$ ” as “not $Pred(x)$ ” or the “negation of $Pred(x)$.” For example,

$$\{n \in \mathbb{N} \mid \neg(n < 5)\} = \{5, 6, 7, \dots\},$$

since $\neg(n < 5)$ evaluates to true if and only if $n < 5$ evaluates to false, which happens if and only if n is larger than or equal to 5.

In general we have the following correspondence between predicate negation and set complement:

$$\{x \in X \mid \neg \text{Pred}(x)\} = X \setminus \{x \in X \mid \text{Pred}(x)\}. \quad (\text{A.10})$$

We can combine (A.9), (A.9), and (A.10) to obtain more complex identities. If $P(x)$ and $Q(x)$ are predicates, then

$$\begin{aligned} \{x \in X \mid \neg(P(x) \wedge Q(x))\} &= \{x \in X \mid \neg P(x) \vee \neg Q(x)\}, \\ \{x \in X \mid \neg(P(x) \vee Q(x))\} &= \{x \in X \mid \neg P(x) \wedge \neg Q(x)\}. \end{aligned} \quad (\text{A.11})$$

These identities have counterparts for set operations. For some set X , if and $Y \subset X$ and $Z \subset X$, then

$$\begin{aligned} X \setminus (Y \cap Z) &= (X \setminus Y) \cup (X \setminus Z), \\ X \setminus (Y \cup Z) &= (X \setminus Y) \cap (X \setminus Z). \end{aligned}$$

When the set X is understood, we can write these as

$$\begin{aligned} (Y \cap Z)^c &= Y^c \cup Z^c, \\ (Y \cup Z)^c &= Y^c \cap Z^c. \end{aligned}$$

These identities are called **de Morgan's rules**.

A.1.8 Permutations and combinations

Given a set X with a finite number n of elements, we sometimes wish to construct a subset with a fixed number $m \leq n$ of elements. The number of such subsets is given by

$$\binom{n}{m} = \frac{n!}{m!(n-m)!}, \quad (\text{A.12})$$

where the exclamation point denotes the factorial function. The notation $\binom{n}{m}$ is read “ n choose m ”. It gives the number of **combinations** of m elements from the set n .

A combination is a set, so order does not matter. Sometimes, however, order matters. Suppose for example that $X = \{a, b, c\}$. The number of subsets with two elements is

$$\binom{3}{2} = \frac{3!}{2!1!} = \frac{6}{2} = 3.$$

These subsets are $\{a,b\}$, $\{a,c\}$, and $\{b,c\}$. Suppose instead that we wish to construct *ordered* subsets of X with two elements. In other words, we wish to consider $[a,b]$ to be distinct from $[b,a]$ (note the temporary use of square brackets to avoid confusion with unordered sets). Such ordered subsets are called **permutations**. The number of m -element permutations of a set of size n is given by

$$\frac{n!}{(n-m)!}. \quad (\text{A.13})$$

The number of permutations is a factor of $m!$ larger than the number of combinations in A.12. For example, the number of 2-element permutations of $X = \{a,b,c\}$ is six. They are (a,b) , (a,c) , (b,c) , (b,a) , (c,a) , and (c,b) .

A.1.9 Product sets

The **Cartesian product** $X \times Y$ of two sets X and Y consists of all pairs of elements (x,y) with $x \in X$ and $y \in Y$, i.e.

$$X \times Y = \{(x,y) \mid x \in X, y \in Y\}.$$

The product of two sets may be visualized as in Figure A.2. These pictures are informal, to be used only to reinforce intuition. In Figure A.2(a), the set $X = [0,6]$ is represented by a horizontal line segment, and the set $Y = [1,8]$ is represented by the vertical line segment. The product set $X \times Y = [0,6] \times [1,8]$ is represented by the rectangle whose lower left corner is the pair $(0,1)$ and upper right corner is $(6,8)$.

In Figure A.2(b), the discrete set $X = \{1,2,3,4,5,6\}$ is represented by six points, while $Y = [1,8]$ is represented the same as before. The product set is depicted by six vertical line segments, one for each element of X . For example, the fifth segment from the left is the set $\{(5,y) \mid 1 \leq y \leq 8\}$. One point in that set is shown.

In Figure A.2(c), the product of two discrete sets is shown as an array of points. Unless these are ordered sets, there is no significance to the the left-to-right or top-to-bottom order in which the points are shown. In all three cases in the figure, there is no significance to the choice to depict the first set in the product $X \times Y$ on the horizontal axis, and the second set on the vertical axis. We could have done it the other way around. Although there is no significance to which is depicted on the vertical axis and which on the horizontal, there *is* significance to the order of X and Y in $X \times Y$. The set $X \times Y$ is not the same as $Y \times X$ unless $X = Y$.

Basics: Tuples, strings, and sequences

Given N sets, X_1, X_2, \dots, X_N , (which may be identical), an **N -tuple** is an ordered collection of one element from each set. It is written in parentheses, as in

$$(x_1, x_2, \dots, x_N), \quad \text{where}$$

$$x_i \in X_i \text{ for each } i \in \{1, 2, \dots, N\}.$$

The elements of an N -tuple are called its **components** or **coordinates**. Thus x_i is the i -th component or coordinate of (x_1, \dots, x_N) . The order in which the components are given is important; it is part of the definition of the N -tuple. We can use a variable to refer to the entire N -tuple, as in $x = (x_1, \dots, x_N)$.

Frequently the sets from which the tuple components are drawn are all identical, as in

$$(x_1, x_2, \dots, x_N) \in X^N.$$

This notation means simply that each component in the tuple is a member of the same set X . Of course, this means that a tuple may contain identical components. For example, if $X = \{a, b, c\}$ then (a, a) is a 2-tuple over X .

Recall that a permutation is ordered, like a tuple, but like a set and unlike a tuple, it does not allow duplicate elements. In other words, (a, a) is not a permutation of $\{a, b, c\}$. So a permutation is not the same as a tuple. Similarly, an ordered set does not allow duplicate elements, and thus is not the same as a tuple.

We define the set of finite **sequences** over X to be

$$\{(x_1, \dots, x_N) \mid x_i \in X, 1 \leq i \leq N, N \in \mathbb{N}_0\}.$$

where if $N = 0$ we call the sequence the **empty sequence**. This allows us to talk about tuples without specifying N . Finite sequences are also called **strings**, although by convention, strings are written differently, omitting the parentheses and commas, as in

$$x_1 x_2 \cdots x_N.$$

We may even wish to allow N to be infinite. We define the set of **infinite sequence** over a set X to be

$$\{(x_1, x_2, \dots) \mid x_i \in X, i \in \mathbb{N}_0\}.$$

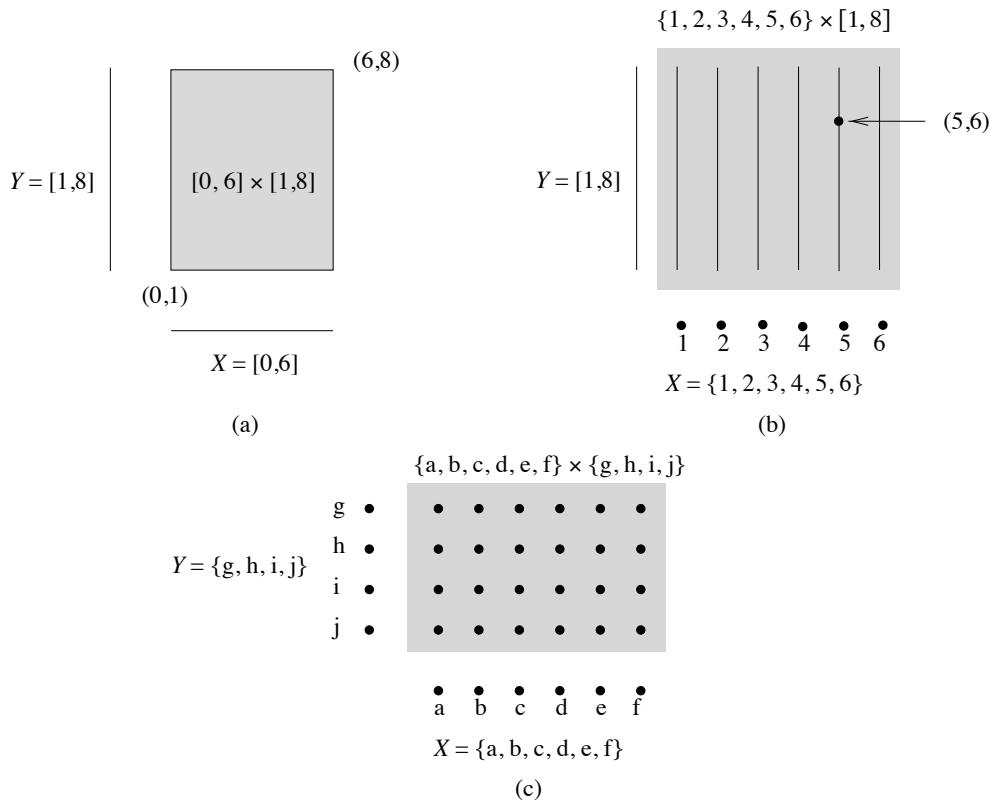


Figure A.2: Visualization of product sets. (a) The rectangle depicts the product set $[0, 6] \times [1, 8]$. (b) Together, the six vertical lines depict the product set $\{1, \dots, 6\} \times [1, 8]$. (c) The array of dots depicts the set $\{a, b, c, d, e, f\} \times \{g, h, i, j\}$.

We generalize the product notation to three or more sets. Thus if X, Y, Z are sets, then $X \times Y \times Z$ is the set of all triples or 3-tuples,

$$X \times Y \times Z = \{(x, y, z) \mid x \in X, y \in Y, z \in Z\},$$

and if there are N sets, X_1, X_2, \dots, X_N , their product is the set consisting of N -tuples,

$$X_1 \times \dots \times X_N = \{(x_1, \dots, x_N) \mid x_i \in X_i, i = 1, \dots, N\}. \quad (\text{A.14})$$

We can alternatively write (A.14) as

$$\boxed{\prod_{i=1}^N X_i.} \quad (\text{A.15})$$

The large Π operator indicates a **product of sets**.

$X \times X$ is also written as X^2 . The N -fold product of the same set X is also written as X^N . For example, \mathbb{R}^N is the set of all N -tuples of real numbers, and \mathbb{C}^N is the set of all N -tuples of complex numbers. In symbols,

$$\boxed{\begin{aligned} \mathbb{R}^N &= \{x = (x_1, \dots, x_N) \mid x_i \in \mathbb{R}, i = 1, \dots, N\}, \\ \mathbb{C}^N &= \{z = (z_1, \dots, z_N) \mid z_i \in \mathbb{C}, i = 1, \dots, N\}. \end{aligned}}$$

Predicates on product sets

A variable over $X \times Y$ is denoted by a pair (x, y) , with x as the variable over X and y as the variable over Y . We can use predicates in x and y to define subsets of $X \times Y$.

Example A.1: The set

$$\{(x, y) \in [0, 1] \times [0, 2] \mid x \leq y\} \quad (\text{A.16})$$

can be depicted by the shaded region in Figure A.3. The unshaded triangle depicts the set

$$\{(x, y) \in [0, 1] \times [0, 2] \mid x \geq y\}. \quad (\text{A.17})$$

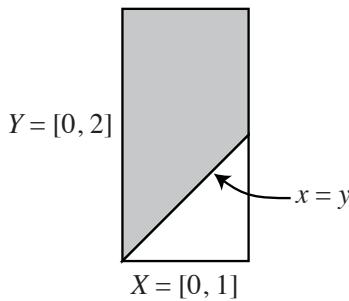


Figure A.3: The rectangle depicts the set $[0, 1] \times [0, 2]$, the shaded region depicts the set given by (A.16), and the unshaded triangle depicts the set given by (A.17).

