

Feedback Systems: An Introduction for Scientists and Engineers

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DRAFT v2.4a (16 September 2006)
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Preface

This book provides an introduction to the basic principles and tools for design and analysis of feedback systems. It is intended to serve a diverse audience of scientists and engineers who are interested in understanding and utilizing feedback in physical, biological, information, and economic systems. To this end, we have chosen to keep the mathematical prerequisites to a minimum while being careful not to sacrifice rigor in the process. Advanced sections, marked by the “dangerous bend” symbol shown to the right, contain material that is of a more advanced nature and can be skipped on first reading.



This book was originally developed for use in an experimental course at Caltech involving students from a wide variety of disciplines. The course consisted of undergraduates at the junior and senior level in traditional engineering disciplines, as well as first and second year graduate students in engineering and science. This included graduate students in biology, computer science and economics, requiring a broad approach that emphasized basic principles and did not focus on applications in any one given area.

A web site has been prepared as a companion to this text:

<http://www.cds.caltech.edu/~murray/amwiki>

The web site contains a database of frequently asked questions, supplemental examples and exercises, and lecture materials for a course based on this text. It also contains the source code for many examples in the book, as well as libraries to implement the techniques described in the text. Most of the code was originally written using MATLAB M-files, but was also tested with LabVIEW MathScript to ensure compatibility with both packages. Most files can also be run using other scripting languages such as Octave, SciLab and SysQuake. [Author’s note: the web site is under construction as of this writing and some features described in the text may not yet be available.]

Because of its intended audience, this book is organized in a slightly unusual fashion compared to many other books on feedback and control. In particular, we introduce a number of concepts in the text that are normally reserved for second year courses on control (and hence often not available to students who are not control systems majors). This has been done at the expense of certain “traditional” topics, which we felt that the astute student could learn on their own (and are often explored through the exercises). Examples of topics that we have included are nonlinear dynamics, Lyapunov stability, reachability and observability, and fundamental limits of performance and robustness. Topics that we have de-emphasized include root locus techniques, lead/lag compensation (although this is essentially covered in Chapters 10 and 11), and detailed rules for generating Bode and Nyquist plots by hand.

The first half of the book focuses almost exclusively on so-called “state-space” control systems. We begin in Chapter 2 with a description of modeling of physical, biological and information systems using ordinary differential equations and difference equations. Chapter 3 presents a number of examples in some detail, primarily as a reference for problems that will be used throughout the text. Following this, Chapter 4 looks at the dynamic behavior of models, including definitions of stability and more complicated nonlinear behavior. We provide advanced sections in this chapter on Lyapunov stability, because we find that it is useful in a broad array of applications (and frequently a topic that is not introduced until much later in one’s studies).

The remaining three chapters of the first half of the book focus on linear systems, beginning with a description of input/output behavior in Chapter 5. In Chapter 6, we formally introduce feedback systems by demonstrating how state space control laws can be designed. This is followed in Chapter 7 by material on output feedback and estimators. Chapters 6 and 7 introduce the key concepts of reachability and observability, which give tremendous insight into the choice of actuators and sensors, whether for engineered or natural systems.

The second half of the book presents material that is often considered to be from the field of “classical control.” This includes the transfer function, introduced in Chapter 8, which is a fundamental tool for understanding feedback systems. Using transfer functions, one can begin to analyze the stability of feedback systems using loop analysis, which allows us to reason about the closed loop behavior (stability) of a system from its open loop characteristics. This is the subject of Chapter 9, which revolves around the Nyquist stability criterion.

In Chapters 10 and 11, we again look at the design problem, focusing first on proportional-integral-derivative (PID) controllers and then on the more general process of loop shaping. PID control is by far the most common design technique in control systems and a useful tool for any student. The chapter on loop shaping introduces many of the ideas of modern control theory, including the sensitivity function. In Chapter 12, we pull together the results from the second half of the book to analyze the fundamental tradeoffs between robustness and performance. This is also a key chapter illustrating the power of the techniques that have been developed.

The book is designed for use in a 10–15 week course in feedback systems that can serve to introduce many of the key concepts that are needed in a variety of disciplines. For a 10 week course, Chapters 1–6 and 8–11 can each be covered in a week’s time, with some dropping of topics from the final chapters. A more leisurely course, spread out over 14–15 weeks, could cover the entire book, with two weeks on modeling (Chapters 2 and 3)—particularly for students without much background in ordinary differential equations—and two weeks on robust performance (Chapter 12).

In choosing the set of topics and ordering for the main text, we necessarily left out some tools which will cause many control systems experts to raise their eyebrows (or choose another textbook). Overall, we believe that the early focus on state space systems, including the concepts of reachability and observability, are of such importance to justify trimming other topics to make room for them. We also included some relatively advanced material on fundamental tradeoffs and limitations of performance, feeling that these provided such insight into the principles of feedback that they could not be left for later. Throughout the text, we have attempted to maintain a balanced set of examples that touch many disciplines, relying on the companion web site for more discipline specific examples and exercises. Additional notes covering some of the “missing” topics are available on the web.

One additional choice that we felt was very important was the decision not to rely on the use of Laplace transforms in the book. While this is by far the most common approach to teaching feedback systems in engineering, many students in the natural and information sciences may lack the necessary mathematical background. Since Laplace transforms are not required in any essential way, we have only made a few remarks to tie things together for students with that background. Of course, we make tremendous use of *transfer functions*, which we introduce through the notion of response to exponential inputs, an approach we feel is much more accessible to a broad array of scientists and engineers.

Acknowledgments

The authors would like to thank the many people who helped during the preparation of this book. The idea for writing this book came in part from a report on future directions in control [Mur03] to which Stephen Boyd, Roger Brockett, John Doyle and Gunter Stein were major contributors. Kristi Morgenson and Hideo Mabuchi helped teach early versions of the course at Caltech on which much of the text is based and Steve Waydo served as the head TA for the course taught at Caltech in 2003–04 and provide numerous comments and corrections. [Author’s note: additional acknowledgments to be added.] Finally, we would like to thank Caltech, Lund University and the University of California at Santa Barbara for providing many resources, stimulating colleagues and students, and a pleasant working environment that greatly aided in the writing of this book.

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Notation

Throughout the text we make use of some fairly standard mathematical notation that may not be familiar to all readers. We collect some of that notation here, for easy reference.

term := expr When we are defining a term or a symbol, we will use the notation := to indicate that the term is being defined. A variant is =:, which is used when the term being defined is on the right hand side of the equation.

$\dot{x}, \ddot{x}, \dots, x^{(n)}$ We use the shorthand \dot{x} to represent the time derivative of x , \ddot{x} for the second derivative with respect to time and $x^{(n)}$ for the n th derivative. Thus

$$\dot{x} = \frac{dx}{dt} \quad \ddot{x} = \frac{d^2x}{dt^2} = \frac{d}{dt} \frac{dx}{dt} \quad x^{(n)} = \frac{d^{n-1}x}{dt^{n-1}}$$

\mathbb{R} The set of real numbers.

\mathbb{R}^n The set of vectors of n real numbers.

$\mathbb{R}^{m \times n}$ The set of $m \times n$ real-valued matrices.

\mathbb{C} The set of complex numbers.

\arg The “argument” of a complex number $z = a + jb$ is the angle formed by the vector z in the complex plane; $\arg z = \arctan(b/a)$.

\angle The angle of a complex number (in degrees); $\angle z = \arg z \cdot 180/\pi$.

$\|\cdot\|$ The norm of a quantity. For a vector $x \in \mathbb{R}^n$, $\|x\| = \sqrt{x^T x}$, also called the 2-norm and sometimes written $\|x\|_2$. Other norms include the ∞ -norm $\|\cdot\|_\infty$ and the 1-norm $\|\cdot\|_1$.

Chapter 1

Introduction

Feedback is a central feature of life. The process of feedback governs how we grow, respond to stress and challenge, and regulate factors such as body temperature, blood pressure, and cholesterol level. The mechanisms operate at every level, from the interaction of proteins in cells to the interaction of organisms in complex ecologies.

Mahlon B. Hoagland and B. Dodson, *The Way Life Works*, 1995 [HD95].

In this chapter we provide an introduction to the basic concept of *feedback* and the related engineering discipline of *control*. We focus on both historical and current examples, with the intention of providing the context for current tools in feedback and control. Much of the material in this chapter is adopted from [Mur03] and the authors gratefully acknowledge the contributions of Roger Brockett and Gunter Stein for portions of this chapter.

1.1 What is Feedback?

The term *feedback* is used to refer to a situation in which two (or more) dynamical systems are connected together such that each system influences the other and their dynamics are thus strongly coupled. By dynamical system, we refer to a system whose behavior changes over time, often in response to external stimulation or forcing. Simple causal reasoning about a feedback system is difficult because the first system influences the second and the second system influences the first, leading to a circular argument. This makes reasoning based on cause and effect tricky and it is necessary to analyze the system as a whole. A consequence of this is that the behavior of feedback systems is often counterintuitive and it is therefore necessary to resort to formal methods to understand them.

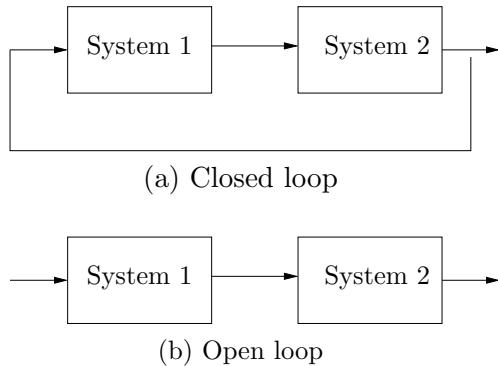


Figure 1.1: Open and closed loop systems.

Figure 1.1 illustrates in block diagram form the idea of feedback. We often use the terms *open loop* and *closed loop* when referring to such systems. A system is said to be a closed loop system if the systems are interconnected in a cycle, as shown in Figure 1.1a. If we break the interconnection, we refer to the configuration as an open loop system, as shown in Figure 1.1b.

As the quote at the beginning of this chapter illustrates, a major source of examples for feedback systems is from biology. Biological systems make use of feedback in an extraordinary number of ways, on scales ranging from molecules to microbes to organisms to ecosystems. One example is the regulation of glucose in the bloodstream, through the production of insulin and glucagon by the pancreas. The body attempts to maintain a constant concentration of glucose, which is used by the body's cells to produce energy. When glucose levels rise (after eating a meal, for example), the hormone insulin is released and causes the body to store excess glucose in the liver. When glucose levels are low, the pancreas secretes the hormone glucagon, which has the opposite effect. The interplay between insulin and glucagon secretions throughout the day help to keep the blood-glucose concentration constant, at about 90 mg per 100 ml of blood.

An early engineering example of a feedback system is the centrifugal governor, in which the shaft of a steam engine is connected to a flyball mechanism that is itself connected to the throttle of the steam engine, as illustrated in Figure 1.2. The system is designed so that as the speed of the engine increases (perhaps due to a lessening of the load on the engine), the flyballs spread apart and a linkage causes the throttle on the steam engine to be closed. This in turn slows down the engine, which causes the flyballs to come back together. When properly designed, the flyball governor

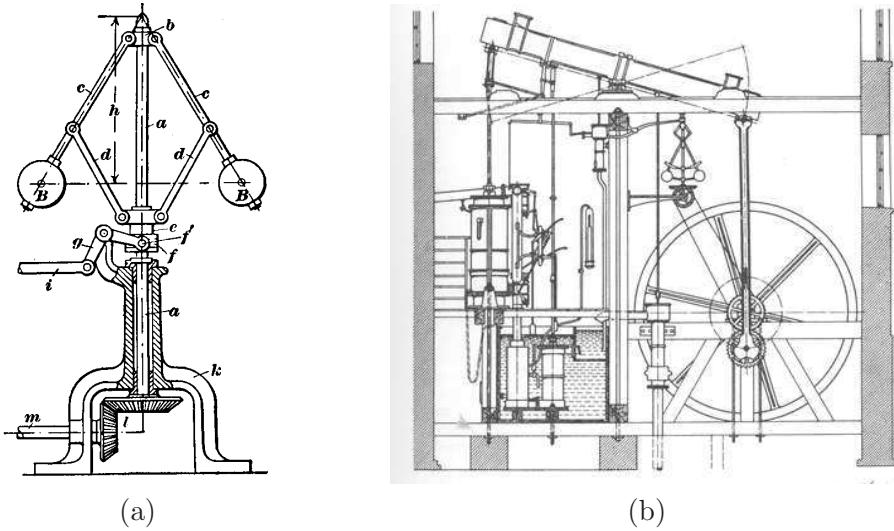


Figure 1.2: The centrifugal governor (a), developed in the 1780s, was an enabler of the successful Watt steam engine (b), which fueled the industrial revolution. Figures courtesy Richard Adamek (copyright 1999) and Cambridge University.

maintains a constant speed of the engine, roughly independent of the loading conditions.

Feedback has many interesting properties that can be exploited in designing systems. As in the case of glucose regulation or the flyball governor, feedback can make a system very resilient towards external influences. It can also be used to create linear behavior out of nonlinear components, a common approach in electronics. More generally, feedback allows a system to be very insensitive both to external disturbances and to variations in its individual elements.

Feedback has potential disadvantages as well. If applied incorrectly, it can create dynamic instabilities in a system, causing oscillations or even runaway behavior. Another drawback, especially in engineering systems, is that feedback can introduce unwanted sensor noise into the system, requiring careful filtering of signals. It is for these reasons that a substantial portion of the study of feedback systems is devoted to developing an understanding of dynamics and mastery of techniques in dynamical systems.

Feedback systems are ubiquitous in both natural and engineered systems. Control systems maintain the environment, lighting, and power in our buildings and factories, they regulate the operation of our cars, consumer electronics and manufacturing processes, they enable our transportation and

communications systems, and they are critical elements in our military and space systems. For the most part, they are hidden from view, buried within the code of embedded microprocessors, executing their functions accurately and reliably. Feedback has also made it possible to increase dramatically the precision of instruments such as atomic force microscopes and telescopes.

In nature, homeostasis in biological systems maintains thermal, chemical, and biological conditions through feedback. At the other end of the size scale, global climate dynamics depend on the feedback interactions between the atmosphere, oceans, land, and the sun. Ecologies are filled with examples of feedback, resulting in complex interactions between animal and plant life. Even the dynamics of economies are based on the feedback between individuals and corporations through markets and the exchange of goods and services.

1.2 What is Control?

The term “control” has many meanings and often varies between communities. In this book, we define control to be the use of algorithms and feedback in engineered systems. Thus, control includes such examples as feedback loops in electronic amplifiers, set point controllers in chemical and materials processing, “fly-by-wire” systems on aircraft, and even router protocols that control traffic flow on the Internet. Emerging applications include high confidence software systems, autonomous vehicles and robots, real-time resource management systems, and biologically engineered systems. At its core, control is an *information* science, and includes the use of information in both analog and digital representations.

A modern controller senses the operation of a system, compares that against the desired behavior, computes corrective actions based on a model of the system’s response to external inputs, and actuates the system to effect the desired change. This basic *feedback loop* of sensing, computation, and actuation is the central concept in control. The key issues in designing control logic are ensuring that the dynamics of the closed loop system are stable (bounded disturbances give bounded errors) and that they have the desired behavior (good disturbance rejection, fast responsiveness to changes in operating point, etc). These properties are established using a variety of modeling and analysis techniques that capture the essential physics of the system and permit the exploration of possible behaviors in the presence of uncertainty, noise and component failures.

A typical example of a modern control system is shown in Figure 1.3.

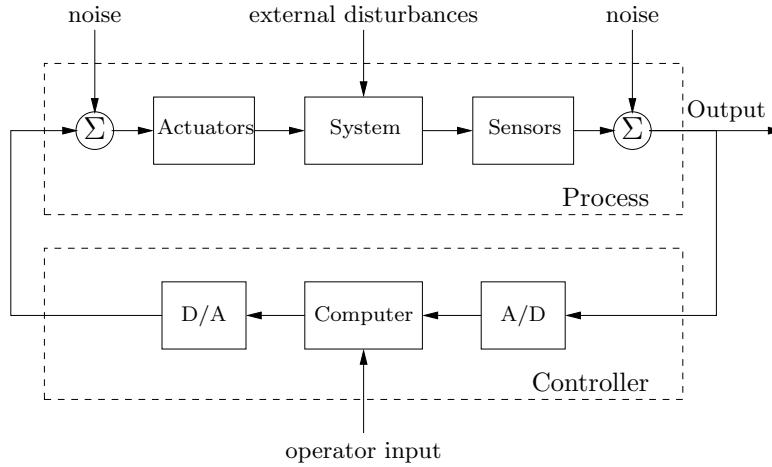


Figure 1.3: Components of a computer controlled system.

The basic elements of sensing, computation and actuation are clearly seen. In modern control systems, computation is typically implemented on a digital computer, requiring the use of analog-to-digital (A/D) and digital-to-analog (D/A) converters. Uncertainty enters the system through noise in sensing and actuation subsystems, external disturbances that affect the underlying system physics, and uncertain dynamics in the physical system (parameter errors, unmodeled effects, etc). The algorithm that computes the control action as a function of the sensor values is often called a *control law*.

Control engineering relies on and shares tools from physics (dynamics and modeling), computer science (information and software) and operations research (optimization and game theory), but it is also different from these subjects in both insights and approach.