Example A.2: The solid line in Figure A.4(a) represents the set

$$\{(x,y) \in \mathbb{R}^2 \mid x+y=1\},$$

the shaded region (including the solid line) depicts

$$\{(x,y) \in \mathbb{R}^2 \mid x+y \geq 1\},$$

and the unshaded region (excluding the solid line) depicts

$$\{(x,y) \in \mathbb{R}^2 \mid x+y < 1\}.$$

Similarly the shaded region in Figure A.4(b) depicts the set

$$\{(x,y) \in \mathbb{R}^2 \mid -x+y \geq 1\}.$$

The overlap region in Figure A.4 (c) depicts the intersection of the two shaded regions, and corresponds to the conjunction of two predicates:

$$\{(x,y) \in \mathbb{R}^2 \mid [x+y \geq 1] \wedge [-x+y \geq 1]\}.$$

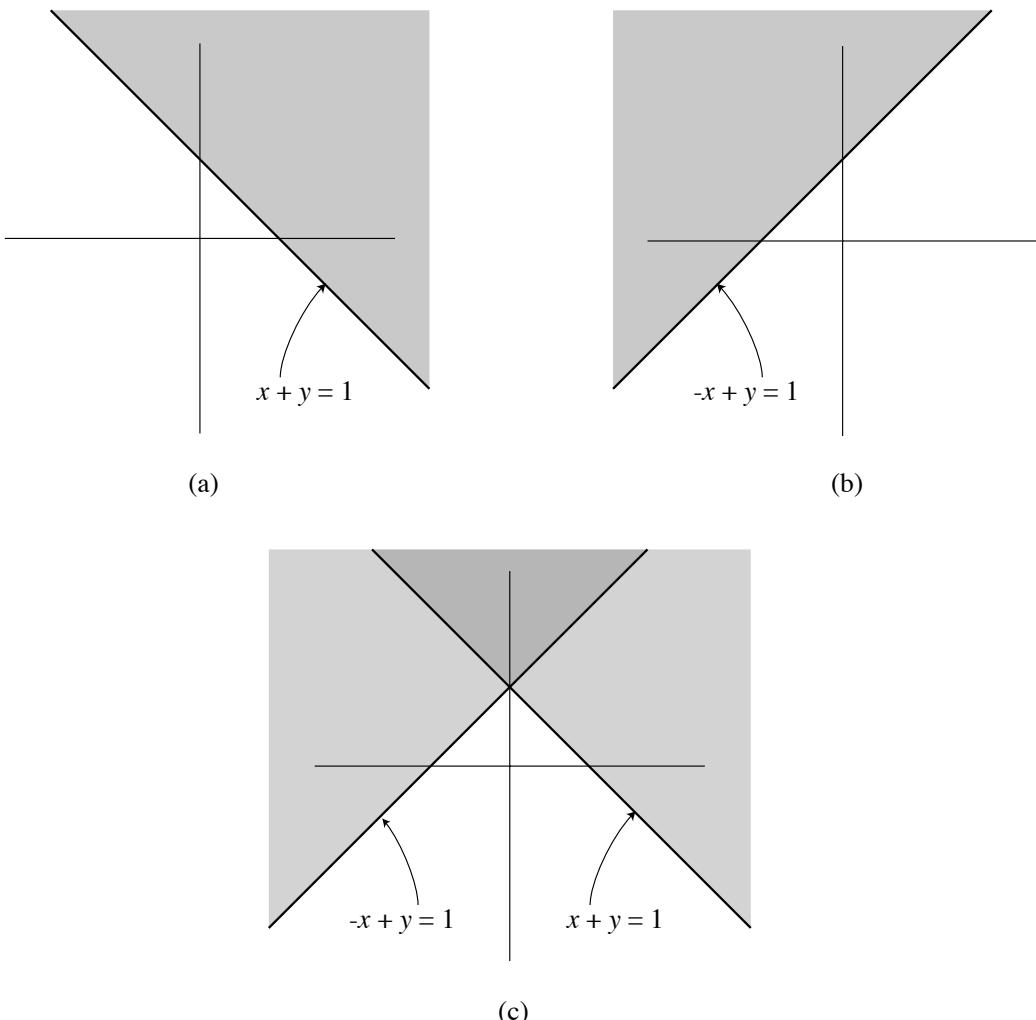


Figure A.4: (a) The solid line depicts the subset of \mathbb{R}^2 satisfying the predicate $x+y=1$. The shaded region satisfies $x+y \geq 1$. (b) The solid line satisfies $-x+y=1$, and the shaded region satisfies $-x+y \geq 1$. (c) The overlap region satisfies $[x+y \geq 1] \wedge [-x+y \geq 1]$.

A.1.10 Evaluating an expression

We have evaluated expressions several times in this appendix, each time relying on our mathematical ability with simple expressions. We can develop systematic methods for evaluating expressions that rely less on intuition, and can therefore handle more complicated and intricate expressions.

Some examples of patterns of expressions are:

- A, B, \mathbb{N}, \dots , names of sets
- $A = \{\text{list of elements}\}$
- $x \in A, x \notin A$, set membership
- $A = B, B \subset A$, and $A \supset B$, set inclusion
- $A \cap B, A \cup B, X \times Y, X \setminus A, A^c$, set operations
- x, y, \dots , names of variables
- $P(x), Q(x), \dots$, predicates in x
- $\forall x \in \text{Set}, P(x)$ and $\exists x \in \text{Set}, Q(x)$, assertions obtained by quantification
- $\text{NewSet} = \{x \in \text{Set} \mid \text{Pred}(x)\}$, set definition
- $P(x) \wedge Q(x), P(x) \vee Q(x), \neg(P(x))$, predicate operations

The patterns define the rules of grammar of the notation. The notation itself consists of **expressions**, which are composed of

- **constants**, such as numbers and pre-defined sets,
- **variables**, which are names that are not pre-defined,
- **operators**, such as \in, \cap, \cup , or $=$ (as an assertion),
- **quantifiers**, such as \forall and \exists , or
- **definitions**, namely $=$ (as an assignment).

An expression is **well-formed** if it conforms to the established patterns.⁴ For example, if P, Q and R are predicates, then the syntax implies that

$$\neg[(\neg(P(x)) \vee Q(x)) \wedge [P(x) \vee [R(x) \wedge \neg(P(x))]]] \quad (\text{A.18})$$

is also a predicate. Just as in the case of a computer language, you learn the syntax of mathematical expressions through practice.⁵

In an expression, constants have a single meaning. For example, “20” is a number, “Berkeley” is a city, and the constant “true” has a truth value. By contrast, a variable, such as x , has no single meaning, unless it has been defined (which turns it into a constant). An expression on constants has a single meaning. For example, “ $10 + 3$ ” means “13.” However, “ $x + 3$ ” has no single meaning, unless x has been defined. We say that in the expression “ $x + 3$,” x is a **free variable**. An expression with a free variable acquires a single meaning when that free variable is given a single meaning, if it is well formed with that meaning. For example, “ $x + 3$,” has meaning 13 if x has meaning 10, but it is not well formed if x has meaning *Berkeley*.

Quantifiers remove free variables from expressions.

Example A.3: In the expression “ $x = 0$,” x is free. In the expression “ $\exists x \in \mathbb{R}, x = 0$,” x is no longer free. In fact, this expression has value *true*. In the expression “ $\forall x \in \mathbb{R}, x = 0$,” again x is not free, but this expression has value *false*. The expression “ $\exists y \in \mathbb{R}, x + 1 = y$ ” still has free x . However, “ $\forall x \in \mathbb{R}, \exists y \in \mathbb{R}, x + 1 = y$ ” has no free variables, and has value *true*. The expression “ $\forall x \in \mathbb{R}, x + 7$,” however, is not well formed. It has neither free variables nor a value.

A **predicate expression** is one that either has a meaning that is a truth value (*true* or *false*), or can have such a meaning if its free variables are appropriately defined. Expression (A.18) is an example a predicate expression.

⁴In this text, we do not attempt to define precisely what these established patterns are. To do so, we would have to define a **grammar**, something that can be done formally, but is beyond our scope.

⁵The syntax of a language is the set of rules (or patterns) whereby words can be combined to form grammatical or well-formed sentences. Thus the syntax of the ‘C’ language is the set of rules that a sequence of characters (the code) must obey to be a C program. A C compiler checks whether the code conforms to the syntax. Of course, even if the code obeys the syntax, it may not be what you intend; i.e. it may not execute the intended computation.

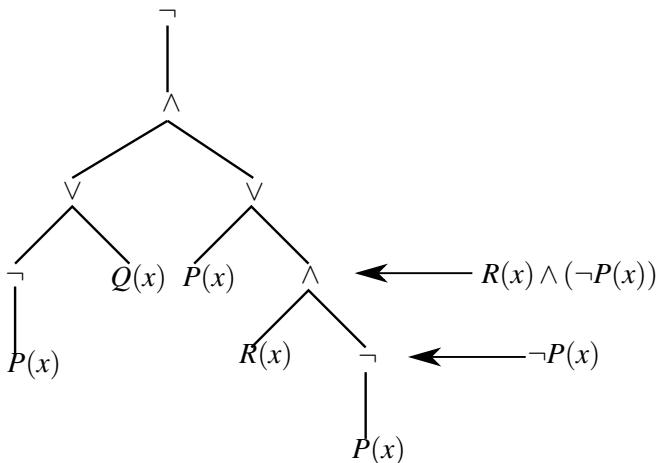


Figure A.5: Parse tree for the expression (A.18).

Expressions also contain **punctuation**, such as parentheses. These help define the relationships among the components of the expression. It is beyond the scope of this book to define completely the rules for constructing expressions⁶, but we can hint at the issues with a brief discussion of parsing.

Parsing

To show that (A.18) is indeed a well-formed predicate expression, we must show that it can be constructed using the syntax. We do this by **parsing** the expression (A.18) with the help of matching brackets and parentheses. Parsing the expression will also enable us to evaluate it in a systematic way.

The result is the parse tree shown in Figure A.5. The leaves of this tree (the bottom-most nodes) are labeled by the elementary predicates P, Q, R , and the other nodes of the tree are labeled by one of the predicate operations \wedge, \vee, \neg . Each of the intermediate nodes corresponds to a sub-predicate of (A.18). Two such sub-predicates are shown in the figure. The last leaf on the right is labeled $P(x)$. Its parent node is labeled \neg , and so that parent node corresponds to the sub-predicate $\neg(P(x))$. Its parent node is labeled \wedge ,

⁶A text on compilers for computer programming languages will typically do this.

and it has another child node labeled $R(x)$, so this node corresponds to the sub-predicate $R(x) \wedge \neg(P(x))$.

If we go up the tree in this way, we can see that the top of the tree (the root node) indeed corresponds to the predicate (A.18). Since at each intermediate node, the sub-predicate is constructed using the syntax, the root node is a well-formed predicate.

Evaluating

Suppose we know whether the predicates $P(x), Q(x), R(x)$ evaluate to true or false for some value of x . Then we can use the parse tree to figure out whether the predicate (A.18) evaluates to true or false. To do this, we begin with the known truth values at the leaves of the parse tree, use the meaning of the predicate operations to figure out the truth values of the sub-predicates corresponding to the parents of the leaf nodes, and then the parents of those nodes, and work our way up the tree to figure out the truth value of the predicate (A.18) at the root node. In Figure A.6 the parse tree is annotated with the truth values of each of the nodes. Since the root node is annotated ‘false,’ we conclude that (A.18) evaluates to false.

Truth tables

The way in which the predicate operations transform the truth values is given in the following **truth table**:

$P(x)$	$Q(x)$	$\neg P(x)$	$P(x) \wedge Q(x)$	$P(x) \vee Q(x)$
<i>true</i>	<i>true</i>	<i>false</i>	<i>true</i>	<i>true</i>
<i>true</i>	<i>false</i>	<i>false</i>	<i>false</i>	<i>true</i>
<i>false</i>	<i>true</i>	<i>true</i>	<i>false</i>	<i>true</i>
<i>false</i>	<i>false</i>	<i>true</i>	<i>false</i>	<i>false</i>

Consider a particular row of this table, say the first row. The first two entries specify that $P(x)$ is true and $Q(x)$ is true. The remaining three entries give the corresponding truth values for $\neg P(x)$, $P(x) \wedge Q(x)$ and $P(x) \vee Q(x)$, namely, $\neg P(x)$ is false, $P(x) \wedge Q(x)$ is true, and $P(x) \vee Q(x)$ is true. The four rows correspond to the four possible truth value assignments of $P(x)$ and $Q(x)$. This truth table can be used repeatedly to evaluate any well-formed expression given the truth value of $P(x)$ and $Q(x)$.

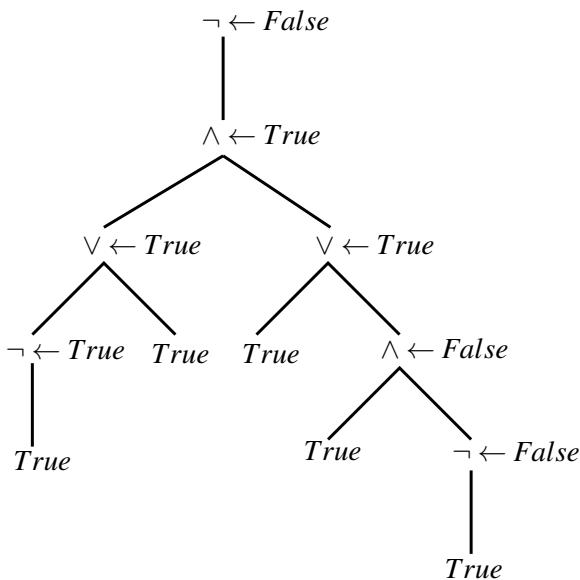


Figure A.6: Parse tree for the expression (A.18) annotated with the truth values of each of the nodes.

Thus, given the truth values of predicates $P_1(x), \dots, P_n(x)$, the truth value of any well-formed expression involving these predicates can be obtained by a computer algorithm that constructs the parse tree and uses the truth table above. Such algorithms are used to evaluate logic circuits.