Perhaps the strongest area of overlap between control and other disciplines is in modeling of physical systems, which is common across all areas of engineering and science. One of the fundamental differences between control-oriented modeling and modeling in other disciplines is the way in which interactions between subsystems (components) are represented. Control relies on input/output modeling that allows many new insights into the behavior of systems, such as disturbance rejection and stable interconnection. Model reduction, where a simpler (lower-fidelity) description of the dynamics is derived from a high fidelity model, is also very naturally described in an input/output framework. Perhaps most importantly, modeling in a control context allows the design of *robust* interconnections between

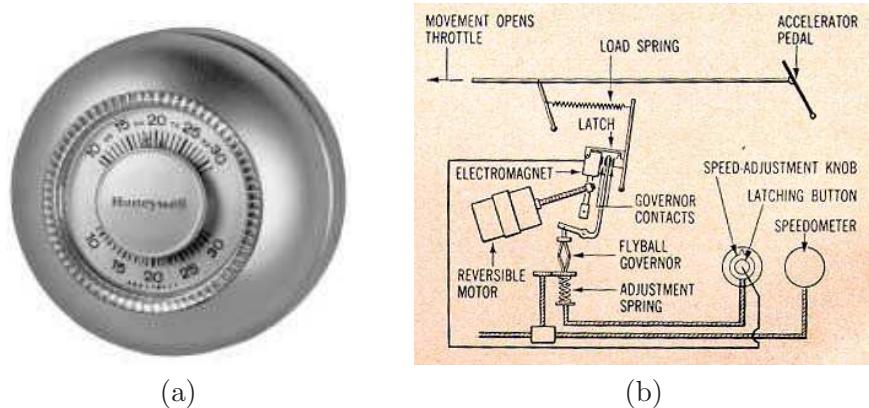


Figure 1.4: Early control devices: (a) Honeywell T86 thermostat, originally introduced in 1953, (b) Chrysler cruise control system, introduced in the 1958 Chrysler Imperial (note the centrifugal governor) [Row58].

subsystems, a feature that is crucial in the operation of all large engineered systems.

Control is also closely associated with computer science, since virtually all modern control algorithms for engineering systems are implemented in software. However, control algorithms and software are very different from traditional computer software. The physics (dynamics) of the system are paramount in analyzing and designing them and their real-time nature dominates issues of their implementation.

1.3 Feedback Examples

Feedback has many interesting and useful properties. It makes it possible to design precise systems from imprecise components and to make physical variables in a system change in a prescribed fashion. An unstable system can be stabilized using feedback and the effects of external disturbances can be reduced. Feedback also offers new degrees of freedom to a designer by exploiting sensing, actuation and computation. In this section we survey some of the important applications and trends for feedback in the world around us.

Early Technological Examples

The proliferation of control in engineered systems has occurred primarily in the latter half of the 20th century. There are some familiar exceptions, such as the centrifugal governor described earlier and the thermostat (Figure 1.4a), designed at the turn of the century to regulate temperature of buildings.

The thermostat, in particular, is often cited as a simple example of feedback control that everyone can understand. Namely, the device measures the temperature in a building, compares that temperature to a desired set point, and uses the “feedback error” between these two to operate the heating plant, e.g. to turn heating on when the temperature is too low and to turn it off when the temperature is too high. This explanation captures the essence of feedback, but it is a bit too simple even for a basic device such as the thermostat. Actually, because lags and delays exist in the heating plant and sensor, a good thermostat does a bit of anticipation, turning the heater off before the error actually changes sign. This avoids excessive temperature swings and cycling of the heating plant.

This modification illustrates that, even in simple cases, good control system design is not entirely trivial. It must take into account the dynamic behavior of the object being controlled in order to do a good job. The more complex the dynamic behavior, the more elaborate the modifications. In fact, the development of a thorough theoretical understanding of the relationship between dynamic behavior and good controllers constitutes the most significant intellectual accomplishment of the control community, and the codification of this understanding into powerful computer aided engineering design tools makes all modern control systems possible.

There are many other control system examples that have developed over the years with progressively increasing levels of sophistication and impact. An early system with broad public exposure was the “cruise control” option introduced on automobiles in 1958 (see Figure 1.4b). With cruise control, ordinary people experienced the dynamic behavior of closed loop feedback systems in action—the slowdown error as the system climbs a grade, the gradual reduction of that error due to integral action in the controller, the small (but unavoidable) overshoot at the top of the climb, etc. More importantly, by experiencing these systems operating reliably and robustly, the public learned to trust and accept feedback systems, permitting their increasing proliferation all around us. Later control systems on automobiles have had more concrete impact, such as emission controls and fuel metering systems that have achieved major reductions of pollutants and increases in



Figure 1.5: The F-18 aircraft, one of the first production military fighters to use “fly-by-wire” technology, and the X-45 (UCAV) unmanned aerial vehicle. Photographs courtesy of NASA Dryden Flight Research Center.

fuel economy.

In the industrial world, control systems have been a key enabling technology for everything from factory automation (starting with numerically controlled machine tools), to process control in oil refineries and chemical plants, to integrated circuit manufacturing, to power generation and distribution. Early use of regulators for manufacturing systems has evolved to the use of hundreds or even thousands of computer controlled subsystems in major industrial plants.

Aerospace and Transportation

Aerospace and transportation systems encompass a collection of critically important application areas where control is a central technology. These application areas represent a significant part of the modern world’s overall technological capability. They are also a major part of its economic strength, and they contribute greatly to the well being of its people.

In aerospace, control has been a key technological capability tracing back to the very beginning of the 20th century. Indeed, the Wright brothers are correctly famous not simply for demonstrating powered flight but *controlled* powered flight. Their early Wright Flyer incorporated moving control surfaces (vertical fins and canards) and warpable wings that allowed the pilot to regulate the aircraft’s flight. In fact, the aircraft itself was not stable, so continuous pilot corrections were mandatory. This early example of controlled flight is followed by a fascinating success story of continuous improvements in flight control technology, culminating in the very high performance, highly

reliable automatic flight control systems we see on modern commercial and military aircraft today.

Similar success stories for control technology occurred in many other application areas. Early World War II bombsights and fire control servo systems have evolved into today's highly accurate radar-guided guns and precision-guided weapons. Early failure-prone space missions have evolved into routine launch operations, manned landings on the moon, permanently manned space stations, robotic vehicles roving Mars, orbiting vehicles at the outer planets, and a host of commercial and military satellites serving various surveillance, communication, navigation, and earth observation needs. Cars have advanced from manually tuned mechanical/pneumatic technology to computer-controlled operation of all major functions, including fuel injection, emission control, cruise control, braking, and cabin comfort.

Current research in aerospace and transportation systems is investigating the application of feedback to higher levels of decision making, including logical regulation of operating modes, vehicle configurations, payload configurations, and health status. These have historically been performed by human operators, but today that boundary is moving, and control systems are increasingly taking on these functions. Another dramatic trend on the horizon is the use of large collections of distributed entities with local computation, global communication connections, very little regularity imposed by the laws of physics, and no possibility of imposing centralized control actions. Examples of this trend include the national airspace management problem, automated highway and traffic management, and the command and control for future battlefields.

Information and Networks

The rapid growth of communication networks provides several major opportunities and challenges for control. Although there is overlap, we can divide these roughly into two main areas: control *of* networks and control *over* networks.

Control of networks is a large area, spanning many topics, including congestion control, routing, data caching, and power management. Several features of these control problems make them very challenging. The dominant feature is the extremely large scale of the system; the Internet is probably the largest feedback control system man has ever built. Another is the decentralized nature of the control problem: local decisions must be made quickly and based only on local information. Stability is complicated by the presence of varying time lags, as information about the network state

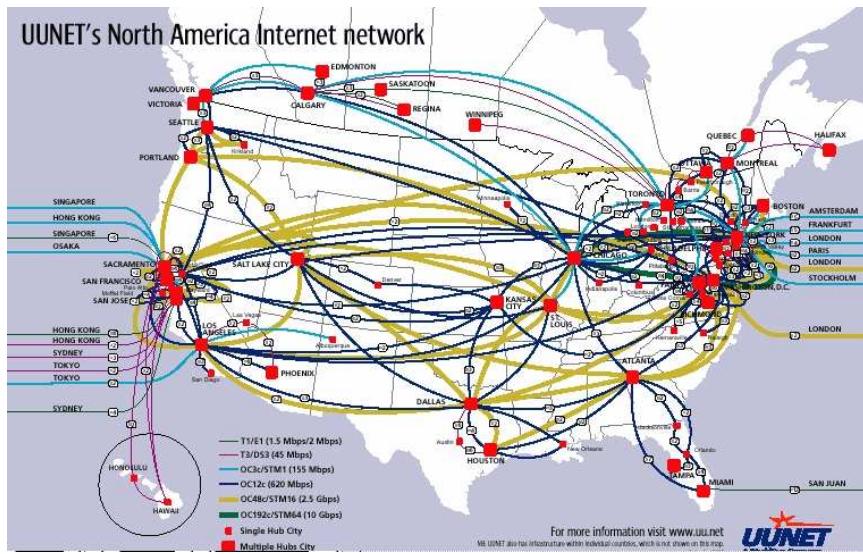


Figure 1.6: UUNET network backbone for North America. Figure courtesy of WorldCom.

can only be observed or relayed to controllers after a delay, and the effect of a local control action can be felt throughout the network only after substantial delay. Uncertainty and variation in the network, through network topology, transmission channel characteristics, traffic demand, available resources, and the like, may change constantly and unpredictably. Other complicating issues are the diverse traffic characteristics—in terms of arrival statistics at both the packet and flow time scales—and the different requirements for quality of service that the network must support.

Resources that must be managed in this environment include computing, storage and transmission capacities at end hosts and routers. Performance of such systems is judged in many ways: throughput, delay, loss rates, fairness, reliability, as well as the speed and quality with which the network adapts to changing traffic patterns, changing resource availability, and changing network congestion. The robustness and performance of the global Internet is a testament to the use of feedback to meet the needs of society in the face of these many uncertainties.

While the advances in information technology to date have led to a global Internet that allows users to exchange information, it is clear that the next phase will involve much more interaction with the physical environment and the increased use of control over networks. Networks of sensor and actuator nodes with computational capabilities, connected wirelessly or by wires,



Figure 1.7: “Spirit”, one of the two Mars Exploratory Rovers, and Sony AIBO Entertainment Robot. Photographs courtesy of Jet Propulsion Laboratory and Sony.

can form an orchestra that controls our physical environment. Examples include automobiles, smart homes, large manufacturing systems, intelligent highways and networked city services, and enterprise-wide supply and logistics chains.

Robotics and Intelligent Machines

Whereas early robots were primarily used for manufacturing, modern robots include wheeled and legged machines capable of competing in robotic competitions and exploring planets, unmanned aerial vehicles for surveillance and combat, and medical devices that provide new capabilities to doctors. Future applications will involve both increased autonomy and increased interaction with humans and with society. Control is a central element in all of these applications and will be even more important as the next generation of intelligent machines are developed.

The goal of cybernetic engineering, already articulated in the 1940s and even before, has been to implement systems capable of exhibiting highly flexible or “intelligent” responses to changing circumstances. In 1948, the MIT mathematician Norbert Wiener gave a widely read account of cybernetics [Wie48]. A more mathematical treatment of the elements of engineering cybernetics was presented by H.S. Tsien in 1954, driven by problems related to control of missiles [Tsi54]. Together, these works and others of that time form much of the intellectual basis for modern work in robotics and control.

Two accomplishments that demonstrate the successes of the field are the Mars Exploratory Rovers and entertainment robots such as the Sony AIBO, shown in Fig. 1.7. The two Mars Exploratory Rovers, launched by the Jet Propulsion Laboratory (JPL), maneuvered on the surface of Mars

for over two years starting in January 2004 and sent back pictures and measurements of their environment. The Sony AIBO robot debuted in June of 1999 and was the first “entertainment” robot to be mass marketed by a major international corporation. It was particularly noteworthy because of its use of AI technologies that allowed it to act in response to external stimulation and its own judgment. This “higher level” of feedback is key element of robotics, where issues such as task-based control and learning are prevalent.

Despite the enormous progress in robotics over the last half century, the field is very much in its infancy. Today’s robots still exhibit extremely simple behaviors compared with humans, and their ability to locomote, interpret complex sensory inputs, perform higher level reasoning, and cooperate together in teams is limited. Indeed, much of Wiener’s vision for robotics and intelligent machines remains unrealized. While advances are needed in many fields to achieve this vision—including advances in sensing, actuation, and energy storage—the opportunity to combine the advances of the AI community in planning, adaptation, and learning with the techniques in the control community for modeling, analysis, and design of feedback systems presents a renewed path for progress.

Materials and Processing

The chemical industry is responsible for the remarkable progress in developing new materials that are key to our modern society. Process manufacturing operations require a continual infusion of advanced information and process control technologies in order for the chemical industry to maintain its global ability to deliver products that best serve the customer reliably and at the lowest cost. In addition, several new technology areas are being explored that will require new approaches to control to be successful. These range from nanotechnology in areas such as electronics, chemistry, and biomaterials to thin film processing and design of integrated microsystems to supply chain management and enterprise resource allocation. The payoffs for new advances in these areas are substantial, and the use of control is critical to future progress in sectors from semiconductors to pharmaceuticals to bulk materials.

There are several common features within materials and processing that pervade many of the applications. Modeling plays a crucial role, and there is a clear need for better solution methods for multidisciplinary systems combining chemistry, fluid mechanics, thermal sciences, and other disciplines at a variety of temporal and spatial scales. Better numerical methods for

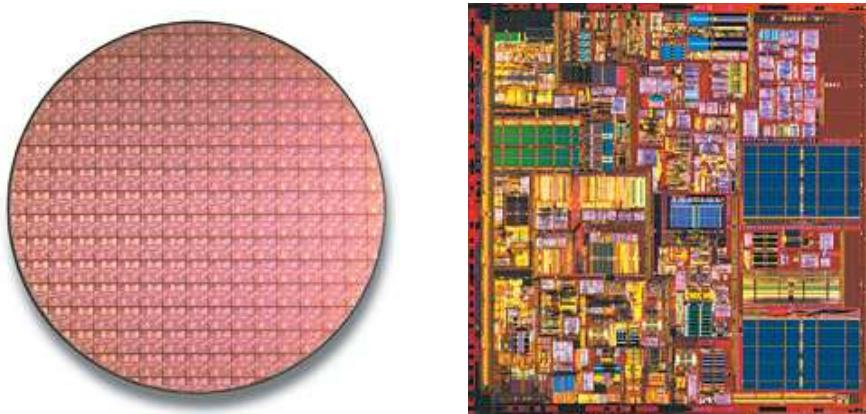


Figure 1.8: Intel Pentium IV wafer and die. Photographs courtesy of Intel.

traversing these scales and designing, controlling, and optimizing under uncertainty are also needed. And control techniques must make use of increased *in situ* measurements to control increasingly complex phenomena.

In addition to the continuing need to improve product quality, several other factors in the process control industry are drivers for the use of control. Environmental statutes continue to place stricter limitations on the production of pollutants, forcing the use of sophisticated pollution control devices. Environmental safety considerations have led to the design of smaller storage capacities to diminish the risk of major chemical leakage, requiring tighter control on upstream processes and, in some cases, supply chains. And large increases in energy costs have encouraged engineers to design plants that are highly integrated, coupling many processes that used to operate independently. All of these trends increase the complexity of these processes and the performance requirements for the control systems, making the control system design increasingly challenging.

As in many other application areas, new sensor technology is creating new opportunities for control. Online sensors—including laser backscattering, video microscopy, ultraviolet, infrared, and Raman spectroscopy—are becoming more robust and less expensive and are appearing in more manufacturing processes. Many of these sensors are already being used by current process control systems, but more sophisticated signal processing and control techniques are needed to more effectively use the real-time information provided by these sensors. Control engineers can also contribute to the design of even better sensors, which are still needed, for example, in the microelectronics industry. As elsewhere, the challenge is making use of the

large amounts of data provided by these new sensors in an effective manner. In addition, a control-oriented approach to modeling the essential physics of the underlying processes is required to understand fundamental limits on observability of the internal state through sensor data.

Instrumentation

Feedback has had a major impact on instrumentation. Consider for example an accelerometer, where early instruments consisted of a mass suspended on a spring with a deflection sensor. The precision of such an instrument depends critically on accurate calibration of spring and the sensor. There is also a design compromise because a weak spring gives high sensitivity but also low bandwidth. An accelerometer based on feedback uses instead a voice coil to keep the mass at a given position and the acceleration is proportional to the current through the voice coil. In such an instrument the precision depends entirely on the calibration of the voice coil and does not depend on the sensor, which is only used as the feedback signal. The sensitivity bandwidth compromise is also avoided. This way of using feedback was applied to practically all engineering fields and it resulted in instruments with drastically improved performance. The development of inertial navigation where position is determined from gyroscopes and accelerometers which permits accurate guidance and control of vehicles is a spectacular example.

There are many other interesting and useful applications of feedback in scientific instruments. The development of the mass spectrometer is an early example. In a paper from 1935 by Nier it is observed that the deflection of the ions depend on both the magnetic and the electric fields. Instead of keeping both fields constant, Nier let the magnetic field fluctuate and the electric field was controlled to keep the ratio of the fields constant. The feedback was implemented using vacuum tube amplifiers. The scheme was crucial for the development of mass spectroscopy.

Another example is the work by the Dutch Engineer van der Meer. He invented a clever way to use feedback to maintain a high density and good quality of the beam of a particle accelerator. The idea is to sense particle displacement at one point in the accelerator and apply a correcting signal at another point. The scheme, called stochastic cooling, was awarded the Nobel Prize in Physics in 1984. The method was essential for the successful experiments in CERN when the existence of the particles W and Z was first demonstrated.

The 1986 Nobel Prize in Physics—awarded to Binnig and Rohrer for their design of the scanning tunneling microscope—is another example of

clever use of feedback. The key idea is to move a narrow tip on a cantilever beam across the surface and to register the forces on the tip. The deflection of the tip was measured using tunneling which gave an extreme accuracy so that individual atoms could be registered.

A severe problem in astronomy is that turbulence in the atmosphere blurs images in telescopes because of variations in diffraction of light in the atmosphere. The blur is of the order of an arc-second in a good telescope. One way to eliminate the blur is to move the telescope outside the Earth's atmosphere as is done with the Hubble telescope. Another way is to use feedback to eliminate the effects of the variations in a telescope on the Earth which is the idea of "adaptive optics." The reference signal is a bright star or an artificial laser beam projected into the atmosphere. The actuator is a deformable mirror which can have hundreds or thousands of elements. The error signal is formed by analyzing the shape of the distorted wave form from the reference. This signal is sent to the controller which adjusts the deformable mirror. The light from the observed star is compensated because it is also reflected in the deformable mirror before it is sent to the detector. The wave lengths used for observation and control are often different. Since diffraction in the atmosphere changes quite rapidly the response time of the control system must be of the order of milliseconds.

Feedback in Nature

Many cutting edge problems in the natural sciences involve understanding aggregate behavior in complex large-scale systems. This behavior "emerges" from the interaction of a multitude of simpler systems, with intricate patterns of information flow. Representative examples can be found in fields ranging from embryology to seismology. Researchers who specialize in the study of specific complex systems often develop an intuitive emphasis on analyzing the role of feedback (or interconnection) in facilitating and stabilizing aggregate behavior, and it is often noted that one can only have hope of deep understanding if it is somehow possible for theories of collective phenomenology to be robust to inevitable uncertainties in the modeling of fine-scale dynamics and interconnection.

While sophisticated theories have been developed by domain experts for the analysis of various complex systems, the development of rigorous methodology that can discover and exploit common features and essential mathematical structure is just beginning to emerge. Advances in science and technology are creating new understanding of the underlying dynamics and the importance of feedback in a wide variety of natural and technological

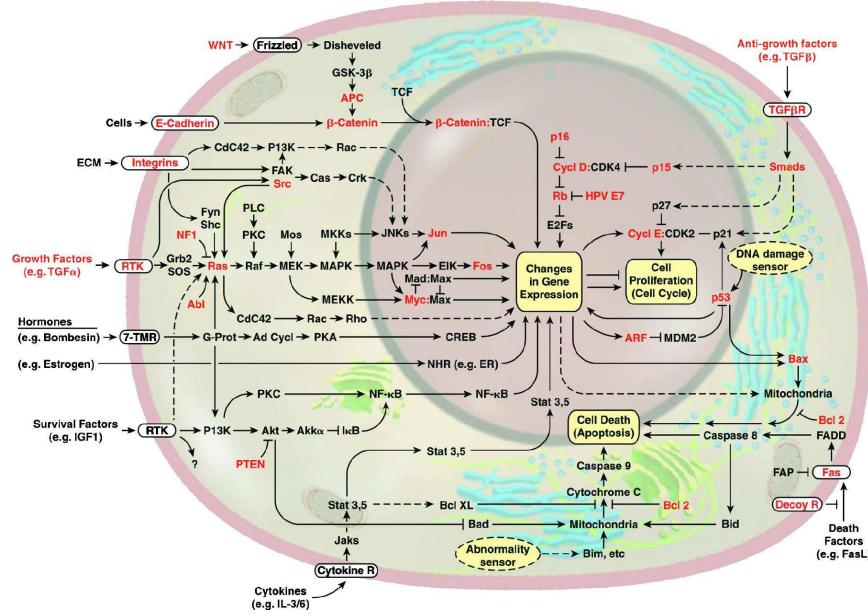


Figure 1.9: The wiring diagram of the growth signaling circuitry of the mammalian cell [HW00].

systems We briefly highlight four application areas here.

Biological Systems. At a variety of levels of organization—from molecular to cellular to organismal to populational—biology is becoming more accessible to approaches that are commonly used in engineering: mathematical modeling, systems theory, computation, and abstract approaches to synthesis. Conversely, the accelerating pace of discovery in biological science is suggesting new design principles that may have important practical applications in man-made systems. This synergy at the interface of biology and engineering offers unprecedented opportunities to meet challenges in both areas. The principles of feedback and control are central to many of the key questions in biological engineering and will play an enabling role in the future of this field.

A major theme currently underway in the biology community is the science of reverse (and eventually forward) engineering of biological control networks (such as the one shown in Figure 1.9). There are a wide variety of biological phenomena that provide a rich source of examples for control, including gene regulation and signal transduction; hormonal, immunological, and cardiovascular feedback mechanisms; muscular control and locomotion; active sensing, vision, and proprioception; attention and consciousness; and

population dynamics and epidemics. Each of these (and many more) provide opportunities to figure out what works, how it works, and what we can do to affect it.

Ecosystems. In contrast to individual cells and organisms, emergent properties of aggregations and ecosystems inherently reflect selection mechanisms which act on multiple levels, and primarily on scales well below that of the system as a whole. Because ecosystems are complex, multiscale dynamical systems, they provide a broad range of new challenges for modeling and analysis of feedback systems. Recent experience in applying tools from control and dynamical systems to bacterial networks suggests that much of the complexity of these networks is due to the presence of multiple layers of feedback loops that provide robust functionality to the individual cell. Yet in other instances, events at the cell level benefit the colony at the expense of the individual. Systems level analysis can be applied to ecosystems with the goal of understanding the robustness of such systems and the extent to which decisions and events affecting individual species contribute to the robustness and/or fragility of the ecosystem as a whole.

Quantum Systems. While organisms and ecosystems have little to do with quantum mechanics in any traditional scientific sense, complexity and robustness issues very similar to those described above can be identified in the modern study of quantum systems. In large part, this sympathy arises from a trend towards wanting to control quantum dynamics and to harness it for the creation of new technological devices. At the same time, physicists are progressing from the study of elementary quantum systems to the study of large aggregates of quantum components, and it has been recognized that dynamical complexity in quantum systems increases exponentially faster with system size than it does in systems describable by classical (macroscopic) physics. Factors such as these are prompting the physics community to search broadly for new tools for understanding robust interconnection and emergent phenomena.

Modern scientific research is rapidly evolving a field of *quantum engineering*. Driven by technology goals in areas such as quantum information processing, nano-electromechanical sensing, chemical synthesis, trace gas detection, and ultrahigh-bandwidth optical communication, researchers are beginning to formulate strategies for achieving robust performance with physical devices or systems in which quantum mechanical effects are prominent. Mathematical tools from control and dynamical systems for analysis and synthesis could have a profound impact on activities of this kind. A schematic diagram of a modern quantum control experiment is shown in Figure 1.10a.

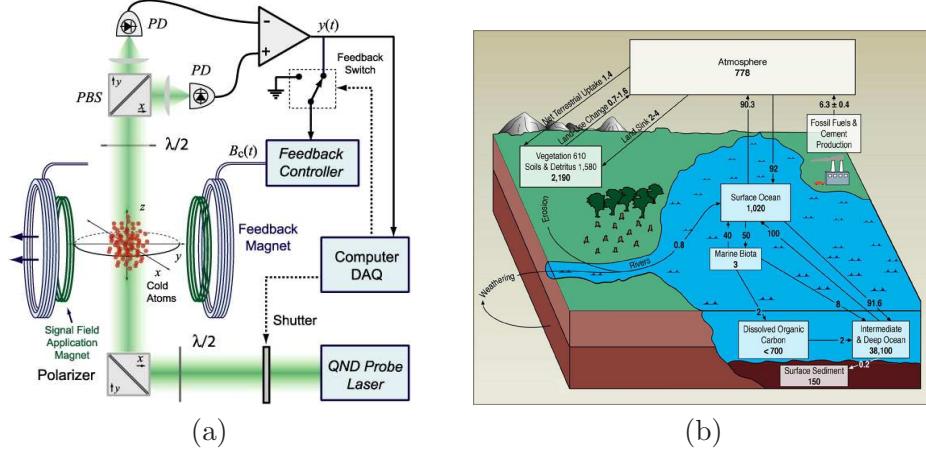


Figure 1.10: Examples of feedback systems in nature: (a) quantum control system and (b) global carbon cycle.

Environmental Science. It is now indisputable that human activities have altered the environment on a global scale. Problems of enormous complexity challenge researchers in this area and first among these is to understand the feedback systems that operate on the global scale. One of the challenges in developing such an understanding is the multiscale nature of the problem, with detailed understanding of the dynamics of microscale phenomena such as microbiological organisms being a necessary component of understanding global phenomena, such as the carbon cycle illustrated Figure 1.10b.

Other Areas

The previous sections have described some of the major application areas for control. However, there are many more areas where ideas from control are being applied or could be applied. Some of these include: economics and finance, including problems such as pricing and hedging options; energy systems, including load distribution and power management for the electrical grid; and manufacturing systems, including supply chains, resource management and scheduling, and factory automation.

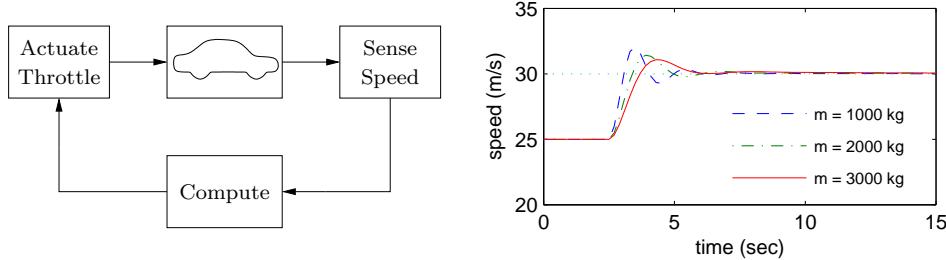


Figure 1.11: A simple feedback system for controlling the speed of a vehicle.

1.4 Feedback Properties

Feedback is a powerful idea which, as we have seen, is used extensively in natural and technological systems. The principle of feedback is very simple: base correcting actions on the difference between desired and actual performance. In engineering, feedback has been rediscovered and patented many times in many different contexts. The use of feedback has often resulted in vast improvements in system capability and these improvements have sometimes been revolutionary, as discussed above. The reason for this is that feedback has some truly remarkable properties. In this section we will discuss some of the properties of feedback that can be understood intuitively. This intuition will be formalized in the subsequent chapters.

Robustness to Uncertainty

One of the key uses of feedback is to provide robustness to uncertainty. By measuring the difference between the sensed value of a regulated signal and its desired value, we can supply a corrective action. If the system undergoes some change that affects the regulated signal, then we sense this change and try to force the system back to the desired operating point. This is precisely the effect that Watt exploited in his use of the centrifugal governor on steam engines.

As an example of this principle, consider the simple feedback system shown in Figure 1.11a. In this system, the speed of a vehicle is controlled by adjusting the amount of gas flowing to the engine. A simple “proportional plus integral” feedback is used to make the amount of gas depend on both the error between the current and desired speed, and the integral of that error. The plot on the right shows the results of this feedback for a step change in the desired speed and a variety of different masses for the car

(which might result from having a different number of passengers or towing a trailer). Notice that independent of the mass (which varies by a factor of 3), the steady state speed of the vehicle always approaches the desired speed and achieves that speed within approximately 5 seconds. Thus the performance of the system is robust with respect to this uncertainty.

Another early example of the use of feedback to provide robustness was the negative feedback amplifier. When telephone communications were developed, amplifiers were used to compensate for signal attenuation in long lines. The vacuum tube was a component that could be used to build amplifiers. Distortion caused by the nonlinear characteristics of the tube amplifier together with amplifier drift were obstacles that prevented development of line amplifiers for a long time. A major breakthrough was invention of the feedback amplifier in 1927 by Harold S. Black, an electrical engineer at the Bell Telephone Laboratories. Black used negative feedback which reduces the gain but makes the amplifier very insensitive to variations in tube characteristics. This invention made it possible to build stable amplifiers with linear characteristics despite nonlinearities of the vacuum tube amplifier.

Design of Dynamics

Another use of feedback is to change the dynamics of a system. Through feedback, we can alter the behavior of a system to meet the needs of an application: systems that are unstable can be stabilized, systems that are sluggish can be made responsive, and systems that have drifting operating points can be held constant. Control theory provides a rich collection of techniques to analyze the stability and dynamic response of complex systems and to place bounds on the behavior of such systems by analyzing the gains of linear and nonlinear operators that describe their components.

An example of the use of control in the design of dynamics comes from the area of flight control. The following quote, from a lecture by Wilbur Wright to the Western Society of Engineers in 1901 [McF53], illustrates the role of control in the development of the airplane:

“Men already know how to construct wings or airplanes, which when driven through the air at sufficient speed, will not only sustain the weight of the wings themselves, but also that of the engine, and of the engineer as well. Men also know how to build engines and screws of sufficient lightness and power to drive these planes at sustaining speed ... Inability to balance and steer still confronts students of the flying problem. ... When this one



Figure 1.12: The Curtiss-Sperry E in 1912 (left) and a closeup of the Sperry Autopilot (right).

feature has been worked out, the age of flying will have arrived, for all other difficulties are of minor importance.”

The Wright brothers thus realized that control was a key issue to enable flight. They resolved the compromise between stability and maneuverability by building an airplane, Kitty Hawk, that was unstable but maneuverable. Kitty Hawk had a rudder in the front of the airplane, which made the plane very maneuverable. A disadvantage was the necessity for the pilot to keep adjusting the rudder to fly the plane: if the pilot let go of the stick the plane would crash. Other early aviators tried to build stable airplanes. These would have been easier to fly, but because of their poor maneuverability they could not be brought up into the air. By using their insight and skillful experiments the Wright brothers made the first successful flight with Kitty Hawk in 1905.

Since it was quite tiresome to fly an unstable aircraft, there was strong motivation to find a mechanism that would stabilize an aircraft. Such a device, invented by Sperry, was based on the concept of feedback. Sperry used a gyro-stabilized pendulum to provide an indication of the vertical. He then arranged a feedback mechanism that would pull the stick to make the plane go up if it was pointing down and vice versa. The Sperry autopilot is the first use of feedback in aeronautical engineering and Sperry won a prize in a competition for the safest airplane in Paris in 1912. Figure 1.12 shows the Curtiss-Sperry seaplane and the Sperry autopilot. The autopilot is a good example of how feedback can be used to stabilize an unstable system and hence “design the dynamics” of the aircraft.

One of the other advantages of designing the dynamics of a device is that it allows for increased modularity in the overall system design. By us-

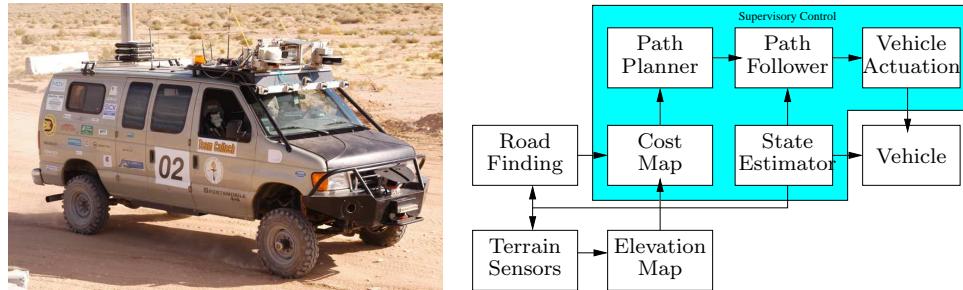


Figure 1.13: DARPA Grand Challenge: (a) “Alice,” Team Caltech’s entry in the 2005 competition. (b) Networked control architecture used by Alice.

ing feedback to create a system whose response matches a desired profile, we can hide the complexity and variability that may be present inside a subsystem. This allows creation us to create more complex systems by not having to simultaneously tune the response of a large number of interacting components. This was one of the advantages of Black’s use of negative feedback in vacuum tube amplifiers: the resulting device had a well-defined linear input/output response that did not depend on the individual characteristics of the vacuum tubes begin used.

Higher Levels of Automation

A major trend in the use of feedback is its use in higher levels of automation and decision making. A good example of this is the DARPA Grand Challenge, a competition sponsored by the US government to build a vehicle that could autonomously drive itself across the desert. Caltech competed in the 2005 Grand Challenge using a modified Ford E-350 offroad van, nicknamed “Alice.” It was fully automated, including electronically controlled steering, throttle, brakes, transmission, and ignition. Its sensing systems included 4 black and white cameras sampling at 30 Hz (arranged in two stereo pairs), 1 color camera for finding roads, 5 LADAR (laser radar) units scanning at 10 Hz, and a GPS/IMU package capable of providing full position and orientation at 2.5 millisecond temporal resolution. Computational resources included 7 high speed servers connected together through a 1 Gb/s Ethernet switch. A picture of the vehicle is shown in Figure 1.13a.

Custom software was used to control the vehicle. The control system architecture is shown in Figure 1.13b. This information-rich feedback system fused data from multiple cameras and LADAR units to determine a digital elevation map for the terrain around it and then used this map to compute

a speed map that estimated the speed at which the vehicle could drive in the environment. The map was modified to include additional information where roads were identified (through vision-based algorithms) and where no data was present (due to hills or temporary sensor outages). This speed map was then used by an optimization-based planner to determine the path that would allow the vehicle to make the most progress in a fixed period of time. The commands from the planner were sent to a trajectory tracking algorithm that compared the desired vehicle position to its estimated position (from GPS/IMU data) and issued appropriate commands to the steering, throttle and brake actuators. Finally, a supervisor control module performed higher level tasks, including implementing strategies for making continued forward progress if one of the hardware or software components failed temporarily (either due to external or internal conditions).

The software and hardware infrastructure that was developed enabled the vehicle to traverse long distances at substantial speeds. In testing, Alice drove itself over 500 kilometers in the Mojave Desert of California, with the ability to follow dirt roads and trails (if present) and avoid obstacles along the path. Speeds of over 50 km/hr were obtained in fully autonomous mode. Substantial tuning of the algorithms was done during desert testing, in part due to the lack of systems-level design tools for systems of this level of complexity. Other competitors in the race (including Stanford, which one the competition) used algorithms for adaptive control and learning, increasing the capabilities of their systems in unknown environments. Together, the competitors in the grand challenge demonstrated some of the capabilities for the next generation of control systems and highlighted many research directions in control at higher levels of decision making.

Drawbacks of Feedback

While feedback has many advantages, it also has some drawbacks. Chief among these is the possibility for instability if the system is not designed properly. We are all familiar with the effects of “positive feedback” when the amplification on a microphone is turned up too high in a room. This is an example of a feedback instability, something that we obviously want to avoid. This is tricky because of the uncertainty that feedback was introduced to compensate for: not only must we design the system to be stable with the nominal system we are designing for, but it must remain stable under all possible perturbations of the dynamics.

In addition to the potential for instability, feedback inherently couples different parts of a system. One common problem that feedback inherently

injects measurement noise into the system. In engineering systems, measurements must be carefully filtered so that the actuation and process dynamics do not respond to it, while at the same time insuring that the measurement signal from the sensor is properly coupled into the closed loop dynamics (so that the proper levels of performance are achieved).

Another potential drawback of control is the complexity of embedding a control system into a product. While the cost of sensing, computation, and (to a lesser extent) actuation has decreased dramatically in the past few decades, the fact remains that control systems are often very complicated and hence one must carefully balance the costs and benefits. An early engineering example of this is the use of microprocessor-based feedback systems in automobiles. The use of microprocessors in automotive applications began in the early 1970s and was driven by increasingly strict emissions standards, which could only be met through electronic controls. Early systems were expensive and failed more often than desired, leading to frequent customer dissatisfaction. It was only through aggressive improvements in technology that the performance, reliability and cost of these systems allowed them to be used in a transparent fashion. Even today, the complexity of these systems is such that it is difficult for an individual car owner to fix problems. There have also been spectacular failures due to unexpected interactions.