A.2 Functions

In the notation

$$f: X \rightarrow Y, \quad (\text{A.19})$$

X and Y are sets, and f is the name of a **function**. The function is an assignment rule that assigns a value in Y to each element in X . If the element in X is x , then the value is written $f(x)$.

We read (A.19) as “ f is (the name of) a function from X into (or to) Y .” We also say that f maps X into Y . The set X is called the **domain** of f , written $X = \text{domain}(f)$, the set Y is called the **range** of f , written $Y = \text{range}(f)$.⁷ When the domain and range are understood from the context, we write “ f ” by itself to represent the function or the map. If x is a variable over X , we also say “ f is a function of x .”

Example A.4: Let the set $Students$ contain all the students in this class. Each element of $Students$ is represented by a student’s name,

$$Students = \{\text{John Brown}, \text{Jane Doe}, \dots\}.$$

We assign to each name in $Students$ the student’s marks in the final examination, a number between 0 and 100. This name-to-marks assignment is an example of a function. Just as we give names to sets (e.g. $Students$), we give names to functions. In this example the function might be named $Score$. When we evaluate the function $Score$ at any name, we get the marks assigned to that name. We write this as

$$Score(\text{John Brown}) = 90, Score(\text{Jane Doe}) = 91.2, \dots$$

⁷In some mathematics texts, the set Y which we call the range is called the **codomain**, and $\text{range}(f)$ is defined to be the set of all values that f takes, i.e., $\text{range}(f) = \{f(x) \mid x \in X\}$. However, we will not use this terminology.

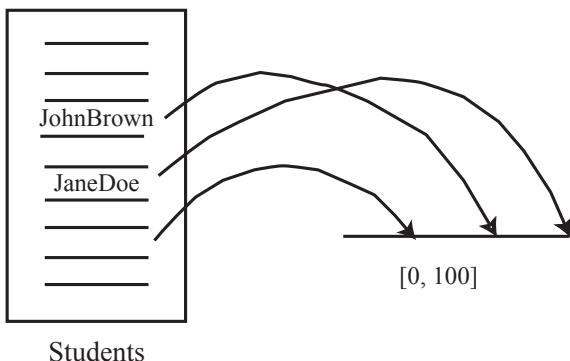
Figure A.7: Illustration of *Score*.

Figure A.7 illustrates the function *Score*. Three things are involved in defining *Score*: the set *Students*, the set $[0, 100]$ of possible marks, and the assignment of marks to each name. In the figure this assignment is depicted by the arrows: the tail of the arrow points to a name and the head of the arrow points to the marks assigned to that name. We denote these three things by

$$\text{Score} : \text{Students} \rightarrow [0, 100]$$

which we read as “*Score* is a function from *Students* into $[0, 100]$.” The domain of the function *Score* is *Students*, and the range of *Score* is $[0, 100]$.

It is easy to imagine other functions with the same domain *Students*. For example, *Height* assigns to each student his or her height measured in cm, *SSN* assigns students their social security number, and *Address* assigns students their address. The range of these functions is different. The range of *Height* might be defined to be $[0, 200]$ (200 cm is about 6.5 feet). Since a social security number is a 9-digit number, we can take $\{0, 1, \dots, 9\}^9$ to be the range of *SSN*. And we can take the range of *Address* to be Char^{100} , assuming that an address can be expressed as a string of 100 characters, including blank spaces.

We usually use lower case letters for function names, such as f, g, h , or more descriptive names such as *Score*, *Voice*, *Video*, *SquareWave*, *AMSignal*.

Avoid a bad habit: It is important to distinguish between a function f and its value $f(x)$ at a particular point $x \in \text{domain}(f)$. The function f is a *rule* that assigns a value in $\text{range}(f)$ to each $x \in \text{domain}(f)$, whereas $f(x)$ is a *point* or element in $\text{range}(f)$. Unfortunately, too many books encourage the bad habit by using ‘ $f(x)$ ’ as a shorthand for ‘ f is a function of x .’ If you keep the distinction between f and $f(x)$, it will be easier to avoid confusion when we study systems.

A.2.1 Defining functions

To define a function, you must give the domain, the range, and the rule that produces an element in the range given an element in the domain. There are many ways to do this, as explored in much more depth in Chapter 2. Here we mention only two. The first is enumeration. That is, in tabular form or some other form, each possible value in the domain is associated with a value in the range. This method would be appropriate for the *Score* function, for example. Alternatively, functions can be mathematically defined by the prototype: define $f : X \rightarrow Y$,

$$\forall x \in X, \quad f(x) = \text{expression in } x.$$

The ‘expression in x ’ may be specified by an algebraic expression, by giving the graph of f , by a table, or by a procedure.

A.2.2 Tuples and sequences as functions

An N -tuple $x = (x_1, \dots, x_N) \in X^N$ can be viewed as a function

$$x: \{1, \dots, N\} \rightarrow X.$$

For each integer in $\{1, \dots, N\}$, it assigns a value in X . An infinite sequence y over the set Y can also be viewed as a function

$$y: \mathbb{N} \rightarrow Y,$$

or

$$y: \mathbb{N}_0 \rightarrow Y,$$

depending on whether you wish to begin indexing the sequence at zero or one (both conventions are widely used). This view of sequences as functions is in fact our model for discrete-time signals and event traces, as developed in Chapter 1.

A.2.3 Function properties

A function $f: X \rightarrow Y$ is **one-to-one** if

$$\forall x_1 \in X \text{ and } \forall x_2 \in X, \quad x_1 \neq x_2 \Rightarrow f(x_1) \neq f(x_2).$$

Here the logical symbol ‘ \Rightarrow ’ means ‘**implies**’ so the expression is read: if x_1, x_2 are two different elements in X , then $f(x_1), f(x_2)$ are different.

Example A.5: The function $Cube: \mathbb{R} \rightarrow \mathbb{R}$ given by

$$\forall x \quad Cube(x) = x^3,$$

is one-to-one, because if $x_1 \neq x_2$, then $x_1^3 \neq x_2^3$. But $Square$ is not one-to-one because, for example, $Square(1) = Square(-1)$.

A function $f: X \rightarrow Y$ is **onto** if

$$\forall y \in Y, \exists x \in X, \text{ such that } f(x) = y.$$

The expression above reads: ‘For each y in Y , there exists x in X such that $f(x) = y$.’

Accordingly, f is onto if for every y in its range there is some x in its domain such that $y = f(x)$.

Example A.6: The function $Cube: \mathbb{R} \rightarrow \mathbb{R}$ is one-to-one and onto, while $Square: \mathbb{R} \rightarrow \mathbb{R}$ is not onto. However, $Square: \mathbb{R} \rightarrow \mathbb{R}_+$ is onto.

A.3 Summary

Sets are mathematical objects representing collections of elements. A variable is a representative for an element of a set. A predicate over a set is an expression involving a variable that evaluates to true or false when the variable is assigned a particular element

Probing Further: Infinite sets

The size of a set A , denoted $|A|$, is the number of elements it contains. By counting, we immediately know that $\{1, 2, 3, 4\}$ and $\{a, b, c, d\}$ have the same number of elements, whereas $\{1, 2, 3\}$ has fewer elements. It is more difficult to compare the number of elements in the following infinite sets:

$$A = \mathbb{N} = \{1, 2, 3, 4, \dots\}, B = \{2, 3, 4, 5, \dots\}, C = [0, 1].$$

At first, we might say that A has one more element than B , since A includes B and has one additional element, $1 \in A$. However, these two sets have the same size.

The **cardinality** of a set is the number of elements in the set, but generalized to handle infinite sets. Comparing the cardinality of two sets is done by matching elements using one-to-one functions. Consider two sets A and B . We say that A has a smaller cardinality than B , written $|A| \leq |B|$, if there exists a one-to-one function mapping A into B . We say that A and B have the same cardinality, written $|A| = |B|$, if $|A| \leq |B|$ and $|B| \leq |A|$.

The cardinality of the infinite set $A = \mathbb{N}$ is denoted \aleph_0 , read “**aleph zero**” (aleph is the first letter of the Hebrew alphabet). It is quite easy to prove using the definition of cardinality that $n < \aleph_0$ for any finite number n . We can now show that the cardinality of B is also \aleph_0 . There is a one-to-one function $f: A \rightarrow B$, namely

$$\forall n \in A, \quad f(n) = n + 1,$$

so that $|A| \leq |B|$, and there is a one-to-one function $g: B \rightarrow A$, namely

$$\forall n \in B, \quad g(n) = n - 1,$$

so that $|B| \leq |A|$. A similar argument can be used to show that the set of even numbers and the set of odd numbers also have cardinality \aleph_0 .

It is more difficult to show that the cardinality of $\mathbb{N} \times \mathbb{N}$ is also \aleph_0 . To see this, consider a one-to-one function $h: \mathbb{N}^2 \rightarrow \mathbb{N}$ (see Figure A.8),

$$h((1, 1)) = 1, h((2, 1)) = 2, h((2, 2)) = 3, h((1, 2)) = 4, h((1, 3)) = 5, \dots$$

Since a rational number m/n can be identified with the pair $(m, n) \in \mathbb{N}^2$, we have shown that the cardinality of the set of rational numbers is \aleph_0 .

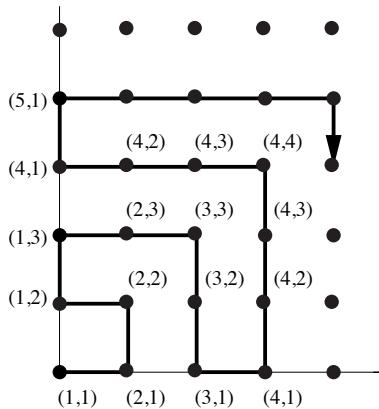


Figure A.8: A correspondence between \mathbb{N}^2 and \mathbb{N} .

of the set. Predicates are used to construct new sets from existing sets. If the variable in a predicate is quantified, the expression becomes an assertion.

Sets can be combined using the operations of union, intersection and complement. The corresponding operations on predicates are disjunction, conjunction and negation. New sets can also be obtained by the product of sets.

Functions are mathematical objects representing a relationship between two sets, the domain and the range. We have introduced the following patterns of expressions for functions

- $f, g, h, Score, \dots$, names of functions,
- $f : X \rightarrow Y, X = \text{domain}(f), Y = \text{range}(f)$, a function from X to Y ,

A function $f : X \rightarrow Y$ assigns to each value $x \in X$ a value $f(x) \in Y$.

Probing Further: Even bigger sets

We can show that the cardinality of $[0, 1]$ is strictly larger than that of \mathbb{N} ; i.e. $|[0, 1]| > |\mathbb{N}|$. Since the function $f: \mathbb{N} \rightarrow [0, 1]$ defined by

$$\forall n \in \mathbb{N}, \quad f(n) = 1/n$$

is one-to-one, we have $|\mathbb{N}| \leq |[0, 1]|$. However, we can show that there is no one-to-one function in the other direction. If there were such a function $g: [0, 1] \rightarrow \mathbb{N}$, then it would be possible to enumerate all the elements of $[0, 1]$ in an ordered list,

$$[0, 1] = \{x^1, x^2, x^3, \dots\}. \quad (\text{A.20})$$

(The superscript here is not raising to a power, but just indexing.) We can show that this is not possible. If we express each element of $[0, 1]$ by its decimal expansion (ignoring the element 1.0), this list looks like

$$\begin{aligned} x^1 &= 0.x_1^1 x_2^1 x_3^1 \dots \\ x^2 &= 0.x_1^2 x_2^2 x_3^2 \dots \\ x^3 &= 0.x_1^3 x_2^3 x_3^3 \dots \\ &\dots \end{aligned}$$

Construct any number $y \in [0, 1]$ with the decimal expansion

$$y = 0.y_1 y_2 y_3 \dots$$

such that for each i , $y_i \neq x_i^i$ where x_i^i is the i -th term in the decimal expansion of x^i . Clearly such a number exists and is in $[0, 1]$. But then for every i , $y \neq x^i$, so that y cannot be in the list $\{x^1, x^2, x^3, \dots\}$. Thus, the list (A.20) is not complete.

The cardinality of $[0, 1]$ is denoted \aleph_1 , pronounced “aleph one,” and is strictly greater than \aleph_0 . In this sense we can say that the continuum $[0, 1]$ has more elements than the denumerable set \mathbb{N} , even though both sets have infinite size. The obvious question is whether there are cardinalities larger than \aleph_1 . In fact, there are sets of ever higher cardinality,

$$\aleph_0 < \aleph_1 < \aleph_2 \dots$$

and sets with cardinality larger than all of these!

Exercises

Each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **E** In the spirit of Figure A.2, give a picture of the following sets:

- (a) $\{1, 2, 3\}$,
- (b) $[0, 1] \times \{0, 1\}$,
- (c) $[0, 1] \times [a, b]$.
- (d) $\{1, 2, 3\} \times \{a, b\}$,
- (e) $\{a, b\} \times [0, 1]$.