Feedforward

When using feedback that there must be an error before corrective actions are taken. Feedback is thus reactive. In some circumstances it is possible to measure a disturbance before it enters the system and this information can be used to take corrective action before the disturbance has influenced the system. The effect of the disturbance is thus reduced by measuring it and generating a control signal that counteracts it. This way of controlling a system is called *feedforward*. Feedforward is particularly useful to shape the response to command signals because command signals are always available. Since feedforward attempts to match two signals, it requires good process models otherwise the corrections may have the wrong size or it may be badly timed.

The ideas of feedback and feedforward are very general and appear in many different fields. In economics, feedback and feedforward are analogous to a market-based economy versus a planned economy. In business a pure feedforward strategy corresponds to running a company based on extensive strategic planning while a feedback strategy corresponds to a pure reactive

approach. The experience in control indicates that it is often advantageous to combine feedback and feedforward. Feedforward is particularly useful when disturbances can be measured or predicted. A typical example is in chemical process control where disturbances in one process may be due to processes upstream. The correct balance of the approaches requires insight and understanding of their properties.

Positive Feedback

In most of this text, we will consider the role of negative feedback, in which we attempt to regulate the system by reacting to disturbances in a way that decreases the effect of those disturbances. In some systems, particularly biological systems, *positive feedback* can play an important role. In a system with positive feedback, the increase in some variable or signal leads to a situation in which that quantity is further through its dynamics. This has a destabilizing effect and is usually accompanied by a saturation that limits the growth of the quantity. Although often considered undesirable, this behavior is used in biological (and engineering) systems to obtain a very fast response to a condition or signal.

1.5 Simple Forms of Feedback

The idea of feedback to make corrective actions based on the difference between the desired and the actual value can be implemented in many different ways. The benefits of feedback can be obtained by very simple feedback laws such as on-off control, proportional control and PID control. In this section we provide a brief preview of some of the topics that will be studied more formally in the remainder of the text.

A simple feedback mechanism can be described as follows:

$$u = \begin{cases} u_{\max} & \text{if } e > 0 \\ u_{\min} & \text{if } e < 0 \end{cases} \quad (1.1)$$

where $e = r - y$ is the difference between the reference signal and the output of the system. Figure 1.14a shows the relation between error and control. This control law implies that maximum corrective action is always used.

The feedback in equation (1.1) is called *on-off control*. One of its chief advantages is that it is simple and there are no parameters to choose. On-off control often succeeds in keeping the process variable close to the reference, such as the use of a simple thermostat to maintain the temperature of a

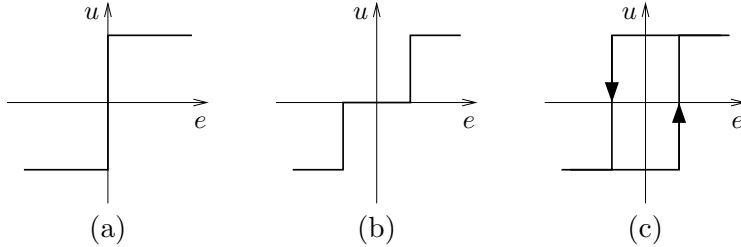


Figure 1.14: Controller characteristics for ideal on-off control (a), and modifications with dead zone (b) and hysteresis (c).

room. It typically results in a system where the controlled variables oscillate, which is often acceptable if the oscillation is sufficiently small.

Notice that in equation (1.1) the control variable is not defined when the error is zero. It is common to have some modifications either by introducing hysteresis or a dead zone (see Figure 1.14b and 1.14c).

The reason why on-off control often gives rise to oscillations is that the system over reacts since a small change in the error will make the actuated variable change over the full range. This effect is avoided in *proportional control*, where the characteristic of the controller is proportional to the control error for small errors. This can be achieved by making the control signal proportional to the error, which gives the control law

$$u = \begin{cases} u_{\max} & \text{if } e > e_{\max} \\ ke & \text{if } e_{\min} \leq e \leq e_{\max} \\ u_{\min} & \text{if } e < e_{\min}, \end{cases} \quad (1.2)$$

where k is the controller gain, $e_{\min} = u_{\min}/k$, and $e_{\max} = u_{\max}/k$. The interval (e_{\min}, e_{\max}) is called the *proportional band* because the behavior of the controller is linear when the error is in this interval:

$$u = k(r - y) = ke \quad \text{if } e_{\min} \leq e \leq e_{\max}. \quad (1.3)$$

While a vast improvement over on-off control, proportional control has the drawback that the process variable often deviates from its reference value. In particular, if some level of control signal is required for the system to maintain a desired value, then we must have $e \neq 0$ in order to generate the requisite input.

This can be avoided by making the control action proportional to the

integral of the error:

$$u(t) = k_i \int_0^t e(\tau) d\tau. \quad (1.4)$$

This control form is called *integral control* and k_i is the integral gain. It can be shown through simple arguments that a controller with integral action will have zero “steady state” error (Exercise 5). The catch is that there may not always be a steady state because the system may be oscillating. This property has been rediscovered many times and is one of the properties that have strongly contributed to the wide applicability of integral controllers.

An additional refinement is to provide the controller with an anticipative ability by using a prediction of the error. A simple prediction is given by the linear extrapolation

$$e(t + T_d) \approx e(t) + T_d \frac{de(t)}{dt},$$

which predicts the error T_d time units ahead. Combining proportional, integral and derivative control we obtain a controller that can be expressed mathematically as follows:

$$\begin{aligned} u(t) &= ke(t) + k_i \int_0^t e(\tau) d\tau + k_d \frac{de(t)}{dt} \\ &= k \left(e(t) + \frac{1}{T_i} \int_0^t e(\tau) d\tau + T_d \frac{de(t)}{dt} \right) \end{aligned} \quad (1.5)$$

The control action is thus a sum of three terms: the past as represented by the integral of the error, the present as represented by the proportional term, and the future as represented by a linear extrapolation of the error (the derivative term). This form of feedback is called a *PID controller* and its action is illustrated in Figure 1.15.

The PID controller is very useful and is capable of solving a wide range of control problems. The PI controller, in which the derivative term is omitted, is one of the most common forms of the controller. It is quoted that about 90% of all control problems can be solved by PID control, although many of these controllers are actually PI controllers because derivative action is often not included. There are more advanced controllers which differ from the PID controller by using more sophisticated methods for prediction.

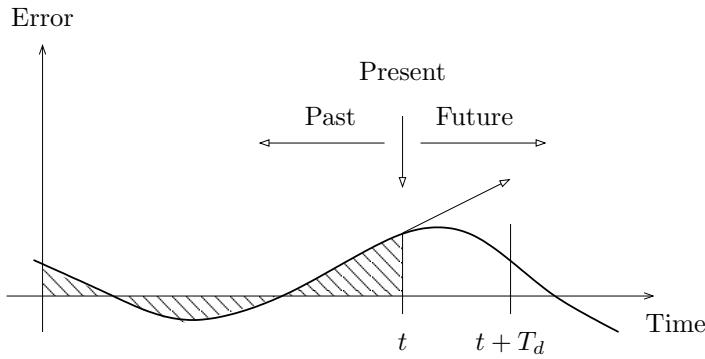


Figure 1.15: A PID controller takes control action based on past, present and future control errors.

1.6 Control Tools

The development of a control system consists of the tasks modeling, analysis, simulation, architectural design, design of control algorithms, implementation, commissioning and operation. Because of the wide use of feedback in a variety of applications, there has been substantial mathematical development in the field of control theory. In many cases the results have also been packaged in software tools that simplifies the design process. We briefly describe some of the tools and concepts here.

Modeling

Models play an essential role in analysis and design of feedback systems. Several sophisticated tools have been developed to build models that are suited for control.

Models can often be obtained from first principles and there are several modeling tools in special domains such as electric circuits and multibody systems. Since control applications cover such a wide range of domains it is also desirable to have modeling tools that cut across traditional discipline boundaries. Such modeling tools are now emerging, with the models obtained by cutting a system into subsystems and writing equations for balance of mass, energy and momentum, and constitutive equations that describe material properties for each subsystem. Object oriented programming can be used very effectively to organize the work and extensive symbolic computation can be used to simplify the equations. Models and components can then be organized in libraries for efficient reuse. Modelica [Til01] is an example of a modeling tool of this type.

Modeling from input/output data or system identification is another approach to modeling that has been developed in control. Direct measurement of the response to step input is commonly used in the process industry to tune proportional-integral (PI) controllers. More accurate models can be obtained by measuring the response to sinusoidal signals, which is particularly useful for systems with fast response time. Control theory has also developed new techniques for modeling dynamics and disturbances, including input/output representations of systems (how disturbances propagate through the system) and data-driven system identification techniques. The use of “forced response” experiments to build models of systems is well developed in the control field and these tools find application in many disciplines, independent of the use of feedback.

Finally, one of the hallmarks of modern control engineering is the development of model reduction techniques that allow a hierarchy of models to be constructed at different levels of fidelity. This was originally motivated by the need to produce low complexity controllers that could be implemented with limited computation. The theory is well developed for linear systems and is now used to produce models of varying levels of complexity with bounds on the input/output errors corresponding to different approximations. Model reduction for general classes of nonlinear systems is an important unsolved problem.

The impact of modeling on engineering and control over the past 50 years has been profound. Today, entire products are designed using only models, with the first prototype being a fully working system. Doing this requires an enormous amount of infrastructure in simulation tools, detailed physical models, and experience in using models. Moving forward, this infrastructure becomes even more important as suppliers of components compete and sell their products based on detailed models of their systems which implement the specifications of their products sometimes before the system has even been built.

Analysis

Control theory has developed an extensive collection of theory and software tools for analysis of feedback systems. These tools include stability analysis for both linear and nonlinear systems, performance measures for input/output systems, and evaluation of robustness. For robustness analysis, the tools are particularly sophisticated in the case of linear dynamical systems, where it is possible to analyze the stability and performance of the system in the presence of external disturbances, parametric uncertainty

(e.g., unknown values of parameters such as mass or reaction rates), and unmodeled dynamics. In the case of unmodeled dynamics, one can even reason about the performance of a system without knowing the precise behavior of every subsystem, a very powerful concept.

In almost all cases, the theory used for analysis of feedback systems is implemented in software tools that can be used in computer aided design environments. Two very common environments for this analysis are MATLAB and Mathematica. In both cases, toolboxes are available that implement the common calculations described in this text (and many more) and these have become indispensable aides for modern design. More sophisticated tools, capable of constructing and analyzing very complex hierarchical models, are also available for more discipline-specific environments.

An important point to remember about systems analysis is that it relies on models to describe the behavior of the system. In the simplest case, these models are simulated to provide information about how the system will respond to a given set of initial conditions, disturbances, and environment. But modern computational tools can do much more than just simulate the system, and can provide very sophisticated analyses that answer questions about the parametric behavior of systems, tradeoffs between different design factors, and even provide certificates (proofs) of performance. These tools are very well developed for linear systems, but recent advances in nonlinear analysis are quickly extending these results to larger and larger classes of systems.

Synthesis

In addition to tools for analysis of feedback systems, theory and software has also been developed for synthesizing feedback systems. As an example, consider the control system depicted in Figure 1.3 on page 5. Given models of the process to be controlled, it is today possible to automatically synthesize a control algorithm that satisfies a given performance specification. A typical approach to doing this would involve first obtaining a nonlinear model for the process that captured the key behavior that one was interested in. This model would then be “linearized” around a desired operating point (this is described in Chapter 5) and a performance condition specified (usually as a function that one wishes to minimize). Given the linear model and the control specification, a feedback law can be computed that is the optimal law for the given specification.

Modern implementation environments continue by allowing this control algorithm to be “autocoded”, so that programming code implementing the

control logic is automatically generated. This has the advantage that the code generator can be carefully verified so that the resulting algorithm is correct (as opposed to hand coding the algorithm, which can lead to errors in translation). This autocoded control logic is then downloaded to a dedicated computing platform with the proper interfaces to the hardware and implemented. In addition to simple feedback algorithms, most modern control environments allow complex decision-making logic to be constructed via block diagrams and this is also automatically compiled and downloaded to a computer that is connected to the hardware.

This mechanism for generating control algorithms directly from specifications has vastly improved the productivity of control engineers and is now standard practice in many application areas. It also provides a clear framework in which new advances, such as real-time, optimization-based control, can be transitioned to applications quickly and efficiently through the generation of standard toolboxes.

1.7 Further Reading

The material in this section draws heavily from the report of the Panel on Future Directions on Control, Dynamics, and Systems [Mur03]. Several recent papers and reports highlighted successes of control [NS99] and new vistas in control [Bro00, Kum01]. A fascinating examination of some of the early history of control in the United States has been written by Mindell [Min02]. Additional historical overviews of the field have been prepared by Bennett [Ben86a, Ben86b] and Mayr [May70], which go back as far as the 1800s. A popular book that describes many control concepts across a wide range of disciplines is “Out of Control” by Kelly [Kel94].

There are many textbooks available that describe control systems in the context of specific disciplines. For engineers, the textbooks by Franklin, Powell and Emami-Naeni [FPEN05], Dorf and Bishop [DB04], Kuo and Golnaraghi [KG02], and Seborg, Edgar and Mellichamp [SEM03] are widely used. A number of books look at the role of dynamics and feedback in biological systems, including Milhorn [Mil66] (now out of print), Murray [Mur04] and Ellner and Guckenheimer [EG05]. There is not yet a textbook targeted specifically at the physics community, although a recent tutorial article by Bechhoefer [Bec05] covers many specific topics of interest to that community.

1.8 Exercises

1. Identify 5 feedback systems that you encounter in your everyday environment. For each system, identify the sensing mechanism, actuation mechanism, and control law. Describe the uncertainty that the feedback system provides robustness with respect to and/or the dynamics that are changed through the use of feedback.
2. Perform the following experiment and explain your results: Holding your head still, move your right or left hand back and forth in front of your face, following it with your eyes. Record how quickly you can move your hand before you begin to lose track of your hand. Now hold your hand still and move your head back and forth, once again recording how quickly you can move before loosing track.
3. Balance yourself on one foot with your eyes closed for 15 seconds. Using Figure 1.3 as a guide, describe the control system responsible for keeping you from falling down. Note that the “controller” will differ from the diagram (unless you are an android reading this in the far future).
4. Download the MATLAB code used to produce Figure 1.11 from the companion web site. Using trial and error, change the parameters of the control law so that the overshoot in the speed is not more than 1 m/s for a vehicle with mass $m = 1000\text{kg}$.
5. We say that an system with a constant input reaches “steady state” if the output of the system approaches a constant value as time increases. Show that a controller with integral action, such as those given in equations (1.4) and (1.5), gives zero error if the closed loop system reaches steady state.

Chapter 2

System Modeling

... I asked Fermi whether he was not impressed by the agreement between our calculated numbers and his measured numbers. He replied, “How many arbitrary parameters did you use for your calculations?” I thought for a moment about our cut-off procedures and said, “Four.” He said, “I remember my friend Johnny von Neumann used to say, with four parameters I can fit an elephant, and with five I can make him wiggle his trunk.”

Freeman Dyson on describing the predictions of his model for meson-proton scattering to Enrico Fermi in 1953 [Dys04].

A model is a precise representation of a system’s dynamics used to answer questions via analysis and simulation. The model we choose depends on the questions we wish to answer, and so there may be multiple models for a single physical system, with different levels of fidelity depending on the phenomena of interest. In this chapter we provide an introduction to the concept of modeling, and provide some basic material on two specific methods that are commonly used in feedback and control systems: differential equations and difference equations.

2.1 Modeling Concepts

A model is a mathematical representation of a physical, biological or information system. Models allow us to reason about a system and make predictions about how a system will behave. In this text, we will mainly be interested in models of dynamical systems describing the input/output behavior of systems and often in so-called “state space” form.

Roughly speaking, a dynamical system is one in which the effects of actions do not occur immediately. For example, the velocity of a car does not

change immediately when the gas pedal is pushed nor does the temperature in a room rise instantaneously when a heater is switched on. Similarly, a headache does not vanish right after an aspirin is taken, requiring time to take effect. In business systems, increased funding for a development project does not increase revenues in the short term, although it may do so in the long term (if it was a good investment). All of these are examples of dynamical systems, in which the behavior of the system evolves with time.

Dynamical systems can be viewed in two different ways: the internal view or the external view. The internal view attempts to describe the internal workings of the system and originates from classical mechanics. The prototype problem was describing the motion of the planets. For this problem it was natural to give a complete characterization of the motion of all planets. This involves careful analysis of the effects of gravitational pull and the relative positions of the planets in a system. A major tool in the internal view is differential equations.

The other view on dynamics originated in electrical engineering. The prototype problem was to describe electronic amplifiers, where it was natural to view an amplifier as a device that transforms input voltages to output voltages and disregard the internal details of the amplifier. This resulted in the input/output, or external, view of systems. For this type of model, much more emphasis is placed on how a system is driven through and external input and how the system evolves in terms of a fixed set of sensed (or output) measurements. A major tool in the external view is the frequency response.

The two different views have been amalgamated in control theory. Models based on the internal view are called internal descriptions, state models, or white box models. The external view is associated with names such as external descriptions, input/output models or black box models. In this book we will mostly use the terms state models and input/output models.

In the remainder of this section we provide an overview of some of the key concepts in modeling. The mathematical details introduced here are explored more fully in the remainder of the chapter.

The Heritage of Mechanics

The study of dynamics originated in the attempts to describe planetary motion. The basis was detailed observations of the planets by Tycho Brahe and the results of Kepler, who found empirically that the orbits of the planets could be well described by ellipses. Newton embarked on an ambitious program to try to explain why the planets move in ellipses and he found that

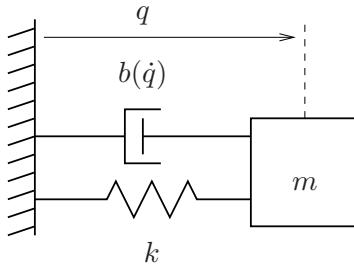


Figure 2.1: Mass and spring system, with nonlinear damping. The position of the mass is denoted by q , with $q = 0$ corresponding to the rest position of the spring.

the motion could be explained by his law of gravitation and the formula that force equals mass times acceleration. In the process he also invented calculus and differential equations. Newton's result was the first example of the idea of reductionism, i.e. that seemingly complicated natural phenomena can be explained by simple physical laws. This became the paradigm of natural science for many centuries.

One of the triumphs of Newton's mechanics was the observation that the motion of the planets could be predicted based on the current positions and velocities of all planets. It was not necessary to know the past motion. The *state* of a dynamical system is a collection of variables that characterizes the motion of a system completely for the purpose of predicting future motion. For a system of planets the state is simply the positions and the velocities of the planets. We call the set of all possible states the *state space*.

A common class of mathematical models for dynamical systems is ordinary differential equations (ODEs). In mechanics, one of the simplest such differential equation is that of a mass and spring system, with damping:

$$m\ddot{q} + c(\dot{q}) + kq = 0. \quad (2.1)$$

This system is illustrated in Figure 2.1. The variable $q \in \mathbb{R}$ represents the position of the mass m with respect to its rest position. We use the notation \dot{q} to denote the derivative of q with respect to time (i.e., the velocity of the mass) and \ddot{q} to represent the second derivative (acceleration). The spring is assumed to be a satisfy Hooke's law, which says that the force is proportional to the displacement. The friction element (damper) is taken as a nonlinear function, $c(\dot{q})$, which can model effects such as stiction and viscous drag. The position q and velocity \dot{q} represent the instantaneous “state” of the system. We say that this system is a *second order system* since the dynamics depend on the second derivative of q .

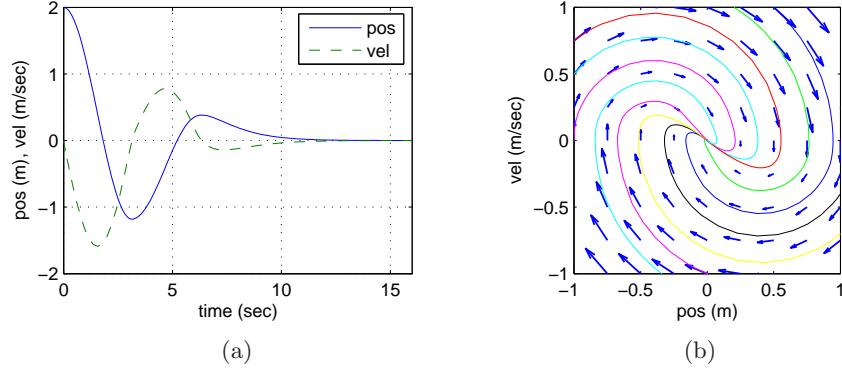


Figure 2.2: Illustration of a state model. A state model gives the rate of change of the state as a function of the state. The plot on the left shows the evolution of the state as a function of time. The plot on the right shows the evolution of the states relative to each other, with the velocity of the state denoted by arrows.

The evolution of the position and velocity can be described using either a time plot or a phase plot, both of which are shown in Figure 2.2. The time plot, on the left, shows the values of the individual states as a function of time. The phase plot, on the right, shows the *vector field* for the system, which gives the state velocity (represented as an arrow) at every point in the state space. In addition, we have superimposed the traces of some of the states from different conditions. The phase plot gives a strong intuitive representation of the equation as a vector field or a flow. While systems of second order (two states) can be represented in this way, it is unfortunately difficult to visualize equations of higher order using this approach.

The ideas of dynamics and state have had a profound influence on philosophy, where they inspired the idea of predestination. If the state of a natural system is known at some time, its future development is completely determined. However, we know that for many natural systems it can be impossible to make predictions of the detailed behavior of the system far into the future. This problem has been resolved in part by the advent of the theory of chaos. As the development of dynamics continued in the 20th century, it was discovered that there are simple dynamical systems that are extremely sensitive to initial conditions; small perturbations may lead to drastic changes in the behavior of the system. The behavior of the system could also be extremely complicated. The emergence of chaos thus resolved the problem of determinism: even if the solution is uniquely determined by the initial conditions, in practice it can be impossible to make predictions

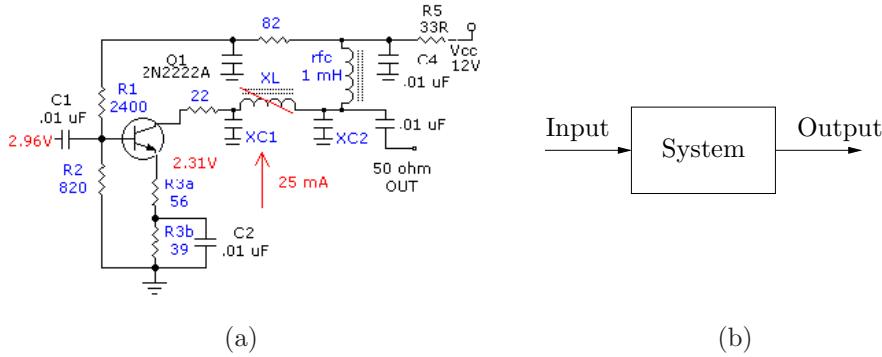


Figure 2.3: Illustration of the input/output view of a dynamical system. The figure on the left shows a detailed circuit diagram for an electronic amplifier; the one on the right its representation as a block diagram.

because of the sensitivity of these initial conditions.

The differential equation (2.1) is called an autonomous system because there are no external influences. Such a model is natural to use for celestial mechanics, because it is difficult to influence the motion of the planets. In many examples, it is useful to model the effects of external disturbances or controlled forces on the system. One way to capture this is to replace equation (2.1) by

$$m\ddot{q} + c(\dot{q}) + kq = u \quad (2.2)$$

where u represents the effect of external influences. The model (2.2) is called a *forced* or *controlled differential equation*. The model implies that the rate of change of the state can be influenced by the *input*, $u(t)$. Adding the input makes the model richer and allows new questions to be posed. For example, we can examine what influence external disturbances have on the trajectories of a system. Or, in the case when the input variable is something that can be modulated in a controlled way, we can analyze whether it is possible to “steer” the system from one point in the state space to another through proper choice of the input.

The Heritage of Electrical Engineering

A very different view of dynamics emerged from electrical engineering, where the design of electronic amplifiers led to a focus on input/output behavior. A system was considered as a device that transformed inputs to outputs, as illustrated in Figure 2.3. Conceptually an input/output model can be

viewed as a giant table of inputs and outputs. Given an input signal $u(t)$, the model should produce the resulting output $y(t)$.

The input/output framework is used in many engineering systems since it allows us to decompose a problem into individual components, connected through their inputs and outputs. Thus, we can take a complicated system such as a radio or a television and break it down into manageable pieces, such as the receiver, demodulator, amplifier and speakers. Each of these pieces has a set of inputs and outputs and, through proper design, these components can be interconnected to form the entire system.

The input/output view is particularly useful for the special class of *linear, time-invariant* systems. This term will be defined more carefully later in this chapter, but roughly speaking a system is linear if the superposition (addition) of two inputs yields an output which is the sum of the outputs that would correspond to individual inputs being applied separately. A system is time-invariant if the output response for a given input does not depend on when that input is applied. (Chapter 5 provides a much more detailed analysis of linear systems.)

Many electrical engineering systems can be modeled by linear, time-invariant systems and hence a large number of tools have been developed to analyze them. One such tool is the *step response*, which describes the relationship between an input that changes from zero to a constant value abruptly (a “step” input) and the corresponding output. As we shall see in the latter part of the text, the step response is extremely useful in characterizing the performance of a dynamical system and it is often used to specify the desired dynamics. A sample step response is shown in Figure 2.4a.

Another possibility to describe a linear, time-invariant system is to represent the system by its response to sinusoidal input signals. This is called the *frequency response* and a rich powerful theory with many concepts and strong, useful results has emerged. The results are based on the theory of complex variables and Laplace transforms. The basic idea behind the frequency response is that we can completely characterize the behavior of a system by its steady state response to sinusoidal inputs. Roughly speaking, this is done by decomposing any arbitrary signal into a linear combination of sinusoids (e.g., by using the Fourier transform) and then using linearity to compute the output by combining the response to the individual frequencies. A sample frequency response is shown in Figure 2.4b.

The input/output view lends itself naturally to experimental determination of system dynamics, where a system is characterized by recording its response to a particular input, e.g. a step or a sweep across a range of frequencies.

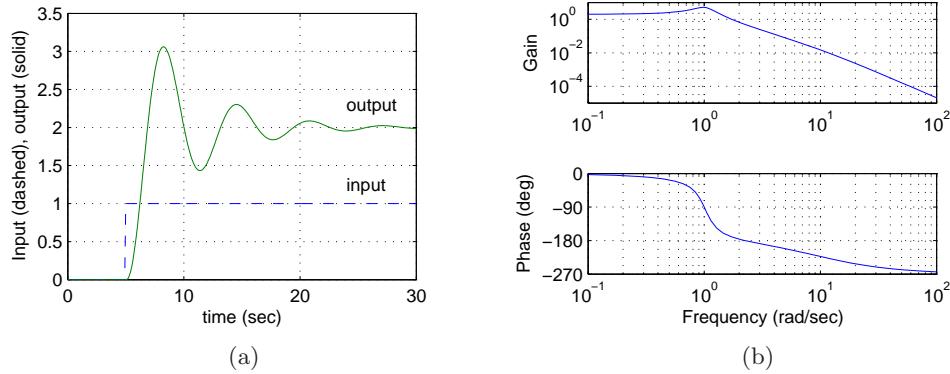


Figure 2.4: Input/output response of a linear system. The step response (a) shows the output of the system due to an input that changes from 0 to 1 at time $t = 5$ s. The frequency response (b) shows the amplitude gain and phase change due to a sinusoidal input at different frequencies.

The Control View

When control theory emerged as a discipline in the 1940s, the approach to dynamics was strongly influenced by the electrical engineering (input/output) view. A second wave of developments in control, starting in the late 1950s, was inspired by mechanics, where the state space perspective was used. In addition, there was a shift over this period from autonomous systems (with no inputs) to those where inputs to the process were available to modify the dynamics of the process. The emergence of space flight is a typical example, where precise control of the orbit is essential.

The models from mechanics were thus modified to include external control forces and sensors, and more general forms of equations were considered. In control, the model given by equation (2.2) was replaced by

$$\begin{aligned} \frac{dx}{dt} &= f(x, u) \\ y &= h(x, u), \end{aligned} \tag{2.3}$$

where x is a vector of “state” variables, u is a vector of control signals, and y a vector of measurements. As before, \dot{x} represents the derivative of x with respect to time, now considered as a vector, and f and h are mappings of their arguments to vectors of the appropriate dimension.

This viewpoint has added to the richness of the classical problems and led to many new concepts. For example it is natural to ask if possible states x can be reached with the proper choice of u (reachability) and if

the measurement y contains enough information to reconstruct the state (observability) (these topics will be addressed in greater detail in Chapters 6 and 7).

A final development in building the control point of view was the emergence of disturbance and model uncertainty as critical elements in the theory. The simple way of modeling disturbances as deterministic signals like steps and sinusoids has the drawback that such signals can be predicted precisely. A much more realistic approach is to model disturbances like random signals. This viewpoint gives a natural connection between prediction and control. The dual views of input/output representations and state space representations are particularly useful when modeling uncertainty, since state models are very convenient to describe a nominal model but uncertainties are easier to describe using input/output models (often via a frequency response description). Uncertainty will be a constant theme throughout the text and will be studied in particular detail in Chapter 12.

An interesting experience in design of control system is that feedback systems can often be analyzed and designed based on comparatively simple models. The reason for this is the inherent robustness of feedback systems. However, other uses of models may require more complexity and more accuracy. One example is feedforward control strategies, where one uses a model to pre-compute the inputs that will cause the system to respond in a certain way. Another area is in system validation, where one wishes to verify that the detailed response of the system performs as it was designed. Because of these different uses of models, it is therefore common to use a hierarchy of models having different complexity and fidelity.

Multi-Domain Modeling

Modeling is an essential element of many disciplines, but traditions and methods from individual disciplines in can be very different from each other, as illustrated by the previous discussion of mechanical and electrical engineering. A difficulty in systems engineering is that it is frequently necessary to deal with heterogeneous systems from many different domains, including chemical, electrical, mechanical and information systems.

To deal with such multi-domain systems, we start by cutting a system into smaller subsystems. Each subsystem is modeled either by balance equations for mass, energy, and momentum or by appropriate descriptions of the information processing in the subsystem. The behavior at the interfaces is captured by describing how the variables of the subsystem behave when the subsystems are interconnected. These interfaces often act by constraining

variables within the individual subsystems to be equal (such as mass, energy or momentum fluxes). The complete model is then obtained by combining the descriptions of the subsystems and the interfaces.

Using this methodology it is possible to build up libraries of subsystems that correspond to physical, chemical and informational components. The procedure mimics the engineering approach where systems are built from subsystems that are themselves built from smaller components. As experience is gained, the components and their interfaces can be standardized and collected in model libraries. In practice, it takes several iterations to obtain a good library that can be reused for many applications.

State models or ordinary differential equations are not suitable for component based modeling of this form because states may disappear when components are connected. This implies that the internal description of a component may change when it is connected to other components. As an illustration we consider two capacitors in an electrical circuit. Each capacitor has a state corresponding to the voltage across the capacitors, but one of the states will disappear if the capacitors are connected in parallel. A similar situation happens with two rotating inertias, each of which are individually modeled using the the angle of rotation and the angular velocity. Two states will disappear when the inertias are joined by a rigid shaft.

This difficulty can be avoided by replacing differential equations by *differential algebraic equations*, which have the form

$$F(z, \dot{z}) = 0$$

where $z \in \mathbb{R}^n$. A simple special case is

$$\dot{x} = f(x, y), \quad g(x, y) = 0 \tag{2.4}$$

where $z = (x, y)$ and $F = (\dot{x} - f(x, y), g(x, y))$. The key property is that the derivative \dot{z} is not given explicitly and there may be pure algebraic relations between the components of the vector z .

A differential equation is an *imperative* description: if it tells how to calculate \dot{x} from x . The differential algebraic equation is a *declarative* description: it gives a relation between z and \dot{z} , without explicitly describing how to compute \dot{z} . The model (2.4) captures the examples of the parallel capacitors and the linked rotating inertias. For example, when two capacitors are connected we simply include the algebraic equation expressing that the voltages across the capacitors are the same.

A practical difficulty with component-based declarative descriptions is a that the model may contain many auxiliary variables. This was a severe limitation for hand calculations, but fortunately there are methods for symbolic

calculation that can be used to eliminate the auxiliary variables. Symbolic calculations can also be used to transform and simplify the models.

Modelica is a language that has been developed to support component based modeling. Differential algebraic equations are used as the basic description, object-oriented programming is used to structure the models. Modelica is used to model the dynamics of technical systems in domains such as, mechanical, electrical, thermal, hydraulic, thermo-fluid, and control subsystems. Modelica is intended to serve as a standard format so that models arising in different domains can be exchanged between tools and users. A large set of free and commercial *Modelica* component libraries are available and are utilized by a growing number of people in industry, research and academia. For further information about *Modelica*, see <http://www.modelica.org>.

2.2 State Space Models

In this section we introduce the two primary forms of models that we use in this text: differential equations and difference equations. Both of these make use of the notions of state, inputs, outputs and dynamics to describe the behavior of a system.

Ordinary Differential Equations

The state of a system is a collection of variables that summarize the past of a system for the purpose of prediction the future. For an engineering system the state is composed of the variables required to account for storage of mass, momentum and energy. A key issue in modeling is to decide how accurately this storage has to be represented. The state variables are gathered in a vector, $x \in \mathbb{R}^n$, called the *state vector*. The control variables are represented by another vector $u \in \mathbb{R}^p$ and the measured signal by the vector $y \in \mathbb{R}^q$. A system can then be represented by the differential equation

$$\begin{aligned}\frac{dx}{dt} &= f(x, u) \\ y &= h(x, u),\end{aligned}\tag{2.5}$$

where $f : \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}^n$ and $h : \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}^q$ are smooth mappings. We call a model of this form a *state space model*.

The dimension of the state vector is called the order of the system. The system is called time-invariant because the functions f and g do not

depend explicitly on time t . It is possible to have more general time-varying systems where the functions do depend on time. The model thus consists of two functions: the function f gives the velocity of the state vector as a function of state x and control u , and the function g gives the measured values as functions of state x and control u .

A system is called linear if the functions f and g are linear in x and u . A linear state space system can thus be represented by

$$\begin{aligned}\frac{dx}{dt} &= Ax + Bu \\ y &= Cx + Du,\end{aligned}$$

where A , B , C and D are constant matrices. Such a system is said to be linear and time-invariant, or LTI for short. The matrix A is called the *dynamics matrix*, the matrix B is called the *control matrix*, the matrix C is called the *sensor matrix* and the matrix D is called the *direct term*. Frequently systems will not have a direct term, indicating that the control signal does not influence the output directly.

A different form of linear differential equations, generalizing the second order dynamics from mechanics, is an equation of the form

$$\frac{d^n q}{dt^n} + a_1 \frac{d^{n-1}q}{dt^{n-1}} + \cdots + a_n q = u, \quad (2.6)$$

where t is the independent (time) variable, $q(t)$ is the dependent (output) variable, and $u(t)$ is the input. This system is said to be an n th order system. This system can be converted into state space form by defining

$$x = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} d^{n-1}q/dt^{n-1} \\ \vdots \\ dq/dt \\ q \end{pmatrix}$$

and the state space equations become

$$\frac{d}{dt} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_{n-1} \\ x_n \end{pmatrix} = \begin{pmatrix} -a_1 x_1 - \cdots - a_n x_n \\ x_1 \\ x_2 \\ \vdots \\ x_{n-1} \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

$$y = x_n.$$

With the appropriate definition of A , B , C and D , this equation is in linear state space form.