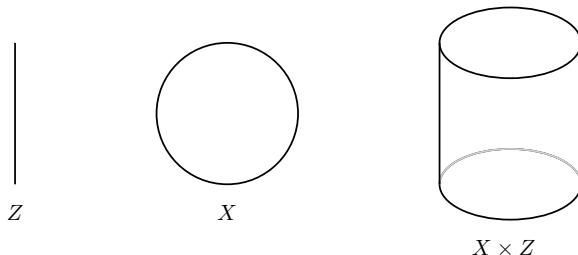
2. **E** How many elements are there in the sets

- (a) $\{1, \dots, 6\}$,
- (b) $\{-2, -1, \dots, 10\}$, and
- (c) $\{0, 1, 2\} \times \{2, 3\}$?

3. **T** Determine which of the following expressions is true and which is false:

- (a) $\forall n \in \mathbb{N}, \quad n > 1$,
- (b) $\exists n \in \mathbb{N}, \quad n < 10$,
- (c) If $A = \{1, 2, 3\}$ and $B = \{2, 3, 4\}$, then $\forall x \in A, \forall y \in B, \quad x \leq y$,
- (d) If $A = \{1, 2, 3\}$ and $B = \{2, 3, 4\}$, then $\forall x \in A, \exists y \in B, \quad x \leq y$,
- (e) If $A = \{1, 2, 3\}$ and $B = \{2, 3, 4\}$, then $\exists x \in A, \forall y \in B, \quad x \leq y$.

4. **T** In the following figure, $X = \{(x, y) \mid x^2 + y^2 = 1\}$ is depicted as a 2-dimensional circle and $Z = [0, 2]$ is shown as a 1-dimensional line segment. Explain why it is reasonable to show the product set as a 3-dimensional cylinder.



5. **E** In the spirit of Figure A.2, give a picture for the product set

$$\{M, Tu, W, Th, F\} \times [8.00, 17.00]$$

and indicate on your drawing the lecture hours for this class.

6. **E** In the spirit of Figure A.2, give a picture for the set $A = \{(x,y) \mid x \in [1,2], y \in [1,2]\}$ and the set $B = \{(x,x) \mid x \in [1,2]\}$. Explain why the two sets are different.
7. **C** Give a precise expression for the predicate below so that *Triangle* is indeed a triangle:

$$\text{Triangle} = \{(x,y) \in \mathbb{R}^2 \mid \text{Pred}(x,y)\}.$$

There are many ways of writing this predicate. One way is to express $\text{Pred}(x,y)$ as the conjunction of three linear inequality predicates. Hint: We used the conjunction of two linear inequality predicates in Figure A.4.

8. **T** If X has m elements and Y has n elements, how many elements are there in $X \times Y$? If X_i has m_i elements, for $i = 1, \dots, I$, for some constant I , then how many elements are there in

$$\prod_{i=1}^{i=I} X_i = X_1 \times \dots \times X_I?$$

9. **T** How many different 10-letter strings are there if each letter is drawn from the set *Alphabet* consisting of the 26 lower case letters of the alphabet? How many such strings are there with *exactly* one occurrence of the letter *a*?
10. **T** Recall that a set cannot contain duplicate elements. Now suppose X contains 10 elements.
- How many two-element combinations of elements from X are there?
 - How many two-element permutations are there?

11. **C** Construct predicates for use in the prototype (A.4) to define the following sets. Define them in terms of examples of sets introduced in this chapter.
- The set of U.S. cities with a population exceeding one million.
 - The male students in the class.
 - The old books in the library.
12. **T** Which of the following expressions is well formed? For those that are well formed, state whether they are assertions. For those that are assertions, evaluate the assertion to true or false. For those that are not assertions, find an equivalent simpler expression.
- $2 \in \{1, 3, 4\}$,
 - $3 \subset \{1, 3, 4\}$,
 - $\{3\} \subset \{1, 2, 3\}$,
 - $2 \cup \{1, 3, 4\}$,
 - $\{2\} \cup \{1, 3, 4\}$,
 - $[2.3, 3.4] = \{x \in \mathbb{R} \mid 2.3 \leq x \leq 3.4\}$,
 - $\{x \in \mathbb{R} \mid x > 3 \wedge x < 4\}$,
 - $[1, 2] \cap [3, 4] = \emptyset$.
13. **E** Define the following sets in terms of the sets named in section A.1.5
- The set of all 10-letter passwords.
 - The set of all 5×6 matrices of real numbers.
 - The set of all complex numbers with magnitude at most 1.
 - The set of all 2-dimensional vectors with magnitude exactly 1.
14. **E** Give the set of all subsets $\wp(X)$ of the set $X = \{a, b, c\}$.
15. **T** Suppose a set X has n elements. Let $\wp(X)$ be the powerset of X . How many elements are there in $\wp(X)$?
16. **T** Use Matlab to depict the following sets using the plot command:
- $\{(t, x) \in \mathbb{R}^2 \mid x = \sin(t), \text{ and } t \in \{0, \frac{1}{20}2\pi, \frac{2}{20}2\pi, \dots, \frac{20}{20}2\pi\}\}$,
 - $\{(y, x) \in \mathbb{R}^2 \mid y = e^x, \text{ and } x \in \{-1, -1 + \frac{1}{20}, -1 + \frac{2}{20}, \dots, 1\}\}$,

(c) $\{(y, x) \in \mathbb{R}^2 \mid y = e^{-x}, \text{ and } x \in \{-1, -1 + \frac{1}{20}, -1 + \frac{2}{20}, \dots, 1\}\}$.

17. **T** Determine which of the following functions is onto, which is one-to-one, and which is neither, and give a short explanation for your answer.

- (a) $\text{License}: \text{CalVehicles} \rightarrow \text{Char}^*$ given by $\forall \text{vehicle} \in \text{CalVehicles}$,
 $\text{License}(\text{vehicle})$ is the California license number of the vehicle
- (b) $f: \mathbb{R} \rightarrow [-2, 2]$, given by $\forall x \in \mathbb{R}$, $f(x) = 2 \sin(x)$
- (c) $f: \mathbb{R} \rightarrow \mathbb{R}$, given by $\forall x \in \mathbb{R}$, $f(x) = 2 \sin(x)$
- (d) $\text{conj}: \mathbb{C} \rightarrow \mathbb{C}$, the complex conjugate function
- (e) $f: \mathbb{C} \rightarrow \mathbb{R}^2$, given by $\forall z \in \mathbb{C}$, $f(z) = (\text{Re}(z), \text{Im}(z))$, where $\text{Re}(z)$ is the real part of z and $\text{Im}(z)$ is the imaginary part of z .
- (f) $M: \mathbb{R}^2 \rightarrow \mathbb{R}^2$, $\forall (x_1, x_2) \in \mathbb{R}^2$,

$$M(x_1, x_2) = (y_1, y_2)$$

where

$$\begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}.$$

(g) $\text{Zero}: \mathbb{R}^4 \rightarrow \mathbb{R}^4$, $\forall x \in \mathbb{R}^4$, $\text{Zero}(x) = (0, 0, 0, 0)$

18. **T** Let A , B , and C be arbitrary sets. Let $f: A \rightarrow A$ and $g: A \rightarrow A$ be two functions with domain and range A . Which of the following assertions is true for all choices of A , B , C , f , and g ?

- (a) $(A \cup B) \setminus C = (A \setminus C) \cup (B \setminus C)$.
- (b) $\wp(A \cup B) = \wp(A) \cup \wp(B)$.
- (c) $f \circ g = g \circ f$.
- (d) If both f and g are one-to-one, then $f \circ g$ is one-to-one.

Note that $f \circ g$ is function composition, defined in Section 2.1.5. $X \setminus Y$ is the complement of Y in X , as explained in Section A.1.6. $\wp(X)$ is the powerset of X .

19. **E** Each of the following expressions is intended to be a predicate expression. Determine whether it is *true* or *false*, or whether it is not well formed, or has a free variable. If it has a free variable, identify the free variable.

- (a) \forall sets x , $x \subset \wp(x)$, where $\wp(x)$ is the powerset of x .

- (b) $\exists x \in \mathbb{R}, \{x \in \mathbb{Z} | x + 3 = 10\}.$
- (c) $\forall n \in \mathbb{N}, n = 2 \Rightarrow (n, n+1) \in \{1, 2, 3\}^2.$
- (d) $\exists x \in \mathbb{N}, x + y = 10.$



Complex Numbers

Contents

B.1	Imaginary numbers	690
B.2	Arithmetic of imaginary numbers	691
B.3	Complex numbers	692
B.4	Arithmetic of complex numbers	693
B.5	Exponentials	694
B.6	Polar coordinates	696
	<i>Basics: From Cartesian to polar coordinates</i>	697
Exercises		701

Complex numbers are used extensively in the modeling of signals and systems for two reasons. The first reason is that complex numbers provide a compact and elegant way to talk simultaneously about the phase and amplitude of sinusoidal signals. Complex numbers are therefore heavily used in Fourier analysis, which represents arbitrary signals in terms of sinusoidal signals. The second reason is that [linear time-invariant systems](#) treat signals that can be described as complex exponential functions in an especially simple way. They simply scale the signals.

These uses of complex numbers are developed in detail in the main body of this text. This appendix summarizes essential properties of complex numbers themselves. We review complex number arithmetic, how to manipulate complex exponentials, Euler's formula,

the polar coordinate representation of complex numbers, and the phasor representation of sinewaves.

B.1 Imaginary numbers

The quadratic equation,

$$x^2 - 1 = 0,$$

has two solutions, $x = +1$ and $x = -1$. These solutions are said to be **roots** of the polynomial $x^2 - 1$. Thus, this polynomial has two roots, $+1$ and -1 .

More generally, the roots of the n -th degree polynomial,

$$x^n + a_1x^{n-1} + \cdots + a_{n-1}x + a_n, \quad (\text{B.1})$$

are defined to be the solutions to the polynomial equation

$$x^n + a_1x^{n-1} + \cdots + a_{n-1}x + a_n = 0. \quad (\text{B.2})$$

The roots of a polynomial provide a particularly useful factorization into first-degree polynomials. For example, we can factor the polynomial $x^2 - 1$ as

$$x^2 - 1 = (x - 1)(x + 1).$$

Notice the role of the roots, $+1$ and -1 . In general, if (B.1) has roots r_1, \dots, r_n , then we can factor the polynomial as follows

$$x^n + a_1x^{n-1} + \cdots + a_{n-1}x + a_n = (x - r_1)(x - r_2) \cdots (x - r_n). \quad (\text{B.3})$$

It is easy to see that if $x = r_i$ for any $i \in \{1, \dots, n\}$, then the polynomial evaluates to zero, so (B.2) is satisfied.

This raises the question whether (B.2) always has a solution for x . In other words, can we always find roots for a polynomial?

The equation

$$x^2 + 1 = 0 \quad (\text{B.4})$$

has no solution for x in the set of real numbers. Thus, it would appear that not all polynomials have roots. However, a surprisingly simple and clever mathematical device changes

the picture dramatically. With the introduction of **imaginary numbers**, mathematicians ensure that all polynomials have roots. Moreover, they ensure that any polynomial of degree n has exactly n factors as in (B.3). The n values r_1, \dots, r_n (some of which may be repeated) are the **roots** of the polynomial.

If we try by simple algebra to solve (B.4) we discover that we need to find x such that

$$x^2 = -1.$$

This suggests that

$$x = \sqrt{-1}.$$

But -1 does not normally have a square root.

The clever device is to define an imaginary number, usually written i or j , that is equal to $\sqrt{-1}$. By definition,¹

$$i \times i = \sqrt{-1} \times \sqrt{-1} = -1.$$

This (imaginary) number, thus, is a solution of the equation $x^2 + 1 = 0$.

For any real number y , iy is an imaginary number. Thus, we can define the set of imaginary numbers as

$$\boxed{\text{ImaginaryNumbers} = \{iy \mid y \in \mathbb{R}, \text{ and } i = \sqrt{-1}\}} \quad (\text{B.5})$$

It is a profound result that this simple device is all we need to guarantee that every polynomial equation has a solution, and that every polynomial of degree n can be factored into n polynomials of degree one, as in (B.3).

B.2 Arithmetic of imaginary numbers

The sum of i (or $i1$) and i is written $i2$. Sums and differences of imaginary numbers simplify like real numbers:

$$i3 + i2 = i5, \quad i3 - i4 = -i.$$

If iy_1 and iy_2 are two imaginary numbers, then

$$\boxed{iy_1 + iy_2 = i(y_1 + y_2), \quad iy_1 - iy_2 = i(y_1 - y_2).} \quad (\text{B.6})$$

¹Here, the operator is ordinary multiplication, not products of sets.

The product of a real number x and an imaginary number iy is

$$x \times iy = iy \times x = ixy.$$

To take the product of two imaginary numbers, we must remember that $i^2 = -1$, and so for any two imaginary numbers, iy_1 and iy_2 , we have

$$iy_1 \times iy_2 = -y_1 \times y_2. \quad (\text{B.7})$$

The result is a real number. We can use rule (B.7) repeatedly to multiply as many imaginary numbers as we wish. For example,

$$i \times i = -1, \quad i^3 = i \times i^2 = -i, \quad i^4 = 1.$$

The ratio of two imaginary numbers iy_1 and iy_2 is a real number

$$\frac{iy_1}{iy_2} = \frac{y_1}{y_2}.$$

B.3 Complex numbers

The sum of a real number x and an imaginary number iy is called a **complex number**. This sum does not simplify as do the sums of two real numbers or two imaginary numbers, and it is written as $x + iy$ or $x + jy$.