An even more general system is obtained by letting the output be a linear combination of the states of the system, i.e.

$$y = b_1x_1 + b_2x_2 + \cdots + b_nx_n + du$$

This system can be modeled in state space as

$$\frac{d}{dt} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_{n-1} \\ x_n \end{pmatrix} = \begin{pmatrix} -a_1 & -a_2 & \dots & -a_n \\ 1 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & \dots & 0 \\ \vdots & & & \ddots & \\ 0 & & & 1 & 0 \end{pmatrix} x + \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \\ 0 \end{pmatrix} u$$

$$y = \begin{pmatrix} b_1 & b_2 & \dots & b_n \end{pmatrix} x + du.$$

This particular form of a linear state space system is called reachable canonical form and will be studied in more detail in later chapters.

Example 2.1 (Balance systems). An example of a class of systems that can be modeled using ordinary differential equations is the class of “balance systems.” A balance system is a mechanical system in which the center of mass is balanced above a pivot point. Some common examples of balance systems are shown in Figure 2.5. The Segway human transportation system (Figure 2.5a) uses a motorized platform to stabilize a person standing on top of it. When the rider leans forward, the vehicle propels itself along the ground, but maintains its upright position. Another example is a rocket (Figure 2.5b), in which a gimbaled nozzle at the bottom of the rocket is used to stabilize the body of the rocket above it. Other examples of balance systems include humans or other animals standing upright or a person balancing a stick on their hand.

Figure 2.5c shows a simplified diagram for a balance system. To model this system, we choose state variables that represent the position and velocity of the base of the system, p and \dot{p} , and the angle and angular rate of the structure above the base, θ and $\dot{\theta}$. We let F represent the force applied at the base of the system, assumed to be in the horizontal direction (aligned with p), and choose the position and angle of the system as outputs. With this set of definitions, the dynamics of the system can be computed using Newtonian mechanics and has the form

$$\begin{pmatrix} (M+m) & -ml \cos \theta \\ -ml \cos \theta & (J+ml^2) \end{pmatrix} \begin{pmatrix} \ddot{p} \\ \ddot{\theta} \end{pmatrix} + \begin{pmatrix} c\dot{p} + ml \sin \theta \dot{\theta}^2 \\ mgl \sin \theta + \gamma \dot{\theta} \end{pmatrix} = \begin{pmatrix} F \\ 0 \end{pmatrix}, \quad (2.7)$$

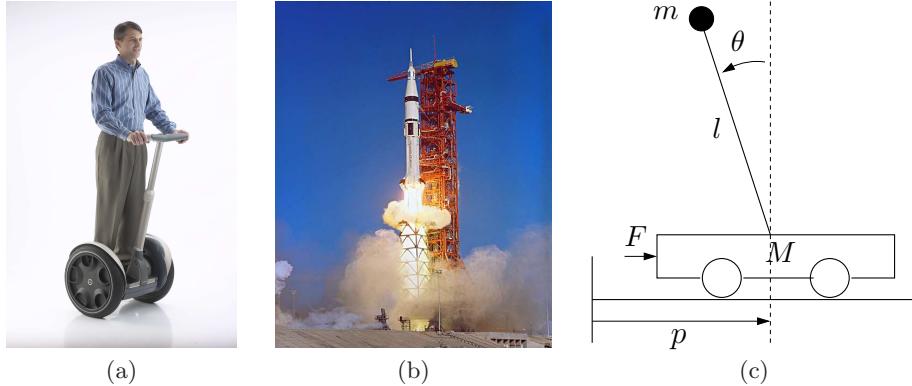


Figure 2.5: Balance systems: (a) Segway human transportation systems, (b) Saturn rocket and (c) simplified diagram. Each of these examples uses forces at the bottom of the system to keep it upright.

where M is the mass of the base, m and J are the mass and moment of inertia of the system to be balanced, l is the distance from the base to the center of mass of the balanced body, c and γ are coefficients of viscous friction, and g is the acceleration due to gravity.

We can rewrite the dynamics of the system in state space form by defining the state as $x = (p, \theta, \dot{p}, \dot{\theta})$, the input as $u = F$ and the output as $y = (p, \theta)$. If we define the total mass and total inertia as

$$M_t = M + m \quad J_t = J + ml^2,$$

respectively, the equations of motion then become

$$\begin{aligned} \frac{d}{dt} \begin{pmatrix} p \\ \theta \\ \dot{p} \\ \dot{\theta} \end{pmatrix} &= \begin{pmatrix} \dot{p} \\ \dot{\theta} \\ \frac{-ml \sin \theta \dot{\theta}^2 + mg(ml^2/J_t) \sin \theta \cos \theta - c\dot{p} + u}{M_t - m(ml^2/J_t) \cos^2 \theta} \\ \frac{-ml^2 \sin \theta \cos \theta \dot{\theta}^2 + M_t g l \sin \theta + cl \cos \theta \dot{p} + \gamma \dot{\theta} + l \cos \theta u}{J_t(M_t/m) - m(l \cos \theta)^2} \end{pmatrix} \\ y &= \begin{pmatrix} p \\ \theta \end{pmatrix}. \end{aligned}$$

In many cases, the angle θ will be very close to 0 and hence we can approximate $\sin \theta \approx \theta$ and $\cos \theta \approx 1$. Furthermore, if $\dot{\theta}$ is small, we can ignore quadratic and higher terms in $\dot{\theta}$. Substituting these approximations

into our equations, we see that we are left with a *linear state space equation*

$$\begin{aligned} \frac{d}{dt} \begin{pmatrix} p \\ \theta \\ \dot{p} \\ \dot{\theta} \end{pmatrix} &= \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & \frac{m^2 l^2 g}{\mu} & \frac{-c J_t}{\mu} & 0 \\ 0 & \frac{M_t m g l}{\mu} & \frac{c l m}{\mu} & \frac{\gamma m}{\mu} \end{pmatrix} \begin{pmatrix} p \\ \theta \\ \dot{p} \\ \dot{\theta} \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ \frac{J_t}{\mu} \\ \frac{l m}{\mu} \end{pmatrix} u \\ y &= \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix} x, \end{aligned}$$

where $\mu = M_t J_t - m^2 l^2 g$. ∇

Example 2.2 (Inverted pendulum). A variation of this example is one in which the location of the base, p , does not need to be controlled. This happens, for example, if we are only interested in stabilizing a rocket's upright orientation, without worrying about the location of base of the rocket. The dynamics of this simplified system is given by

$$\begin{aligned} \frac{d}{dt} \begin{pmatrix} \theta \\ \dot{\theta} \end{pmatrix} &= \begin{pmatrix} \dot{\theta} \\ \frac{m g l}{J_t} \sin \theta - \frac{\gamma}{J_t} \dot{\theta} + \frac{l}{J_t} \cos \theta u \end{pmatrix} \\ y &= \begin{pmatrix} 1 & 0 \end{pmatrix} x, \end{aligned} \tag{2.8}$$

where γ is the coefficient of rotational friction, $J_t = J + ml^2$ and u is the force applied at the base. This system is referred to as an *inverted pendulum*. ∇

Difference Equations

In some circumstances, it is more natural to describe the evolution of a system at discrete instants of time rather than continuously in time. If we refer to each of these times by an integer $k = 0, 1, 2, \dots$, then we can ask how the state of the system changes for each k . Just as in the case of differential equations, we shall define the state to be those sets of variables that summarize the past of the system for the purpose of predicting its future. Systems described in this manner are referred to as *discrete time systems*.

The evolution of a discrete time system can be written in the form

$$\begin{aligned} x_{k+1} &= f(x_k, u_k) \\ y_k &= h(x_k, u_k) \end{aligned} \tag{2.9}$$

where $x_k \in \mathbb{R}^n$ is the state of the system at “time” k (an integer), $u_k \in \mathbb{R}^m$ is the input and $y_k \in \mathbb{R}^p$ is the output. As before, f and h are smooth mappings of the appropriate dimension. We call equation (2.9) a *difference equation* since it tells us now x_{k+1} differs from x_k . The state x_k can either be a scalar or a vector valued quantity; in the case of the latter we use superscripts to denote a particular element of the state vector: x_k^i is the value of the i th state at time k .

Just as in the case of differential equations, it will often be the case that the equations are linear in the state and input, in which case we can write the system as

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k \\ y_k &= Cx_k + Du_k. \end{aligned}$$

As before, we refer to the matrices A , B , C and D as the dynamics matrix, the control matrix, the sensor matrix and the direct term. The solution of a linear difference equation with initial condition x_0 and input u_1, \dots, u_T is given by

$$\begin{aligned} x_k &= A^k x_0 + \sum_{i=0}^k A^i B u_i \\ y_k &= CA^k x_0 + \sum_{i=0}^k CA^i B u_i + Du_k \end{aligned} \tag{2.10}$$

Example 2.3 (Predator prey). As an example of a discrete time system, we consider a simple model for a predator prey system. The predator prey problem refers to an ecological system in which we have two species, one of which feeds on the other. This type of system has been studied for decades and is known to exhibit very interesting dynamics. Figure 2.6 shows a historical record taken over 50 years in the population of lynxes versus hares [Mac37]. As can be seen from the graph, the annual records of the populations of each species are oscillatory in nature.

A simple model for this situation can be constructed using a discrete time model by keeping track of the rate of births and deaths of each species. Letting H represent the population of hares and L represent the population of lynxes, we can describe the state in terms of the populations at discrete periods of time. Letting k be the discrete time index (e.g., the day number), we can write

$$\begin{aligned} H_{k+1} &= H_k + b_r(u)H_k - aL_k H_k \\ L_{k+1} &= L_k - d_f L_k + aL_k H_k, \end{aligned} \tag{2.11}$$

where $b_r(u)$ is the hare birth rate per unit period and as a function of the

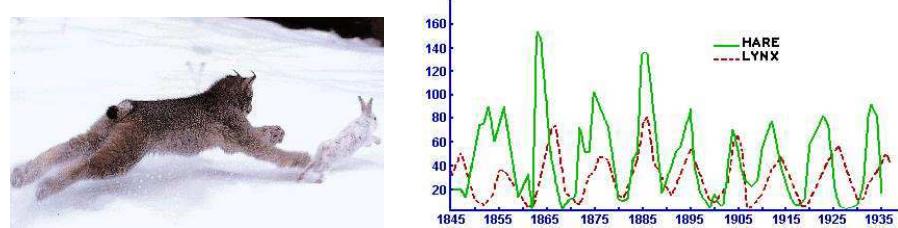


Figure 2.6: Predator versus prey. The photograph shows a Canadian lynx and a snowshoe hare. The graph on the right shows the populations of hares and lynxes between 1845 and 1935 [MS93]. Photograph courtesy Rudolfo's Usenet Animal Pictures Gallery.

food supply u , d_f is the lynx death rate, and a is the interaction term. The interaction term models both the rate at which lynxes eat hares and the rate at which lynxes are produced by eating hares. This model makes many simplifying assumptions—such as the fact that hares never die of old age or causes other than being eaten—but it often is sufficient to answer basic questions about the system.

To illustrate the usage of this system, we can compute the number of lynxes and hares from some initial population. This is done by starting with $x_0 = (H_0, L_0)$ and then using equation (2.11) to compute the populations in the following year. By iterating this procedure, we can generate the population over time. The output of this process for a specific choice of parameters and initial conditions is shown in Figure 2.7. While the details of the simulation are different from the experimental data (to be expected given the simplicity of our assumptions), we see qualitatively similar trends

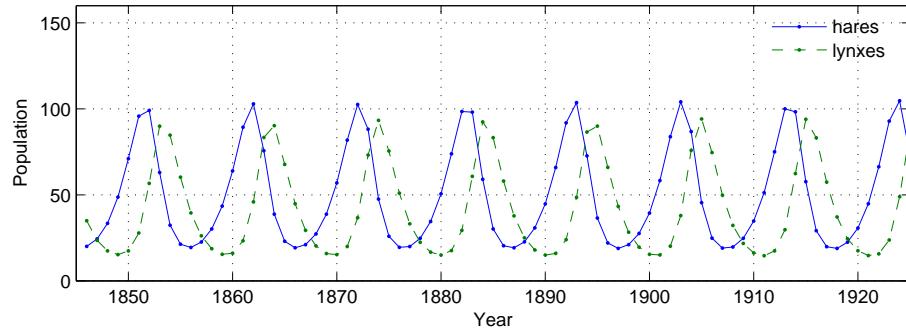


Figure 2.7: A simulation of the predator-prey model with $a = 0.007$, $b_r(u) = 0.7$ and $d = 0.5$.

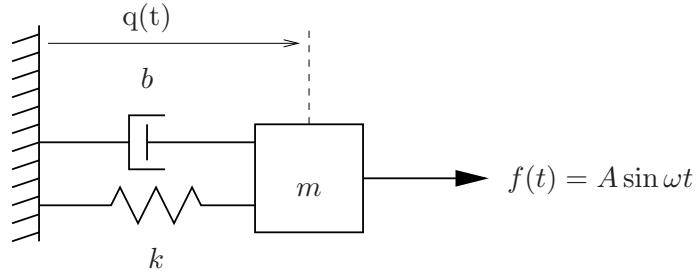


Figure 2.8: A driven mass spring system, with damping.

and hence we can use the model to help explore the dynamics of the system.

▽

Simulation and Analysis

State space models can be used to answer many questions. One of the most common, as we saw in the previous examples, is to predict the evolution of the system state from a given initial condition. While for simple models this can be done in closed form, more often it is accomplished through computer simulation. One can also use state space models to analyze the overall behavior of the system, without making direct use of simulation. For example, we can ask whether a system that is perturbed from an equilibrium configuration will return to that configuration; such a system is said to be *stable*. While one could in principle answer this question by simulating many trajectories, it turns out that we can use analysis techniques to answer this much more easily and completely. We illustrate some of the concepts of simulation and analysis through a series of examples; a more formal treatment is provided in the next chapter.

Example 2.4 (Damped spring mass system). Consider again the damped spring mass system from Section 2.1, but this time with an external force applied, as shown in Figure 2.8. We wish to predict the motion of the system for a periodic forcing function, with a given initial condition, and determine the amplitude, frequency, and decay rate of the resulting motion.

We choose to model the system using a linear ordinary differential equation. Using Hooke's law to model the spring and assuming that the damper exerts a force that is proportional to the velocity of the system, we have

$$m\ddot{q} + c\dot{q} + kq = f(t), \quad (2.12)$$

where m is the mass, q is the displacement of the mass, c is the coefficient of viscous friction, k is the spring constant and f is the applied force. In state space form, using $x = (q, \dot{q})$ as the state, $u = f$ as the input and choosing $y = q$ as the output, we have

$$\begin{aligned}\frac{dx}{dt} &= \begin{pmatrix} x_2 \\ -\frac{c}{m}x_2 - \frac{k}{m}x_1 + u/m \end{pmatrix} \\ y &= x_1.\end{aligned}$$

We see that this is a linear, second order differential equation with one input and one output.

We now wish to compute the response of the system to an input of the form $u = A \sin \omega t$. Although it is possible to solve for the response analytically, we instead make use of computational approach that does not rely on the specific form of this system. Consider the general state space system

$$\frac{dx}{dt} = f(x, u).$$

Given the state x at time t , we can approximate the value of the state at a short time $\epsilon > 0$ later by assuming that x and u are constant over the interval ϵ . This gives us that

$$x(t + \epsilon) = x(t) + \epsilon f(x(t), u(t)). \quad (2.13)$$

Iterating this equation, we can thus solve for x as a function of time. This approximation is known as Euler integration, and is in fact a difference equation if we let ϵ represent the time increment and write $x_k = x(k\epsilon)$. Although modern simulation tools use much more accurate methods than Euler integration, it still illustrates some of the basic tradeoffs.

Returning to our specific example, Figure 2.9 shows the results of computing $x(t)$ using equation (2.13), along with the analytical computation. We see that as h gets smaller, the compute solution converges to the exact solution. The form of the solution is also worth noticing: after an initial transient, the system settles into a period motion that is the same frequency as the input term, but at a different amplitude and slightly shifted in time. The portion of the response after the transient is called the *steady state response* to the input. ∇

In addition to performing simulations, models can also be used to answer other types of questions. Two that are central to the methods described in this text are stability of an equilibrium point and the input/output frequency

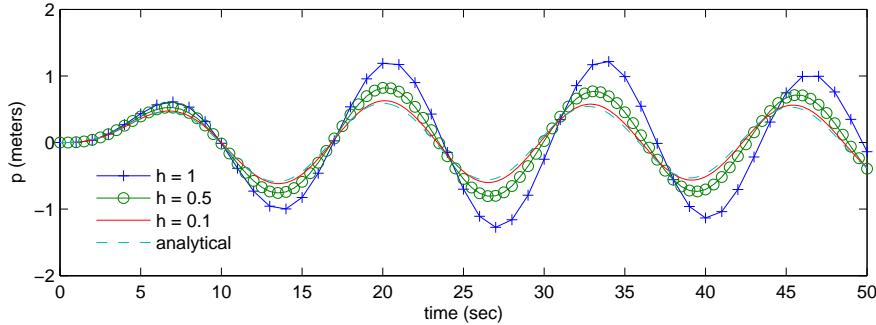


Figure 2.9: Simulation of the forced spring mass system with different simulation time constants.

response. We illustrate these two computations through the examples below, and return to the general computations in later chapters.

Example 2.5 (Stability). Consider the damped spring mass system given in the previous example, but with no input forcing. The equations of motion are given by

$$\frac{dx}{dt} = \begin{pmatrix} x_2 \\ -\frac{b}{m}x_2 - \frac{k}{m}x_1 \end{pmatrix}, \quad (2.14)$$

where x_1 is the position of the mass (relative to the rest position) and x_2 its velocity. We wish to show that if the initial state of the system is away from the rest position, the system will return to the rest position eventually (we will later define this situation to mean that the rest position is *asymptotically stable*). While we could heuristically show this by simulating many, many initial conditions, we seek instead to prove that this is true for *any* initial condition.

To do so, we construct a function $V : \mathbb{R}^n \rightarrow \mathbb{R}$ that maps the system state to a positive real number. For mechanical systems, a convenient choice is the energy of the system,

$$V(x) = \frac{1}{2}kx_1^2 + \frac{1}{2}m\dot{x}_2^2. \quad (2.15)$$

If we look at the time derivative of the energy function, we see that

$$\begin{aligned} \frac{dV}{dt} &= kx_1\dot{x}_1 + mx_2\dot{x}_2 \\ &= kx_1x_2 + mx_2\left(-\frac{b}{m}x_2 - \frac{k}{m}x_1\right) \\ &= -bx_2^2, \end{aligned}$$

which is always either negative or zero. Hence $V(x(t))$ is never increasing and, using a bit of analysis that we will see formally in the next chapter, the individual states must remain bounded.

If we wish to show that the states eventually return to the origin, we must use a more slightly more detailed analysis. Intuitively, we can reason as follows: suppose that for some period of time, $V(x(t))$ stops decreasing. Then it must be true that $\dot{V}(x(t)) = 0$, which in turn implies that $x_2(t) = 0$ for that same period. In that case, $\dot{x}_2(t) = 0$ and we can substitute into the second line of equation (2.14) to obtain:

$$0 = \dot{x}_2 = -\frac{b}{m}x_2 - \frac{k}{m}x_1 = \frac{k}{m}x_1.$$

Thus we must have that x_1 also equals zero and so the only time that $V(x(t))$ can stop decreasing is if the state is at the origin (and hence this system is at its rest position). Since we know that $V(x(t))$ is never increasing (since $\dot{V} \leq 0$), we therefore conclude that the origin is stable (for *any* initial condition).

This type of analysis, called Lyapunov analysis, is considered in detail in Chapter 4 but shows some of the power of using models for analysis of system properties. ∇

Example 2.6 (Frequency response). A second type of analysis that we can perform with models is to compute the output of a system to a sinusoidal input. We again consider the spring mass system, but this time keeping the input and leaving the system in its original form:

$$m\ddot{q} + c\dot{q} + kq = f(t). \quad (2.16)$$

We wish to understand what the response of the system is to a sinusoidal input of the form

$$f(t) = A \sin \omega t.$$

We will see how to do this analytically in Chapter 8, but for now we make use of simulations to compute the answer.

We first begin with the observation that if $q(t)$ is the solution to equation (2.16) with input $f(t)$, then applying an input $f'(t) = 2f(t)$ will give a solution $q'(t) = 2q(t)$ (this is easily verified by substitution). Hence it suffices to look at an input with unit magnitude, $A = 1$. A second observation, which we will prove in Chapter 5, is that the long term response of the system to a sinusoidal input is itself a sinusoid (at the same frequency) and so the output has the form

$$q(t) = g(\omega) \sin(\omega t + \varphi(\omega)),$$

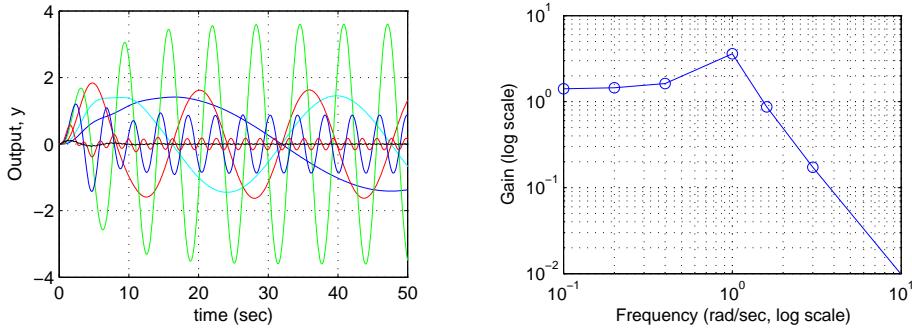


Figure 2.10: A frequency response (magnitude only) computed by measuring the response of individual sinusoids. The figure on the left shows the response of the system to a number of different unit magnitude inputs (at different frequencies). The figure on the right shows this same data in a different way, with the magnitude of the response plotted as a function of the input frequency.

where $g(\omega)$ is the “gain” of the system and $\varphi(\omega)$ is the phase offset.

To compute the frequency response numerically, we can simply simulate the system at a set of frequencies $\omega_1, \dots, \omega_N$ and plot the gain and phase at each of these frequencies. An example of this type of computation is shown in Figure 2.10. ∇

Modeling from Experiments

Since control systems are provided with sensors and actuators it is also possible to obtain models of system dynamics from experiments on the process. The models are restricted to input/output models since only these signals are accessible to experiments, but modeling from experiments can also be combined with modeling from physics through the use of feedback and interconnection.

A simple way to determine a system’s dynamics is to observe the response to a step change in the control signal. Such an experiment begins by setting the control signal to a constant value, then when steady state is established the control signal is changed quickly to a new level and the output is observed. The experiment will thus directly give the step response of the system. The shape of the response gives useful information about the dynamics. It immediately gives an indication of the response time and it tells if the system is oscillatory or if the response is monotone. By repeating the experiment for different steady state values and different amplitudes of

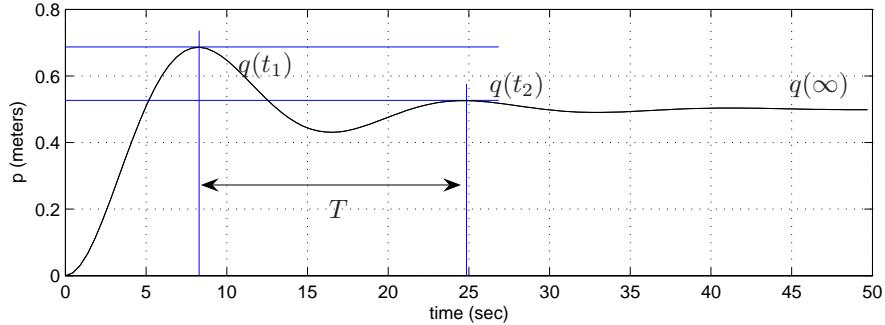


Figure 2.11: Step response for a spring mass system. The magnitude of the step input is $F_0 = 20$ N.

the change of the control signal we can also determine ranges where the process can be approximated by a linear system.

Example 2.7 (Identification of a spring mass system). Consider the spring mass system from Section 2.1, whose dynamics are given by

$$m\ddot{q} + b\dot{q} + kq = u. \quad (2.17)$$

We wish to determine the constants m , b and k by measuring the response of the system to a step input of magnitude F_0 .

We will show in Chapter 5 that when $b^2 < 4km$, the step response for this system from the rest configuration is given by

$$q(t) = \frac{F_0}{k} \left(1 - e^{-\frac{bt}{2m}} \left[\cos\left(\frac{\sqrt{4km-b^2}}{2m} t\right) - \frac{1}{\sqrt{4km-b^2}} \sin\left(\frac{\sqrt{4km-b^2}}{2m} t\right) \right] \right)$$

From the form of the solution, we see that the form of the response is determined by the parameters of the system. Hence, by measuring certain features of the step response we can determine the parameter values.

Figure 2.11 shows the response of the system to a step of magnitude $F_0 = 20$ N, along with some measurements. We start by noting that the steady state position of the mass (after the oscillations die down) is a function of the spring constant, k :

$$q(\infty) = \frac{F_0}{k}, \quad (2.18)$$

where F_0 is the magnitude of the applied force ($F_0 = 1$ for a unit step input). The period of the oscillation can be measured between two peaks and must satisfy

$$\frac{2\pi}{T} = \frac{\sqrt{4km - b^2}}{2m}. \quad (2.19)$$

Finally, the rate of decay of the oscillations is given by the exponential factor in the solution. Measuring the amount of decay between two peaks, we have (using Exercise 2)

$$\log(q(t_1) - F_0/k) - \log(q(t_2) - F_0/k) = \frac{b}{2m}(t_2 - t_1) \quad (2.20)$$

Using this set of three equations, we can solve for the parameters and determine that for the step response in Figure 2.11 we have $m \approx 250$ kg, $b \approx 60$ N-sec/m and $k \approx 40$ N/m. ∇

Modeling from experiments can also be done using many other signals. Sinusoidal signals are commonly used particularly for systems with fast dynamics and very precise measurements can be obtained by exploiting correlation techniques. An indication of nonlinearities can be obtained by repeating experiments with input signals having different amplitudes.

2.3 Schematic Diagrams

To deal with large complex systems, it is useful to have different representations of the system that capture the essential features and hide irrelevant details. In all branches of science and engineering, it is common practice to use some graphical description of systems. They can range from stylistic pictures to drastically simplified standard symbols. These pictures make it possible to get an overall view of the system and to identify the physical components. Examples of such diagrams are shown in Figure 2.12. Schematic diagrams are useful because they give an overall picture of a system, showing different physical processes and their interconnection, and indicating variables that can be manipulated and signals that can be measured.

Block Diagrams

A special graphical representation called *block diagrams* has been developed in control engineering. The purpose of block diagrams is to emphasize the information flow and to hide details of the system. In a block diagram, different process elements are shown as boxes and each box has inputs denoted by lines with arrows pointing toward the box and outputs denoted by lines with arrows going out of the box. The inputs denote the variables that influence a process and the outputs denote signals that we are interested in or signals that influence other subsystems. Block diagrams can also be organized in hierarchies, where individual blocks may themselves contain more detailed block diagrams.

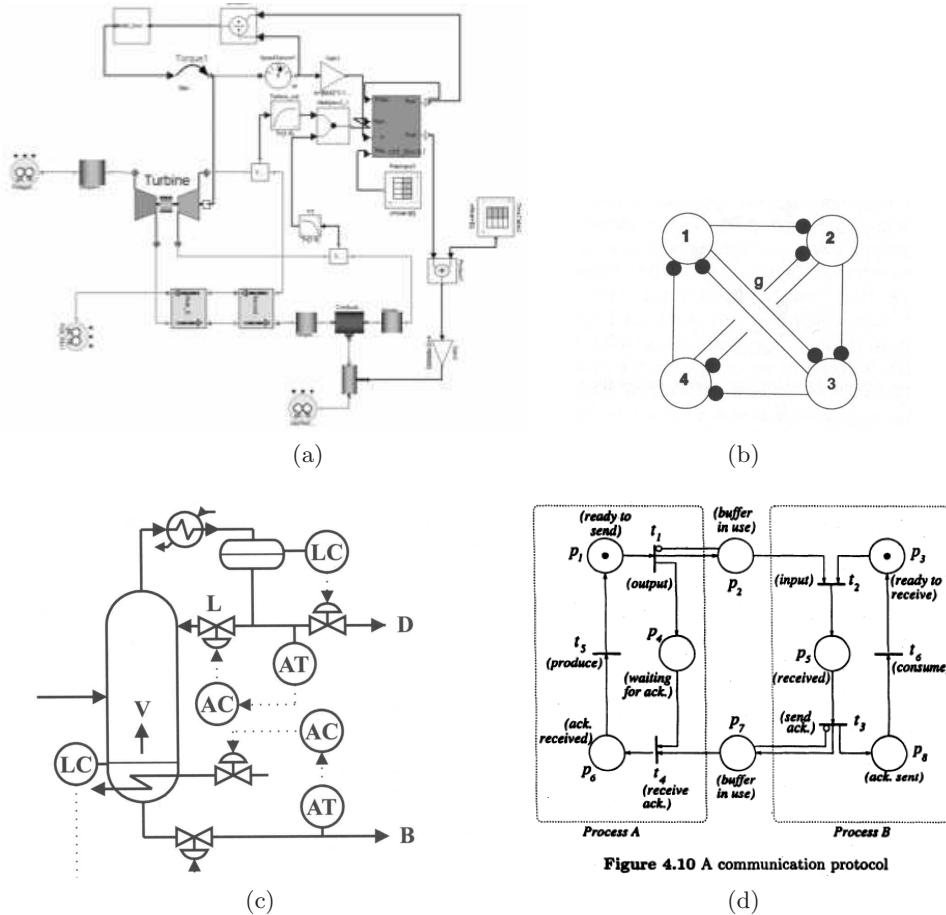


Figure 4.10 A communication protocol

Figure 2.12: Examples of schematic descriptions: (a) schematic picture of a micro gas turbine using Modelica, (b) neuronal network for respiratory control, (c) process and instrumentation diagram and (d) Petri net description of a communication protocol.

Figure 2.13 shows some of the notation that we use for block diagrams. Signals are represented as lines, with arrows to indicate inputs and outputs. The first diagram is the representation for a summation of two signals. An input/output response is represent as a rectangle with the system name (or mathematical description) in the block. Two special cases are a proportional gain, which scales the input by a multiplicative factor, and an integrator, which outputs the integral of the input signal.

Figure 2.14 illustrates the use of a block diagram, in this case for modeling the flight response of a fly. The flight dynamics of an insect are

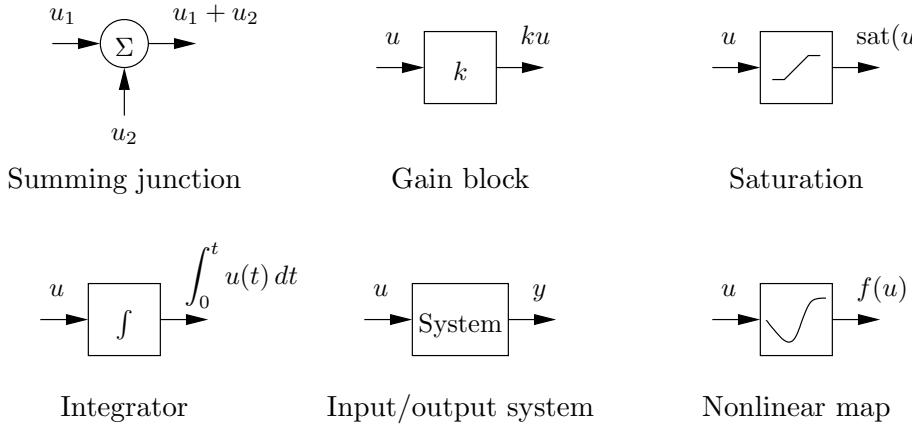


Figure 2.13: Some standard notation for block diagrams.

incredibly intricate, involving a careful coordination of the muscles within the fly to maintain stable flight in response to external stimuli. One known characteristic of flies is their ability to fly upwind by making use of the optical flow in their compound eyes as a feedback mechanism. Roughly speaking, the fly controls its orientation so that the point of contraction of the visual field is centered in its visual field.

To understand this complex behavior, we can decompose the overall dynamics of the system into a series of interconnected subsystems (or “blocks”). Referring to Figure 2.14, we can model the insect navigation system through an interconnection of five blocks. The sensory motor system (a) takes the information from the visual system (b) and generates muscle commands that attempt to steer the fly so that the point of contraction of the visual field is centered.

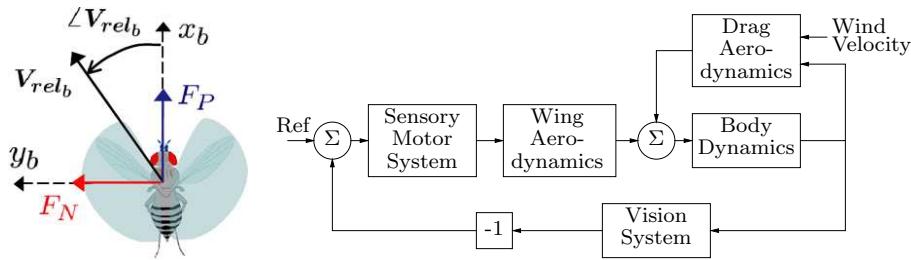


Figure 2.14: A block diagram representation of the flight control system for an insect flying against the wind.

These muscle commands are converted into forces through the flapping of the wings (c) and the resulting aerodynamic forces that are produced. The forces from the wings are combined with the drag on the fly (d) to produce a net force on the body of the fly. The wind velocity enters through the drag aerodynamics. Finally, the body dynamics (e) describe how the fly translates and rotates as a function of the net forces that are applied to it. The insect position, speed and orientation is fed back to the drag aerodynamics and vision systems blocks as inputs.

Each of the blocks in the diagram can itself be a very complicated subsystem. For example, the fly visual system of a tiny fruit fly consists of two complicated compound eyes (with about 700 elements per eye) and the sensory motor system has about 200,000 neurons that are used to process that information. A more detailed block diagram of the insect flight control system would show the interconnections between these elements, but here we have used one block to represent how the motion of the fly affects the output of the visual system and a second block to represent how the visual field is processed by the fly's brain to generate muscle commands. The choice of the level of detail of the blocks and what elements to separate into different blocks often depends on experience and the questions that one wants to answer using the model. One of the powerful features of block diagrams is their ability to hide information about the details of a system that may not be needed to gain an understanding of the essential dynamics of the system.

Modeling Tools

One of the reasons that block diagrams have emerged as a common representation of a model is the development of software tools for manipulating these diagrams. Modern modeling environments provide libraries of standard elements that can be interconnected to form more complex systems. We briefly describe two such environments here.

SIMULINK is a toolbox for MATLAB that allows the user to make use of either pre-defined or custom blocks that represent input/output components. Blocks can themselves be constructed from other blocks, allowing very complex models to be manipulated. *SIMULINK* allows continuous-time and discrete-time blocks to be interspersed, which is useful when building models of computer-controlled systems. Standard blocks include linear and nonlinear ordinary differential equations, summation and gain blocks, and common mathematical operations. Optional toolboxes allow *SIMULINK* diagrams to be compiled into machine executable code, so that controllers can

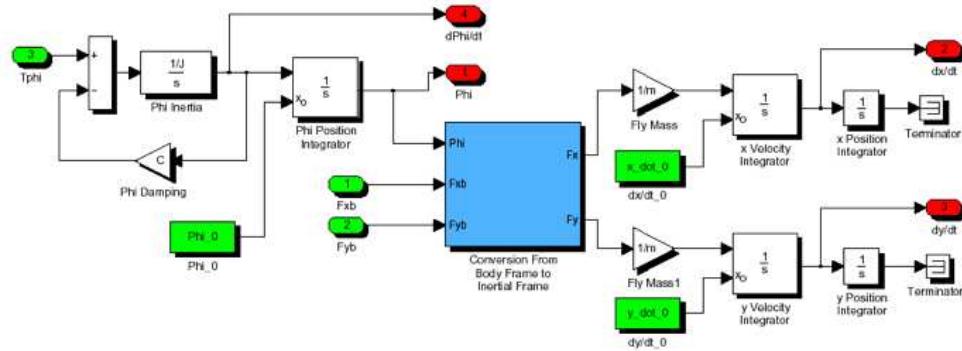


Figure 2.15: An example of a SIMULINK block diagram, corresponding to the body dynamics block of Figure 2.14.

be simulated in SIMULINK and then transferred to a hardware platform for implementation on a physical system. An example of a SIMULINK block diagram is shown in Figure 2.15. This diagram represents the insect body dynamics block of the larger block diagram in Figure 2.14.