Examples of complex numbers are

$$2+i, \quad -3-i2, \quad -\pi+i\sqrt{2}.$$

In general a complex number z is of the form

$$z = x + iy = x + \sqrt{-1}y,$$

where x, y are real numbers. The **real part** of z , written $\text{Re}\{z\}$, is x . The **imaginary part** of z , written $\text{Im}\{z\}$, is y . Notice that, confusingly, the imaginary part is a real number. The imaginary part times i is an imaginary number. So

$$z = \text{Re}\{z\} + i\text{Im}\{z\}.$$

The set of complex numbers, therefore, is defined by

$$\boxed{\mathbb{C} = \{x + iy \mid x \in \mathbb{R}, y \in \mathbb{R}, \text{ and } i = \sqrt{-1}\}}. \quad (\text{B.8})$$

Every real number x is in \mathbb{C} , because $x = x + i0$; and every imaginary number iy is in \mathbb{C} , because $iy = 0 + iy$.

Two complex numbers $z_1 = x_1 + iy_1$ and $z_2 = x_2 + iy_2$ are equal if and only if their real parts are equal and their imaginary parts are equal, i.e. $z_1 = z_2$ if and only if

$$Re\{z_1\} = Re\{z_2\}, \text{ and } Im\{z_1\} = Im\{z_2\}.$$

B.4 Arithmetic of complex numbers

In order to add two complex numbers, we separately add their real and imaginary parts,

$$(x_1 + iy_1) + (x_2 + iy_2) = (x_1 + x_2) + i(y_1 + y_2).$$

The **complex conjugate** of $x + iy$ is defined to be $x - iy$. The complex conjugate of a complex number z is written z^* . Notice that

$$z + z^* = 2Re\{z\}, \quad z - z^* = 2iIm\{z\}.$$

Hence, the real and imaginary parts can be obtained using the complex conjugate,

$$Re\{z\} = \frac{z + z^*}{2}, \text{ and } Im\{z\} = \frac{z - z^*}{2i}.$$

The product of two complex numbers works as expected if you remember that $i^2 = -1$. So, for example,

$$(1 + 2i)(2 + 3i) = 2 + 3i + 4i + 6i^2 = 2 + 7i - 6 = -4 + 7i,$$

which seems strange, but follows mechanically from $i^2 = -1$. In general,

$$\boxed{(x_1 + iy_1)(x_2 + iy_2) = (x_1x_2 - y_1y_2) + i(x_1y_2 + x_2y_1).} \quad (\text{B.9})$$

If we multiply $z = x + iy$ by its complex conjugate z^* we get

$$zz^* = (x + iy)(x - iy) = x^2 + y^2,$$

which is a positive real number. Its positive square root is called the **modulus** or **magnitude** of z , and is written $|z|$,

$$|z| = \sqrt{zz^*} = \sqrt{x^2 + y^2}.$$

How to calculate the ratio of two complex numbers is less obvious, but it is equally mechanical. We convert the denominator into a real number by multiplying both numerator and denominator by the complex conjugate of the denominator,

$$\begin{aligned}\frac{2+3i}{1+2i} &= \frac{2+3i}{1+2i} \times \frac{1-2i}{1-2i} \\ &= \frac{(2+6)+(-4+3)i}{1+4} \\ &= \frac{8}{5} - \frac{1}{5}i.\end{aligned}$$

The general formula is

$$\frac{x_1 + iy_1}{x_2 + iy_2} = \frac{x_1x_2 + y_1y_2}{x_2^2 + y_2^2} + i \frac{-x_1y_2 + x_2y_1}{x_2^2 + y_2^2}. \quad (\text{B.10})$$

In practice it is easier to calculate the ratio as in the example, rather than memorizing formula (B.10).

B.5 Exponentials

Certain functions of real numbers, like the exponential function, are defined by an infinite series. The exponential of a real number x , written e^x or $\exp(x)$, is

$$e^x = \sum_{k=0}^{\infty} \frac{x^k}{k!} = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \dots$$

We also recall the infinite series expansion for \cos and \sin :

$$\begin{aligned}\cos(\theta) &= 1 - \frac{\theta^2}{2} + \frac{\theta^4}{4!} - \dots \\ \sin(\theta) &= \theta - \frac{\theta^3}{3!} + \frac{\theta^5}{5!} - \dots\end{aligned}$$

The exponential of a complex number z is written e^z or $\exp(z)$, and is defined in the same way as the exponential of a real number,

$$e^z = \sum_{k=0}^{\infty} \frac{z^k}{k!} = 1 + z + \frac{z^2}{2!} + \frac{z^3}{3!} + \dots \quad (\text{B.11})$$

Note that $e^0 = 1$, as expected.

The exponential of an imaginary number $i\theta$ is very interesting,

$$\begin{aligned} e^{i\theta} &= 1 + (i\theta) + \frac{(i\theta)^2}{2!} + \frac{(i\theta)^3}{3!} + \dots \\ &= [1 - \frac{\theta^2}{2} + \frac{\theta^4}{4!} - \dots] + i[\theta - \frac{\theta^3}{3!} + \frac{\theta^5}{5!} - \dots] \\ &= \cos(\theta) + i\sin(\theta). \end{aligned}$$

This identity is known as **Euler's formula**:

$$e^{i\theta} = \cos(\theta) + i\sin(\theta). \quad (\text{B.12})$$

Euler's formula is used heavily in this text in the analysis of linear time invariant systems. It allows sinusoidal functions to be given as sums or differences of exponential functions,

$$\cos(\theta) = (e^{i\theta} + e^{-i\theta})/2 \quad (\text{B.13})$$

and

$$\sin(\theta) = (e^{i\theta} - e^{-i\theta})/(2i). \quad (\text{B.14})$$

This proves useful because exponential functions turn out to be simpler mathematically (despite being complex valued) than sinusoidal functions.

An important property of the exponential function is the **product formula**:

$$e^{z_1+z_2} = e^{z_1} e^{z_2}. \quad (\text{B.15})$$

We can obtain many trigonometric identities by combining (B.12) and (B.15). For example, since

$$e^{i\theta} e^{-i\theta} = e^{i\theta-i\theta} = e^0 = 1,$$

and

$$e^{i\theta} e^{-i\theta} = [\cos(\theta) + i\sin(\theta)][\cos(\theta) - i\sin(\theta)] = \cos^2(\theta) + \sin^2(\theta),$$

so we have the identity

$$\cos^2(\theta) + \sin^2(\theta) = 1.$$

Here is another example. Using

$$e^{i(\alpha+\beta)} = e^{i\alpha} e^{i\beta}, \quad (\text{B.16})$$

we get

$$\begin{aligned} \cos(\alpha + \beta) + i\sin(\alpha + \beta) &= [\cos(\alpha) + i\sin(\alpha)][\cos(\beta) + i\sin(\beta)] \\ &= [\cos(\alpha)\cos(\beta) - \sin(\alpha)\sin(\beta)] \\ &\quad + i[\sin(\alpha)\cos(\beta) + \cos(\alpha)\sin(\beta)]. \end{aligned}$$

Since the real part of the left side must equal the real part of the right side, we get the identity,

$$\cos(\alpha + \beta) = \cos(\alpha)\cos(\beta) - \sin(\alpha)\sin(\beta),$$

Since the imaginary part of the left side must equal the imaginary part of the right side, we get the identity,

$$\sin(\alpha + \beta) = \sin(\alpha)\cos(\beta) + \cos(\alpha)\sin(\beta).$$

It is much easier to remember (B.16) than to remember these identities.

B.6 Polar coordinates

The representation of a complex number as a sum of a real and an imaginary number, $z = x + iy$, is called its **Cartesian representation**.

Recall from trigonometry that if x, y, r are real numbers and $r^2 = x^2 + y^2$, then there is a unique number θ with $0 \leq \theta < 2\pi$ such that

$$\cos(\theta) = \frac{x}{r}, \quad \sin(\theta) = \frac{y}{r}.$$

That number is

$$\theta = \cos^{-1}(x/r) = \sin^{-1}(y/r) = \tan^{-1}(y/x).$$

We can therefore express any complex number $z = x + iy$ as

$$z = |z| \left(\frac{x}{|z|} + i \frac{y}{|z|} \right) = |z|(\cos \theta + i \sin \theta) = |z|e^{i\theta},$$

where $\theta = \tan^{-1}(y/x)$. The **angle** or **argument** θ is measured in radians, and it is written as $\arg(z)$ or $\angle z$. So we have the **polar representation** of any complex number z as

$$z = x + iy = re^{i\theta}. \quad (\text{B.17})$$

The two representations are related by

$$r = |z| = \sqrt{x^2 + y^2}$$

and

$$\theta = \arg(z) = \tan^{-1}(y/x).$$

The values x and y are called the **Cartesian coordinates** of z , while r and θ are its **polar coordinates**. Note that r is real and $r \geq 0$.

Figure B.1 depicts the Cartesian and polar representations. Note that for any integer K ,

$$re^{i(2K\pi+\theta)} = re^{i\theta}.$$

Basics: From Cartesian to polar coordinates

The polar representation of a complex number z is

$$z = x + iy = re^{i\theta},$$

where

$$r = |z| = \sqrt{x^2 + y^2} \quad \text{and} \quad \theta = \arg(z) = \tan^{-1}(y/x).$$

However, you must be careful in calculating $\tan^{-1}(y/x)$. For any angle θ ,

$$\tan(\theta) = \tan(\theta + \pi).$$

Thus, for any real number y/x , there are two possible values for $\theta = \tan^{-1}(y/x)$ that lie within the range $[0, 2\pi)$. You should select the one of these that yields a non-negative value for r in

$$z = x + iy = re^{i\theta} = r(\cos(\theta) + i \sin(\theta)).$$

This choice makes it reasonable to interpret r as the magnitude of the complex number.

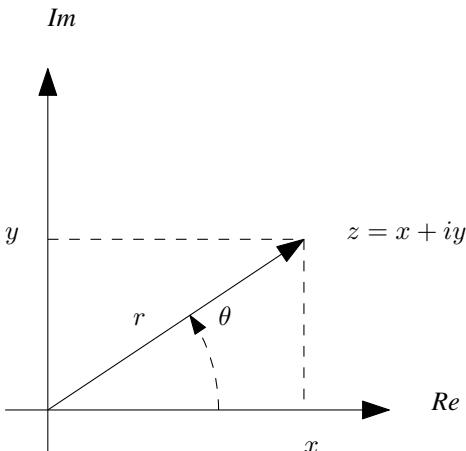


Figure B.1: A complex number z is represented in Cartesian coordinates as $z = x + iy$ and in polar coordinates as $z = re^{i\theta}$. The x -axis is called the **real axis**, the y axis is called the **imaginary axis**. The **angle** θ in radians is measured counter-clockwise from the real axis.

This is because

$$re^{i(2K\pi+\theta)} = re^{i2K\pi}e^{i\theta}$$

and

$$e^{i2K\pi} = \cos(2K\pi) + i\sin(2K\pi) = 1.$$

Thus, the polar coordinates (r, θ) and $(r, \theta + 2K\pi)$ for any integer K represent the same complex number. Thus, the polar representation is not unique; by convention, a unique polar representation can be obtained by requiring that the angle given by a value of θ satisfying $0 \leq \theta < 2\pi$ or $-\pi < \theta \leq \pi$. We normally require $0 \leq \theta < 2\pi$.

Example B.1: The polar representation of the number 1 is $1 = 1e^{i0}$. Notice that it is also true that $1 = 1e^{i2\pi}$, because the sine and cosine are periodic with period 2π . The polar representation of the number -1 is $-1 = 1e^{i\pi}$. Again, it is true that $-1 = 1e^{i3\pi}$, or, in fact, $-1 = 1e^{i\pi+K2\pi}$, for any integer K .

Products of complex numbers represented in polar coordinates are easy to compute. If $z_i = |r_i|e^{i\theta_i}$, then

$$z_1 z_2 = |r_1||r_2|e^{i(\theta_1+\theta_2)}.$$

Thus the magnitude of a product is a product of the magnitudes, and the angle of a product is the sum of the angles,

$|z_1 z_2| = |z_1||z_2|, \quad \angle(z_1 z_2) = \angle(z_1) + \angle(z_2).$

Example B.2: We can use the polar representation to find the n distinct roots of the equation $z^n = 1$. Write $z = re^{i\theta}$, and $1 = 1e^{2k\pi}$, so

$$z^n = r^n e^{in\theta} = 1e^{i2k\pi},$$

which gives $r = 1$ and $\theta = 2k\pi/n$, $k = 0, 1, \dots, n - 1$. These are called the **n roots of unity**. Figure B.2 shows the 5 roots of unity.

Whereas it is easy to solve the polynomial equation $z^n = 1$, solving a general polynomial equation is difficult.

Theorem The polynomial equation

$$z^n + a_1 z^{n-1} + \dots + a_{n-1} z + a_n = 0,$$

where a_1, \dots, a_n are complex constants, has exactly n factors of the form $(z - \alpha_i)$, where $\alpha_1, \dots, \alpha_n$ are called the n roots. In other words, we can always find the factorization,

$$z^n + a_1 z^{n-1} + \dots + a_{n-1} z + a_n = \prod_{k=1}^n (z - \alpha_k).$$

Some of the roots may be identical.

Note that although this theorem ensures the existence of this factorization, it does not suggest a way to find the roots. Indeed, finding the roots can be difficult. Fortunately, software for finding roots is readily available, for example using the Matlab `roots` function.

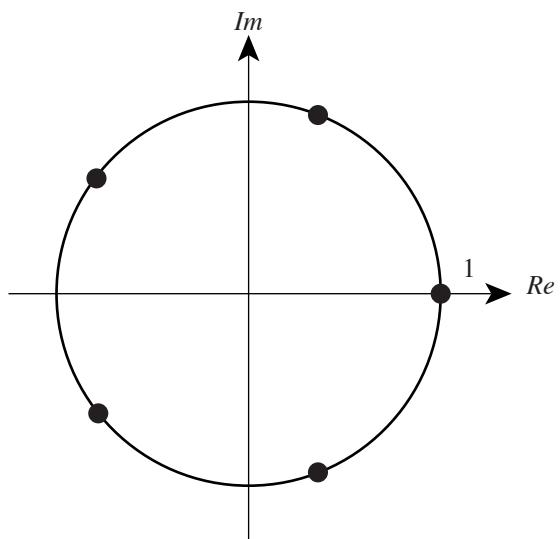


Figure B.2: The 5th roots of unity.

Exercises

Each problem is annotated with the letter **E**, **T**, **C** which stands for exercise, requires some thought, requires some conceptualization. Problems labeled **E** are usually mechanical, those labeled **T** require a plan of attack, those labeled **C** usually have more than one defensible answer.

1. **E** Simplify the following expressions:

(a)

$$\frac{3+4i}{5-6i} \times \frac{3+6i}{4-5i},$$

(b)

$$e^{2+\pi i}.$$

2. **E** Express the following in polar coordinates:

$$2-2i, 2+2i, \frac{1}{2-2i}, \frac{1}{2+2i}, 2i, -2i.$$

3. **E** Depict the following numbers graphically as in Figure B.1:

$$i, -2, -3-i, -1-i.$$

4. **E** Find θ so that

$$Re\{(1+i)e^{i\theta}\} = -1.$$

5. **E** Express the six distinct roots of unity, i.e. the six solutions to

$$z^6 = 1$$

in Cartesian and polar coordinates.

6. **T** Express the six roots of -1 , i.e. the six solutions to

$$z^6 = -1$$

in Cartesian and polar coordinates. Depict these roots as in Figure B.2.

7. **T** Figure out i^n for all positive and negative integers n . (For a negative integer n , $z^{-n} = 1/z^n$.)

8. **T** Factor the polynomial $z^5 + 2$ as

$$z^5 + 2 = \prod_{k=1}^5 (z - \alpha_k),$$

expressing the α_k in polar coordinates.

9. **C** How would you define $\sqrt{1+i}$? More generally, how would you define \sqrt{z} for any complex number z ?
10. **T** The logarithm of a complex number z is written $\log z$ or $\log(z)$. It can be defined as an infinite series, or as the inverse of the exponential, i.e. define $\log z = w$, if $e^w = z$. Using the latter definition, find the logarithm of the following complex numbers:
- $$1, -1, i, -i, 1+i$$
- More generally, if $z \neq 0$ is expressed in polar coordinates, what is $\log z$? For which complex numbers z is $\log z$ not defined?
11. **E** Use Matlab to answer the following questions. Let $z_1 = 2 + 3i$ and $z_2 = 4 - 2i$.
Hint: Consult Matlab help on `i`, `j`, `exp`, `real`, `imag`, `abs`, `angle`, `conj`, and `complex`. Looking up “complex” in the help desk may also be helpful.
- What is $z_1 + z_2$? What are the real and imaginary parts of the sum?
 - Express the sum in polar coordinates.
 - Draw by hand two rays in the complex plane, one from the origin to z_1 and the other from the origin to z_2 . Now draw $z_1 + z_2$ and $z_1 - z_2$ on the same plane. Explain how you might systematically construct the sum and difference rays.
 - Draw two rays in the complex plane to $z_3 = -2 - 3i$ and $z_4 = 3 - 3i$. Now draw $z_3 \times z_4$ and z_3/z_4 .
 - Consider $z_5 = 2e^{i\pi/6}$ and $z_6 = z_5^*$. Express z_6 in polar coordinates. What is $z_5 z_6$?
 - Draw the ray to $z_0 = 1 + 1i$. Now draw rays to $z_n = z_0 e^{in\pi/4}$ for $n = 1, 2, 3, \dots$. How many distinct z_n are there?
 - Find all the solutions of the equation $z^7 = 1$. Hint: Express z in polar coordinates, $z = re^{i\theta}$ and solve for r, θ .
12. **E** This problem explores how complex signals may be visualized and analyzed.

- (a) Use Matlab to plot the complex exponential function as follows:

```
plot(exp((-2+10i)*[0:0.01:1]))
```

The result is a spiraling curve corresponding to the signal $f : [0, 1] \rightarrow \mathbb{C}$ where

$$\forall t \in [0, 1] \quad f(t) = e^{(-2+10i)t}.$$

In the plot window, under the Tools menu item, use ‘Axes properties’ to turn on the grid. Print the plot and on it mark the points for which the function is purely imaginary. Is it evident what values of t yield purely imaginary $f(t)$?

- (b) Find analytically the values of t that result in purely imaginary and purely real $f(t)$.
- (c) Construct four plots, where the horizontal axis represents t and the vertical axis represents the real and imaginary parts of $f(t)$, and the magnitude and angle of $f(t)$. Give these as four subplots.
- (d) Give the mathematical expressions for the four functions plotted above in part (c).

13. **T** Euler’s formula is: for any real number θ ,

$$e^{i\theta} = \cos \theta + i \sin \theta,$$

and the product formula is: for any complex numbers z_1, z_2 ,

$$e^{z_1+z_2} = e^{z_1} e^{z_2}.$$

The following problems show that these two formulas can be combined to obtain many useful identities.

- (a) Express $\sin(2\theta)$ and $\cos(2\theta)$ as sums and products of $\sin \theta$ and $\cos \theta$. **Hint:** Write $e^{i2\theta} = e^{i\theta} e^{i\theta}$ (by the product formula) and then use Euler’s formula.
- (b) Express $\sin(3\theta)$ and $\cos(3\theta)$ also as sums and products of $\sin \theta$ and $\cos \theta$.
- (c) The sum of several sinewaves of the *same* frequency ω but different phases is a sinewave of the same frequency, i.e. given A_k, ϕ_k , $k = 1, \dots, n$, we can find A, ϕ so that

$$A \cos(\omega t + \phi) = \sum_{k=1}^n A_k \cos(\omega t + \phi_k)$$

Express A, ϕ in terms of $\{A_k, \phi_k\}$.

Notation Index

$[D \rightarrow R]$	signal space	28
\circ	function composition	58
Σ	summation	77
D_M	delay (discrete time)	368
D_τ	delay (continuous time)	313
$[A, b, c, d]$	state-space model	585
$*$	convolution	207
$\mathbb{N} = \{1, 2, \dots\}$	natural numbers	656
\dots	ellipsis	656
$\mathbb{N}_0 = \{0, 1, 2, \dots\}$	non-negative integers	656
\in	member	656
\notin	not a member	656
$A \subset B$	subset	657
$A \subseteq B$	subset	657
\emptyset	empty set	657
$=$	assignment or assertion	657
$:=$	assignment	657
$==$	assertion	658
$\wp(X)$	powerset	659
2^X	powerset	659

	such that	660
$NewSet = \{x \in Set \mid Pred(x)\}$	prototype for sets	660
\forall	for all	661
\exists	there exists	662
\mathbb{Z}	integers	662
\mathbb{Z}_+	non-negative integers	662
\mathbb{R}	real numbers	662
\mathbb{R}_+	non-negative real numbers	662
\mathbb{C}	complex numbers	662
$[\alpha, \beta]$	closed interval	663
(α, β)	open interval	663
$(\alpha, \beta]$	semi-open interval	663
$[\alpha, \beta)$	semi-open interval	663
$Binary$	binary values	663
$Binary^*$	binary strings	663
$Bools$	truth values	663
$Bools^*$	sequences of truth values	663
$Char$	alphanumeric characters	663
$Char^*$	strings of alphanumeric characters	663
\cap	intersection	663
\cup	union	663
\wedge	logical and	663
\vee	logical or	663
$A \setminus B$	set subtraction	663
A^c	complement	663
\neg	negation	664
$\binom{n}{m}$	choose	665
$A \times B$	Cartesian product	666
(x_1, x_2, \dots)	tuple	667
$\prod_{i=1}^N X_i$	product of sets	669
X^N	product of sets	669
$f: A \rightarrow B$	function	677
\Rightarrow	implies	680
$ A $	cardinality	681
\aleph_0	aleph zero	681
\aleph_1	aleph one	683

i	imaginary number	691
$Re\{z\}$	real part	692
$Im\{z\}$	imaginary part	692
z^*	complex conjugate	693
$ z $	magnitude of a complex number	694
$\arg z$	argument of a complex number	697
$\angle z$	argument of a complex number	697
$re^{i\theta}$	polar representation	697

Index

- abs*, 52
abs command in Matlab, 702
absent, 102
absolute value, 52
absolutely integrable, 297, 503, 504
absolutely summable, 503, 503
abstraction, 104, 108, 251
abstraction relations, 104
acoustic environment, 364
acoustic environments, 614
action, 237
adaptive equalizer, 39
adders, 400
additivity, 192, 193, 319
Adobe Photoshop, 365
affine, 192
automated guided vehicle, 262
air pressure, 6
air traffic control systems, 4
aleph one, 683, 706
aleph zero, 681, 706
Alexander Graham Bell, 394
algorithm, 63
aliasing, 474, 476
aliasing distortion, 491
allpass filter, 334
alphanumeric characters, 663, 706
AM, 468
amplitude, 9, 331, 689
amplitude modulation, 468
analog signal, 26
analytic, 597
angle, 697
angle command in Matlab, 702
answering service, 99
antenna arrays, 33
anti-aliasing, 482
anti-aliasing filter, 481
anti-causal, 513, 515
anti-lock brakes, 139
aperiodic signals, 298
application layer, 251
application-specific integrated circuit, 149
arcs, 99

- arg, 697
 argument, 697, 707
 arrows, 78, 99
 ASIC, 149
 assembly language, 402
 assertion, 658, 705
 assignment, 240, 657, 705
 assignment rule, 50
 audio, 5, 37, 614
 audio equalization, 619
 audio equalizer, 27
 audio signals, 66
 audio system, 364
 automata, 240
 automated guided vehicle, 262
- Bach, 281
 bandlimiting filter, 35
 bank balance, 201
 base station, 32
 batteries, 32
 beams, 33
 behavior, 69, 112, 119
Behaviors, 112
 bel, 394
 Bell Telephone Labs, 394
 Bell, Alexander Graham, 394
 Berry, Gerard, 176
 BIBO stable, 505
Binary, 20
Binary, 663
 binary, 663, 706
 binary strings, 663
 bits per second, 27
BitStream, 62
BitStreams, 62
 block diagrams, 78
 blurred images, 365
- Bools*, 663
 bounded, 505
 bounded variation, 297, 505
 bounded-input bounded-output stable, 505
 branches, 635
 broadband, 36
 bubble, 99
 butter command in Matlab, 396
 Butterworth filter, 396
- cable, 31
 cable modems, 617
 calculus, 522
 calculus of complex variables, 597
 call center, 2
 capacitors, 640
 cardinality, 681, 706
 carrier frequency, 469
 Cartesian coordinates, 697
 Cartesian product, 5, 666, 706
 Cartesian representation, 696
 cascade composition, 78, 143, 144, 155, 612, 613
 causal, 96, 382, 512, 514
 causal sinusoidal signal, 534, 543, 555
 CD, 7, 37
 CD ROM, 38
 cells, 32
 cellular telephone, 139, 617
 cellular telephones, 32
 channel, 364, 614
Char, 663
*Char**, 663
 characteristic polynomial, 588
 characterstic polynomial, 587
 cheby1 command in Matlab, 396, 398
 cheby2 command in Matlab, 396, 398
 Chebyshev 1 filter, 396

- Chebyshev 2 filter, 396
choose, 665, 706
Church, Alonzo, 176
circle of fifths, 281
circuit, 327, 335, 580, 608
circuit analysis, 323
circular buffering, 401
circular convolution, 450
class, 401
clocks, 240
closed, 663
closed-loop, 344
closed-loop transfer function, 627
coaxial cable, 31
codec, 27
coder, 27
CodeRecognizer, 105
codomain, 6, 56, 677
collision avoidance, 4
color, 13, 14
ColorComputerImage, 15
ColorImage, 13
colormap, 14, 15, 59
ColormapImage, 59
ColormapImages, 48
ColorMapIndexes, 15
column vector, 222
combinations, 665
communication protocols, 247
communication systems, 323
communications, 36, 276
commutativity, 367
compact disc, 7, 37, 476
compact discs, 191
compensator, 614, 622
complement, 663, 687, 706
complex amplitude, 331
complex command in Matlab, 702
complex conjugate, 52, 693, 707
complex exponentials, 322
complex number, 689, 692
complex numbers, 662, 706
complex systems, 318
complex-valued functions, 318
components, 667
composition, 78
computer graphics, 276
ComputerImage, 15
ComputerVoice, 8
computing system, 139
conj command in Matlab, 702
conjugate, 52
conjugate, 52
conjugate symmetric, 332, 338
conjugate symmetry, 332, 380, 449
conjugation property:Laplace transform, 605
conjugation property:Z transform, 546
conjunction, 80, 663
connection restriction, 59, 80
constants, 672, 673
constructive semantics, 176
constructor, 401
continuous time, 5
continuous-time Fourier series, 415
continuous-time Fourier transform, 381, 428
continuous-time signal, 8
continuous-time signals, 22, 72, 313, 414
continuous-time state-space model, 218
continuous-time systems, 72, 226, 313
continuum, 5, 683
contour integral, 601
ContPeriodic_p, 415
contrapositive, 507
control, 28

- control logic, 94
 control signal, 228
 control systems, 323
 controllability, 228
 controller, 28, 260, 276, 628
ContSignals, 72, 414
 conv command in Matlab, 398
 converge absolutely, 503
 convergence in mean square, 296
 convergence of the Fourier series:in mean square, 296
 convergence of the Fourier series:uniform, 295
 convolution, 207, 367, 369, 545, 605, 705
 convolution integral, 369
 convolution sum, 198, 217, 545, 605
 coordinates, 667
 copper, 30
 correctness, 65
 critical path, 139
 crosstalk, 35
 CTFT, 381, 428
 current mode, 237
 cutoff frequency, 396
 cycles per second, 9

 D_M , 315
 D_M , 368
 D_t , 313
 damped oscillator, 230
 damper, 640
 dashpot, 640
 DAT, 38
Data, 21
 data sequences, 21
 dB, 391, 394
 DC, 289
 dc gain, 571

 DC motor, 634
 de Morgan's rules, 665
 decibels, 391, 394
 decision logic, 94
 decision-directed adaptive equalization, 617, 649
 decisions, 616
 declarative, 52, 63, 276, 365
 decoder, 27, 147
 decryption, 27
 definite integral formula, 419
 definite integrals, 522
 definitions, 672
 degree
 of a polynomial, 690
 degrees, 284
 delay, 84, 315, 325, 368, 452, 705
 continuous time, 313
 delay line, 400, 403
 delay:property of Laplace transform, 604
 delay:property of Z transform, 544
 delta function, 520, 529
 delta functions, 371, 493
 demodulation, 468
 denumerable, 683
 derivative controller, 643
 desired signal, 622
 destination mode, 237
 destructive interference, 305, 306
 detection, 27
 determinant, 586
 deterministic, 101
 DFS, 302, 339, 421
 DFS coefficients, 340
 DFT, 421
 difference equation, 574
 difference equations, 74, 312, 395

- differential equation, 326, 579, 640
differential equations, 68, 72, 226, 312, 557
differential precoder, 147
differentiator, 643
digital audio, 37, 191
digital audio tape, 38
digital cellular telephone, 617
digital circuits, 139
digital signal, 26
digital signal processing, 237
digital signal processor, 237
digital telephony, 26
digital video discs, 38
dimension of a matrix, 221
dimension of a system, 189
Dirac delta function, 371, 462, 487, 492, 521, 529
Dirac delta functions, 441, 484, 493, 500
direct current, 289
direct form 1, 404
direct form 2, 405
Dirichlet conditions, 297, 503, 504
DiscPeriodic_p, 415
discrete complex exponential, 324
discrete event, 243
discrete Fourier transform, 421
discrete rectangle, 428, 464
discrete square wave, 423, 463
discrete to continuous conversion, 483
discrete-event phase, 243
discrete-time Fourier series, 302, 339, 421
discrete-time Fourier transform, 379, 424
discrete-time signal, 8, 74
discrete-time signals, 22, 300, 313
discrete-time system, 74, 191
discrete-time systems, 313
DiscreteHorizontalSpace, 15
DiscreteTime, 8
DiscreteVerticalSpace, 15
DiscSignals, 74, 415
DiscToCont, 482
disjunction, 663
Display, 15
distortion, 27, 364, 614, 615
DNA, 3
domain, 6, 56, 677
domain name server, 57
don't care, 151
double, 63
Doubles, 63
DSL modems, 617
DSP, 237
DSP toolbox, 385
DTFT, 379, 424
DTMF, 35
duality, 471
dummy variable, 77, 660
DVD, 38
e-mail application, 247
echo cancellation, 623
echo effect, 197, 212
eigenfunction, 322
eigenvalue, 593
eigenvalues, 587, 588
eigenvector, 609
electrical circuits, 640
electrical power, 11
electromagnetic radiation, 3
electromagnetic waves, 279
elements, 656
ellip command in Matlab, 396, 398
ellipsis, 656, 705
elliptic filter, 396
else, 100

- else arc, 100
 embedded computer, 237
 embedded system, 139
 embedded systems, 402
 empty sequence, 667
 empty set, 657, 705
Encoder, 62
 encoder, 27, 147
 encryption, 27, 36
 end-to-end, 251
 energy, 296
EnglishText, 20
EnglishWords, 20
 enhance, 27
 environment, 260
Equal, 106
 equalization, 614
 equalizer, 365, 614
 equilibrium, 197
 equivalence relations, 104
 error signal, 629
 estimation, 276
 ethernet, 247
 Euler's formula, 330, 695, 703
 Euler's relation, 543
 event stream, 21
 event streams, 94
 event trace, 21
EventSet, 21
EventStream, 21
 exchanging integral and summation, 350
 existential quantification, 661
Exp, 23
 exp, 53
 exp, 694
 exp command in Matlab, 702
 exponential, 53
 complex numbers, 53
 exponential scaling property:Laplace transform, 606
 exponential sequence, 208
 exponential signal, 527, 533
 exponential signal:Z transform, 543
 expressions, 672
 f=ma, 73, 255
 factoring polynomials, 690
 factory automation, 3
 false assertion, 658
 far-end signal, 623
 fast Fourier transform, 303, 422, 438
 feedback, 81, 155, 403
 feedback composition, 612, 626
 feedback control, 612
 feedback control system, 39
 FFT, 303, 422, 438
 fft command in Matlab, 438
 fifth, 281
File, 20
 filter, 364
 filter coefficients, 395
 filter command in Matlab, 398
 filter design, 398
 filter implementation, 398
 filtering, 312, 341
 finite, 304
 finite Fourier series approximation, 289
 finite impulse response, 382, 542
 finite impulse response system, 211
 finite signal, 286
 finite state machine, 98, 236
 finite summation identity, 424
 FIR, 211, 382, 542
 first harmonic, 283
 first-order hold, 483

- fixed point, 82, 156, 159
fixed points, 90
flash memory, 2
focus, 365
for all, 52, 661, 706
forced response, 577, 583
forking, 152
forward-Euler approximation, 608
Fourier analysis, 435
Fourier series, 289, 289, 338
Fourier series coefficients, 339, 415
Fourier series expansion, 289
Fourier transform, 381, 417, 428
Fourier transforms, 414
Fourier, Joseph, 289
fourth-power law, 32
frames, 16
FrameTimes, 16
free variable, 673
frequency, 9, 331
frequency domain, 276, 291
frequency response, 75, 312, 324, 324, 379,
 503, 550, 558
 difference equation, 577
 differential equation, 583
FSM, 98
FT, 381, 428
full duplex, 36
function, 56, 677, 706
function composition, 58, 705
function space, 28
functions, 54, 677
 in Matlab, 64
functions of time, 313
fundamental, 283
fundamental frequency, 289
Gödel, 176
gain, 334, 391
gcd, 294
geometric series identity, 506
geosynchronous, 35
geosynchronous satellite, 625
GHz, 279
Gibb's phenomenon, 291
gigahertz, 279
glitches, 239
grammar, 672, 673
graph, 54
graphics, 276
grayscale, 12
greatest common divisor, 294
ground wire, 11
guard, 100
guards, 237
hand off, 32
hardware, 400
harmonic motion, 70
harmonics, 283, 289
helicopter, 501
Hertz, 9, 278
hertz, 279
hierarchical composition, 154
high fidelity, 364
highpass, 7, 365
homogeneity, 192, 193, 319
HorizontalSpace, 13
hostnames, 57
hot wires, 11
household electrical power, 11
human ear, 364, 619
hybrid, 623
hybrid systems, 232
Hz, 9, 279

- i*, 691
 i command in Matlab, 702
 ideal interpolation, 483
IdealInterpolator, 483
 textbf, 487
 identically zero, 628
 identities, 76
 identity, 204, 229, 384, 412, 506, 533, 564, 696
 identity matrix, 224
 identity:finite summation, 424
 ignition control, 139
 IIR, 208, 215, 382, 395
 IIR systems, 212
 ill-formed, 138, 156, 159
 $Im\{z\}$, 692
 imag command in Matlab, 702
Image, 13
 image enhancement, 3
 Image processing, 276
 image understanding, 276
 images, 12
ImageSet, 16, 29
 imaginary axis, 527
 imaginary number, 691, 707
 imaginary part, 692, 707
 impedance, 623
 imperative, 58, 63, 94, 276, 365
 implementation of filters, 398
 implies, 383, 680, 706
 impulse, 198
 impulse response, 198, 198, 210, 375, 376
 SISO systems, 588
 impulse train, 462, 464
ImpulseGen, 485
 impulses, 371
 incompleteness theorem, 176
Indices, 21
 induction, 203
 inductors, 640
 infinite impulse response, 208, 212, 215, 382, 395
 infinite sequence, 667, 679
 initial conditions, 574, 581
 initial state, 95
 initial value problems, 573
 Initial value theorem, 548
 initial value theorem, 549
 input alphabet, 95
 input signal, 78
 input signals, 95
Inputs, 94
 instantaneous reactions, 138
 integers, 662, 706
Integers16, 7
 integral controller, 643
 integral formula, 419
 integrals, 522
 integration property:Laplace transform, 555
Intensity, 13
 intensity, 285
 interactive voice response, 2
 internal rate of return, 205
 Internet, 29
 sound, 27
 telephony, 35
 internet, 247
 Internet image search, 3
 Internet protocol, 7
 internet protocols, 251
 interpolating, 473
 intersection, 663, 706
 interval, 663, 706
 inverse, 224

- inverse Fourier transform, 417
inverse transform, 538
inverse Z transform, 542
inverses, 416
IP, 7
IP address, 57
Iridium, 33
ITU, 38
iTunes visualizer, 2
IVR, 2
- j*, 691
j command in Matlab, 702
Java, 63, 64, 401
jet engines, 2
- key, 281
kHz, 279
kilohertz, 279
Kirchhoff's voltage law, 327, 580
Kronecker delta function, 198, 371, 464, 520
- Laplace transform, 502, 522, 538
Laurent series, 597
left-sided, 524
left-sided signal, 515
LEO, 33
IHopitalsRule, 65, 385
light, 14
line card, 30
linear, 318
linear distortion, 364
linear function, 192, 192, 217
linear inequality predicates, 685
linear interpolation, 483
linear system, 195, 218, 319
linear time invariant systems, 276
linear time-invariant system, 195
- linear, space-invariant, 365
LinearInterpolator, 483
linearity, 367, 577
of Fourier transforms, 454
linearity:of the Laplace transform, 534
linearity:of the Z transform, 541
LineSignals, 61
local loop, 30
LocalLoop, 61
logical and, 663, 706
logical connectives, 663
logical or, 663, 706
loudness, 237
low-earth-orbit, 33
lowpass, 335, 365
LSI, 365
LTI, 218
LTI differential equation, 579
LTI system, 14, 195, 231, 239, 312, 689
LTI systems, 276, 689
- mac, 402
magnitude, 694, 707
magnitude distortion, 619
magnitude response, 334, 550, 558
major triad, 279, 292
malware, 3
manufacturing defect, 3
Maple, 65
mass-spring-damper system, 640, 644
matching game, 113
Mathematica, 65
Matlab, 64, 76
 abs, 702
 angle, 702
 butter, 396
 cheby1, 396, 398
 cheby2, 396, 398

- complex, 702
 conj, 702
 conv, 398
 ellip, 396, 398
 exp, 702
 fft, 438
 filter, 398
 filter design, 385
 i, 702
 imag, 702
 j, 702
 real, 702
 remez, 387, 388
 roots, 699
 stem, 462, 464
 matrices, 53
 matrix, 221, 221
 matrix exponential, 590
 matrix inverse, 224
 matrix multiplication, 223
 McClellan, 388
 Mealy machines, 104
 medium access layer, 251
 megahertz, 279
 member, 656, 705
 members, 401
 memoryless, 71
 meta data, 38
 method, 67, 401
 MHz, 279
 micropascals, 394
 microwave radio, 31
 millibars, 66
 MIMO, 188, 189, 216
 min, 98
 modal model, 236
 mode, 236, 266
 model, 68
 modem, 36, 617
 modem negotiation, 38
 modes, 236
 modulation, 458
 modulo N counter, 130
 modulus, 694
 moment of inertia, 629
 moment of intertia, 501
 momentum, 256
 Moore machines, 104
 motor, 634
 Motorola, 33
 Motorola DSP56000, 402
Mouthpiece, 61
 moving average, 74, 75, 88, 200, 209, 235, 369, 384, 552
 moving average cross-over method, 235
 MP3, 7
 MP3 player, 2
 muffled sound, 364
 multipath, 305
 multiple-input, multiple-output, 189
 multiple-input, multiple-output system, 188
 multiplicity, 519
 multipliers, 400
 multiply and accumulate, 402
 musical instrument, 283
 musical scale, 281
 NaN, 63, 65
 natural numbers, 4, 656, 662, 705
 natural response, 577, 583
 \mathbb{N} , 4, 656
 near-end signal, 623
 negation, 664, 706
 negative feedback, 627
Network, 62

- network interface card, 247
network layer, 251
neutral wire, 11
newton, 7, 394
Newton's law, 73, 255
Newton's second law of motion, 70
Newton's third law, 502
next state function, 96
nextState, 96, 190
NIC, 247
noise, 27, 35, 622
noise cancellation, 622
noise canceller, 622
noisy environment, 625
non-negative integers, 656, 662, 705
non-negative real numbers, 662, 706
nondeterministic, 101, 107
nondeterministic state machine, 175
norm, 535
normalized frequency, 475
not, 664
not a number, 63, 65
nslookup, 57
nucleotide, 3
Nyquist frequency, 478
Nyquist-Shannon sampling theorem, 481, 488
obfuscated programs, 3
object-oriented languages, 67
octave, 278
one-to-one, 680, 681
OnOff, 40
onto, 680
open, 663
open-loop response, 642
open-loop step response, 642
open-loop transfer function, 627
operational semantics, 176
operators, 672
optical fiber, 31
optics, 365
order, 396, 517, 529, 653
ordered set, 657, 666, 667
ordering, 94
ordering constraint, 95
oscillator, 215
out of phase, 11
output, 96, 190
output alphabet, 95
output equation, 190, 220
output function, 96, 96
output of a state machine, 100
output response, 190, 210, 575, 585, 590
output signal, 78
output signals, 95
Outputs, 94
overloaded, 658
overshoot, 635, 642
- P controller, 628, 630, 643, 652
Pa, 7
packets, 85, 247
parallel composition, 151, 612, 620
parking meter, 108
Parks-McClellan algorithm, 388
parsing, 674
partial fraction expansion, 559, 559
pascal, 7, 394
passband, 387
PD controller, 646
perceived pitch, 477
period, 9
periodic, 300, 304
periodic signal, 285
periodic signals, 415

- periodicity of discrete-time frequency response, 520, 549, 613, 617
 324
 periodicity of the DTFT, 380
 permutations, 666, 667
 phase, 283, 331, 689
 phase response, 334
 phase shift, 11, 334
 phasor, 331
 phoneme, 435
 PID controller, 640, 643
 pitch, 477
 pixel, 15, 24
 plant, 39, 260, 628
 polar coordinates, 697
 polar representation, 697, 707
 pole-zero plot, 517
 poles, 517, 529
 polynomial, 690
 port alphabet, 148
Position, 17
 POSIX time, 4
possibleUpdates, 110
 POTS, 29
 power, 32, 394
 power train, 39
 powerset, 110, 182, 659, 687, 705
 precision, 25
 predicate, 54, 56, 660
 predicate expression, 673
Pressure, 6
 procedure, 63, 64
 procedures, 401
 product form inputs and outputs, 148
 product formula, 695, 703
 product of sets, 669, 706
 programmable DSP, 402
 propagation loss, 32
 proper, 520, 549, 613, 617
 proper subset, 657
 proportional controller, 628, 630
 protocol stack, 251
 protocols, 247, 251
 prototype, 660, 706
 Psychoacoustics, 277
 psychoacoustics, 276
 public address system, 365
 punctuation, 674
PureTone, 9
 quantifiers, 672
 quantization, 24, 25
 radar, 4
 radians, 278, 284
 radians per second, 278
 radio, 3
 radio modem, 139
 radio modems, 617
 radio telephones, 32
 ramp, 409, 597
 range, 677
 rational polynomials, 517, 528
 RC circuit, 326, 335
Re{ z }, 692
 reachable, 147, 179, 181
 reaction, 96, 191
 composite state machines, 138
 reactive, 138, 157
 real command in Matlab, 702
 real numbers, 662, 706
 real part, 692, 707
 real time, 382
 real-valued functions, 318
 \mathbb{R}_+ , 5
 \mathbb{R} , 5

- receiver, 364
receptive, 101, 110
receptiveness, 101
reconstruction, 473
RecordingStudio, 37
rectangle, 428, 464
rectangular pulse, 431
recursion, 403
recursive filter, 395
red eye, 3
redundancy, 37
RedundantBitStreams, 37
Reed-Solomon code, 37
refinement, 236
refinement states, 236
region of convergence, 511, 538
relation, 56, 112
remez command in Matlab, 387, 388
Remez exchange algorithm, 388
renaming, 180
residue
 matrix, 588, 593
residues, 561
resistors, 640
resolution, 24
resonances, 614
rest, 197
retina, 14
reverberation, 230
RGB, 13
right-sided, 523
right-sided signal, 514
ripple, 396
RMS, 11, 11
roaming, 33
robust, 628, 631, 632
RoC, 511
rolloff, 396
root locus, 631, 635
root mean square, 11, 11
roots, 517, 690, 691, 699
roots command in Matlab, 699
roots of unity, 552, 699
router, 85
Routh-Hurwitz, 654
row vector, 222
Russell's paradox, 659
safety, 120
safety-critical system, 2
sample, 7
sample rate, 474
SampledExp, 23
SampledImage, 24
SampledVoice, 22
Sampler, 474
samples, 191
sampling, 22, 473
sampling frequency, 23, 474
sampling interval, 23, 474
sampling period, 23
sampling rate, 23
sampling theorem, 481, 488
satellites, 31, 33
satisfy, 660
sawtooth, 407
scale, 281, 281
second harmonic, 283
self loop, 100
semantics, 176
sensor, 260
sequences, 20, 21, 667, 679
series, 506, 597
series connection, 143
set, 656

- set subtraction, 663, 706
 sets and functions model, 95
 nondeterministic state machines, 110
 Shannon, Claude, 488
 shift invariance, 318, 355
 shift-and-add summation, 287
 shock absorber, 640
 side-by-side composition, 139, 140
 sifting property, 374, 375, 492
 sifting rule, 520, 529
 signal, 2, 4
 mathematical model, 4
 signal flow graph, 403–405
 signal flow graphs, 400
 signal processing, 276, 323
 signal space, 28, 705
 signum function, 53
 simple harmonic motion, 70
 simulates, 115
 simulation, 113, 188, 232
 simulation relation, 114, 115
 Simulink, 76
Sinc, 64
 textbf, 487
 sinc function, 487
 single-input, single-output, 189, 584
 sinusoidal discrete-time signals, 301
 sinusoidal images, 285
 sinusoidal signal, 331
 sinusoidal signal:Laplace transform, 534, 555
StateMachine, 94
 States, 94
 steady-state response, 570
 steady state output, 570
 steady-state response, 579, 584, 632
 stem command in Matlab, 462, 464
 stem plot, 8
 step, 191
- spatial frequency, 285
 spatial resolution, 24
 speech codec, 139
 speech recognition, 435
 spring, 640
 square matrix, 224
 square wave, 418, 423, 442, 461
SquareRoot, 63
 stability criterion for causal systems, 518
 stable, 208
 stable system, 501, 503, 505
 state, 93, 99, 104, 188
 state estimators, 276
 state machine, 94
 state machines, 76
 state response, 96, 101, 190, 203, 210, 226,
 585, 590
 state space, 95, 266
 state trajectory, 210
 state transition, 99
 state transition diagram, 99
 state transitions, 93
 state update equation, 190, 220
 state-determined, 105
 state-determined output, 163, 628, 653
 state-machine models, 232
 state-space model, 93, 190, 196, 208
 continuous-time, 218, 590
 discrete-time, 585, 705

- step number, **95**
step response, **360, 411**
steps, **95**
stock market prices, **384**
stock prices, **75, 235**
stopband, **387**
storage, **27**
strictly proper, **561, 653**
strings, **667**
stuttering element, **233**
stuttering reaction, **97**
stuttering symbol, **97**
subsampling, **482**
subscriber line, **30**
subset, **657, 705**
such that, **660, 706**
summation, **77, 77, 705**
summation identity, **424**
summing signals, **9**
SumOfTones, **9**
superposition, **193**
supervisory control, **260**
suspension system, **640**
switch, **31, 85**
symbolic algebra programs, **65**
symbolic mathematical software, **65**
Symbols, **21**
symmetry of Fourier series, **338**
symmetry of Fourier transforms, **449**
synchronous languages, **139**
synchronous/reactive, **138**
synchronous/reactive systems, **157**
synchrony, **138, 155**
system, **2, 4**

tables, **57**
tapped delay line, **400, 403**
technical stock trading, **235**

telephone, **29**
telephone answering service, **99**
telephone network, **481, 623**
television, **3**
terahertz, **279**
there exists, **662, 706**
three-prong plug, **11**
THz, **279**
timbre, **282**
Time, **6**
time index, **191**
time invariant, **315**
time reversal, **547**
time scaling property:Laplace transform, **606**
time shifting, **452**
time-based models, **232**
time-domain signals, **276, 313**
time-invariant, **191**
time-invariant system, **314**
time-passage phase, **243**
timed automata, **240**
tine, **68, 70**
tip and ring, **623**
torque, **502, 629**
trace, **101**
tracking error, **632**
traction control, **139, 189**
traffic helicopter, **625**
train whistle, **298**
training sequence, **615**
training signals, **39**
transfer function, **503, 511, 523, 546, 577**
 difference equation, **577**
 differential equation, **582**
transient, **88**
transient output, **570**
transient response, **579, 584**

- transition, 99
 transition band, 387
 transition structure, 266
 transitivity of simulation, 116
 translation, 28
 transmission, 27
 transmitter, 364
 transport layer, 251
 transpose, 222
 triad, 279
 triangle inequality, 504
 trigonometric identities, 76, 229, 696
 true assertion, 658
 truncation, 25
 truth table, 675
 truth values, 663, 706
 tuning fork, 68, 70
 tuple, 667, 679, 706
 tuples, 669
 turbines, 2
 Turing, Alan, 176
 twisted pair, 30, 623
 two-sided signal, 513, 525
 type constraint, 143
- ultrasonic, 279
 ultrasound imaging, 2
 uniform convergence, 295
 union, 663, 706
 uniqueness of the Fourier series, 309
 unit circle, 514, 516
 unit delay, 400, 618
 unit ramp, 532, 534, 597
 unit step, 74, 360, 395, 411, 470, 502, 508, 513, 521, 525
UnitDelay, 130, 184
 universal quantification, 52, 661
 Unix time, 4
- unstable, 208
 unstable system, 501
 unvoiced sound, 437
update, 94
 update function, 95, 95, 96
 update table, 103
- variable, 4, 659
 variables, 672
 vector, 222
VerticalSpace, 13
 video, 16
Video', 16
 visual syntax, 78
 vocal chords, 437
Voice, 6
 voice mail, 99
 voice over IP, 7
 voice-quality audio, 7
 voiceband data modem, 36
 voiceband data modems, 617
 voiced sound, 437
Voices, 61
 VoIP, 7
- Wall Street, 76, 235, 384
 watts, 394
 waveform, 6
 wavelength, 14
 weighted delta function, 374
 weighted delta functions, 372
 well-formed, 156, 159, 168, 628
 well-formed expressions, 673
 well-tempered scale, 281
 western musical scale, 281
 Wheatstone bridge, 623
 wildcard, 151
 wireless, 32

Z transform, 502, 510, 538
zero-input output response, 206
zero-input response, 206, 210, 215, 217, 583
 difference equation, 577
zero-input state response, 206, 215
zero-order hold, 483
zero-state impulse response, 210
zero-state output response, 206
zero-state response, 205, 210, 217, 583
 difference equation, 577
zero-state state response, 206
zeroes, 517
ZeroOrderHold, 483
zeros, 529