LabVIEW is a graphical programming language developed by National Instruments that can be executed directly on a wide range of computer platforms and embedded targets. The Simulation Module is an add-on numerical simulation package that includes continuous and discrete-time blocks, non-linear blocks, and various mathematical operations. All LabVIEW functions and toolkits can be used with the Simulation Module, allowing for both off-line simulation and real-time control implementation of complex models. LabVIEW also has a scripting language, *MathScript*, and toolboxes which can be used run many of the examples in this book.

Models for large systems are often built by combining models of different subsystems. Block diagram modeling has severe drawbacks in this context, as discussed in Section 2.1. There is software for modeling and simulation tailored to specific domains that overcome these difficulties. Typical examples are SPICE for electrical circuits, Adams for multi-body mechanical systems, AUTOSIM for cars and SBML (Systems Biology Markup Language) for biological systems. *Modelica* that was discussed in Section 2.1 covers several domains. Dymola from Dynasim is an environment for modeling and simulation of complex systems based on *Modelica*.

2.4 Examples

In this section we introduce some additional examples that illustrate some of the different types of systems for which one can develop differential equation and difference equation models. These examples are specifically chosen from a range of different fields to highlight the broad variety of systems to which feedback and control concepts can be applied. A more detailed set of examples that serve as running examples throughout the text are given in the next chapter.

Motion Control Systems

Motion control system involve the use of computation and feedback to control the movement of a mechanical system. Motion control systems range from nano-positioning systems (atomic force microscopes, adaptive optics), to control systems for the read/write heads in a disk drive of CD player, to manufacturing systems (transfer machines and industrial robots), to automotive control systems (anti-lock breaks, suspension control, traction control), to air and space flight control systems (for airplanes, satellites, rockets and planetary rovers).

Example 2.8 (Vehicle steering). Consider a vehicle with two wheels as shown in Figure 2.16. For the purpose of steering we are interested in a model that describes how the velocity of the vehicle depends on the steer angle δ . To be specific, we will consider the velocity at a point A at the distance a from the rear wheel. We take the wheel base to be b and let θ denote the heading angle and x and y be the coordinates of the point A as shown in Figure 2.16. Since $b = r_0 \tan u$ and $a = r_0 \tan \delta$ we get the following relation between α and the steer angle δ

$$\alpha = \arctan\left(\frac{a \tan \delta}{b}\right). \quad (2.21)$$

Assume that the wheels are rolling without slip, and that the velocity of the rear wheel is v_0 . The vehicle speed at A is $v = v_0 / \cos \alpha$ and we find that the velocity of point A on the vehicle is given by

$$\begin{aligned} \frac{dx}{dt} &= v \cos(\alpha + \theta) = v_0 \frac{\cos(\alpha + \theta)}{\cos \alpha} \\ \frac{dy}{dt} &= v \sin(\alpha + \theta) = v_0 \frac{\sin(\alpha + \theta)}{\cos \alpha}. \end{aligned} \quad (2.22)$$

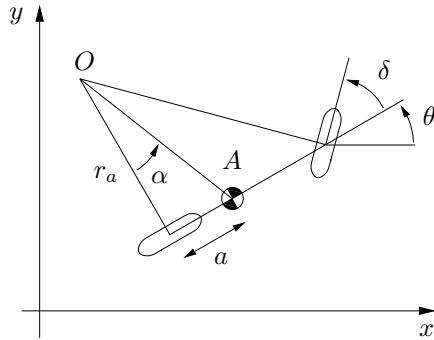


Figure 2.16: Schematic figure of a vehicle with two wheels. The steer angle is δ , and the heading angle is θ .

To see how the angle θ is influenced by the steer angle we observe from Figure 2.16 that the vehicle rotates with the angular velocity v_0/r_0 around the point O . Hence

$$\frac{d\theta}{dt} = \frac{v_0}{r_0} \tan \delta, \quad (2.23)$$

where α is a function of θ given by equation (2.21).

The simple kinematics model given by equations (2.21), (2.22) and (2.23) captures the essence of steering for many vehicles, including an automobile (with the approximate that the two front wheels can be a approximate by a single wheel at the center of the car). The assumption of no slip can be relaxed by adding an extra state variable gives a more realistic model. Such a model describes steering dynamics of cars and ships and pitch dynamics of aircrafts and missiles.

The situation in Figure 2.16 represents the situation when the vehicle moves forward and has front-wheel steering. The case when the vehicle reverses is obtained simply by changing the sign of the velocity. Changing the sign of the velocity also represents a vehicle with rear-wheel steering.

The simple kinematics model captures the essence of steering for many vehicles, including an automobile (with the approximate that the two front wheels can be a approximate by a single wheel at the center of the car). The assumption of no slip can be relaxed by adding an extra state variable gives a more realistic model. Such a model describes steering dynamics of cars and ships and pitch dynamics of aircrafts and missiles. ∇

Example 2.9 (Vectored thrust aircraft). Consider the motion of vectored thrust aircraft, such as the Harrier “jump jet” shown Figure 2.17a. The

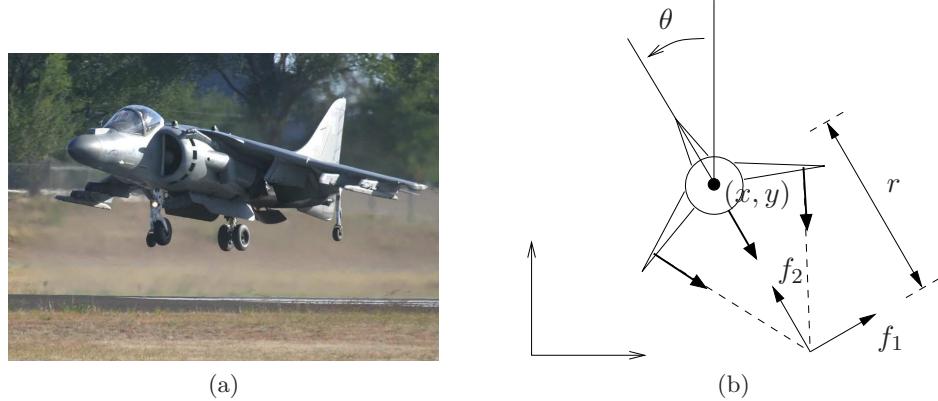


Figure 2.17: Vectored thrust aircraft: (a) Harrier AV-8B military aircraft and (b) a simplified planar model.

Harrier is capable of vertical takeoff by redirecting its thrust downward and through the use of smaller maneuvering thrusters located on its wings. A simplified model of the Harrier is shown in Figure 2.17b, where we focus on the motion of the vehicle in a vertical plane through the wings of the aircraft. We resolve the forces generated by the main downward thruster and the maneuvering thrusters as a pair of forces f_1 and f_s acting at a distance r below the aircraft (determined by the geometry of the engines).

Let (x, y, θ) denote the position and orientation of the center of mass of aircraft. Let m be the mass of the vehicle, J the moment of inertia, g the gravitational constant, and c the damping coefficient. Then the equations of motion for the fan are given by:

$$\begin{aligned} m\ddot{x} &= f_1 \cos \theta - f_2 \sin \theta - c\dot{x} \\ m\ddot{y} &= f_1 \sin \theta + f_2 \cos \theta - mg - c\dot{y} \\ J\ddot{\theta} &= rf_1. \end{aligned}$$

It is convenient to redefine the inputs so that the origin is an equilibrium point of the system with zero input. Letting $u_1 = f_1$ and $u_2 = f_2 - mg$, then the equations become

$$\begin{aligned} m\ddot{x} &= -mg \sin \theta - c\dot{x} + u_1 \cos \theta - u_2 \sin \theta \\ m\ddot{y} &= mg(\cos \theta - 1) - c\dot{y} + u_1 \sin \theta + u_2 \cos \theta \\ J\ddot{\theta} &= ru_1. \end{aligned} \tag{2.24}$$

These equations described the motion of the vehicle as a set of three coupled second order differential equations. ∇

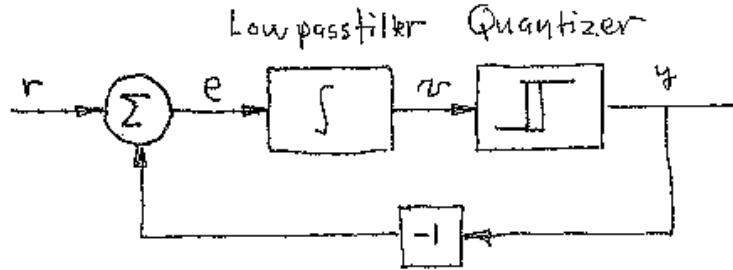


Figure 2.18: Schematic diagram of a delta-sigma converter.

Electronics and Instrumentation

Black's invention of the negative feedback amplifier paved the way for the use of feedback in electronic circuits. Electronics are ubiquitous in the world around us and many electronic devices involve feedback and control systems at a variety of levels. Some of the most common examples include video and audio systems, instrumentation systems, and a whole host control systems in transportation, manufacturing and communication systems.

Example 2.10 (Delta-sigma converters). Delta-sigma converters are used for analog to digital conversion in high-quality audio and communication. Common examples are one-bit AD converters and digital audio amplifiers. Delta-sigma converters are also used to generate pulse-width modulated signals for motor drives. The converter generates an output signal with quantized amplitude that resembles the input signal in the sense that the filtered output is close to the input. In the extreme case of a one-bit converter the output has only two levels.

A schematic diagram of a delta-sigma converter is shown in Figure 2.18. The system is a feedback loop with a quantizer and a low pass filter. A particularly simple version is when the quantizer is a relay with hysteresis and the filter is an integrator. Figure 2.19 shows a simulation of such a converter when the input is a sinusoid. A feedback loop will normally act to make the error small. In this particular case the instantaneous value cannot be made small because the output switches between -1 and 1. The integral of the error is however small because it can be shown that

$$\int_{t_1}^{t_2} |V_{in}(t) - V_{out}(t)| dt \leq a, \quad (2.25)$$

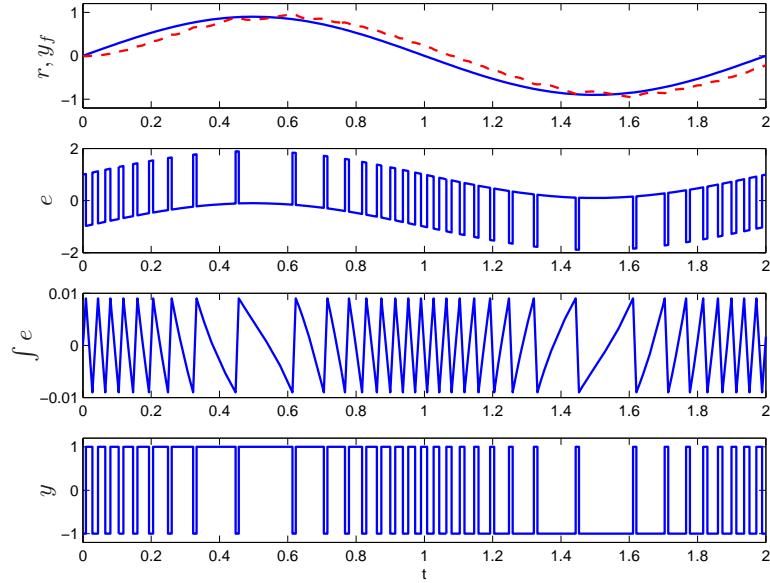


Figure 2.19: Simulation of a delta-sigma converter. The upper curve shows the input r (full) and the filtered output y_f (dashed), the next curves show the error e , the filtered error v and the converter output y . The loop filter is an integrator, the quantizer a relay with hysteresis $a = 0.009$. The pulse output y is filtered with a second order low-pass filter with time constant $T = 0.04s$.

where the interval (t_1, t_2) covers a full cycle, and a is the hysteresis of the relay. The filtered output y_f is also close to the input r .

Digital signals are formed by sampling in time and by quantization in amplitude. The delta-sigma modulator shows that a good digital representation can be obtained with a very crude quantization of the amplitude, only 0 and 1, provided that the time resolution is sufficiently high (oversampling). The pulsed output signal interesting signal form. It encodes the original continuous signal into a pulse-width modulated signal where the average value corresponds to the signal amplitude. The pulse width is proportional to the rate of change of the continuous signals. It is interesting to note that pulsed signals are common in biological systems. ∇

Example 2.11 (Josephson junction). Josephson received the Nobel Prize in Physics 1973 for discovery of the Josephson effect which occurs in two superconducting layers separated by an insulating oxide. Under certain conditions current can pass through the insulator through tunneling of Cooper pairs

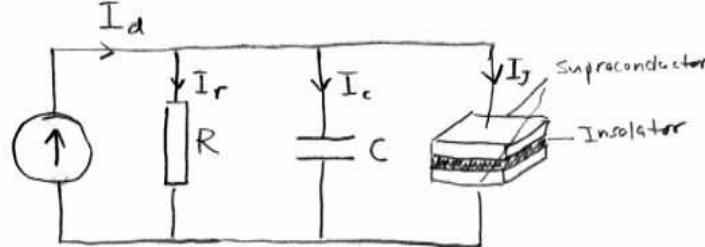


Figure 2.20: An electric circuit with a Josephson junction.

of electrons. The effect has been used to design superconducting quantum interference devices (SQUID), because switching is very fast, in the order of picoseconds. Tunneling in the Josephson junctions is very sensitive to magnetic fields and can therefore be used to measure extremely small magnetic fields, the threshold is as low as 10^{-14} T. Josephson junctions are also used for other precision measurements. The standard volt is now defined as the voltage required to produce a frequency of 483,597.9 GHz in a Josephson junction oscillator.

A schematic diagram of a circuit with a Josephson junction is shown in Figure 2.20. The quantum effects can be modeled by the Schrödinger equation. In spite of this it turns out that the circuit can be modeled as a system with lumped parameters. Let φ be the flux which is the integral of the voltage V across the device, hence

$$V = \frac{d\varphi}{dt}. \quad (2.26)$$

It follows from quantum theory, see Feynman [Fey70], that the current I through the device is a function of the flux φ

$$I = I_0 \sin k\varphi, \quad (2.27)$$

where I_0 is a device parameter, and the Josephson parameter k is given by

$$k = 4\pi \frac{e}{h} V^{-1} s^{-1} = 2 \frac{e}{h} \text{ HzV}^{-1}, \quad (2.28)$$

where $e = 1.602 \times 10^{-19}$ C is the charge of an electron and $h = 6.62 \times 10^{-34}$ V $^{-1}$ s $^{-1}$ is Planck's constant.

The circuit in Figure 2.20 has two storage elements the capacitor and the Josephson junction. We choose the states as the voltage V across the capacitor and the flux φ of the Josephson junction. Let I_R , I_C and I_J be the currents through the resistor, the capacitor and the Josephson junction. We have

$$I_R = \frac{V}{R}, \quad I_C = C \frac{dV}{dt}, \quad I_J = I_0 \sin k\varphi,$$

and a current balance gives

$$I_R + I_C + I_J = I_d,$$

which can be rewritten as

$$C \frac{dV}{dt} = I_d - \frac{V}{R} - I_0 \sin k\varphi.$$

Combining this equation with equation (2.26) gives the following state equation for the circuit

$$\begin{aligned} \frac{d\varphi}{dt} &= V \\ C \frac{dV}{dt} &= -I_0 \sin k\varphi - \frac{V}{R} + I_d. \end{aligned} \tag{2.29}$$

Notice that apart from parameter values equation (2.29) is identical to the equation for the inverted pendulum given in equation (2.8). ∇

Information Systems

Information systems can range from communication systems for transmitting data from one location to another, to software systems that manipulate data or manage enterprise-wide resources, to economies and financial markets, that use prices to reflect current and future value. Feedback is present in all of these systems, although it is often not directly visible.

Example 2.12 (Congestion control). The Internet was created to obtain a large, highly decentralized, efficient, and expandable communication system. The system consists of a large number of interconnected gateways. A message is split into several packets that are transmitted over different paths in the network. The packages are joined to recover the message at the receiver. A message is sent back to the sender when a packet is received. The operation of the system is governed by a simple but powerful decentralized control structure which evolved over time.

The system is governed by two control mechanisms, called protocols: the Transmission Control Protocol (TCP) for end-to-end network communication and the Internet Protocol (IP) for routing packets and for host-to-gateway or gateway-to-gateway communication. The current protocols evolved after some spectacular congestion collapses in the mid 1980s, when throughput unexpectedly could drop by a factor of 1000. The control mechanism in TCP is based on conserving the number of packets in the loop from sender to receiver and back to the sender. The sending rate is increased exponentially when there is no congestion and it is dropped drastically to a very low level when there is congestion.

A simple model for congestion control between N computers connected by a single router is given by the differential equation

$$\begin{aligned}\frac{dx_i}{dt} &= -b \frac{x_i^2}{2} + (b_{\max} - b) \\ \frac{db}{dt} &= \sum_{i=1}^N x_i - c,\end{aligned}\tag{2.30}$$

where $x_i \in \mathbb{R}$, $i = 1, \dots, N$ are the transmission rates for the sources of data, $b \in \mathbb{R}$ is the current buffer size of the router, $b_{\max} > 0$ is the maximum buffer size, and $c > 0$ is the capacity of the link connecting the router to the computers. The \dot{x}_i equation represents the control law that the individual computers use to determine how fast to send data across the network (this version is motivated by a protocol called “Reno”) and the \dot{b} equation represents the rate at which the buffer on the router fills up.

The nominal operating point for the system can be found by setting $\dot{x}_i = \dot{b} = 0$:

$$\begin{aligned}0 &= \frac{x_i^2}{2} + \left(1 - \frac{b_{\max}}{b}\right) \quad \text{for all } i \\ 0 &= \sum_{i=1}^N x_i - c\end{aligned}$$

From the first equation we notice that the equilibria for all the x_i should be the same and it follows that there is a unique equilibrium

$$\begin{aligned}x_i^* &= \frac{c}{N} \quad \text{for all } i \\ b^* &= \frac{2N^2 b_{\max}}{2N^2 + c^2},\end{aligned}$$

which corresponds to each of the sources sending data at rate c/N and the buffer size in the router staying constant.

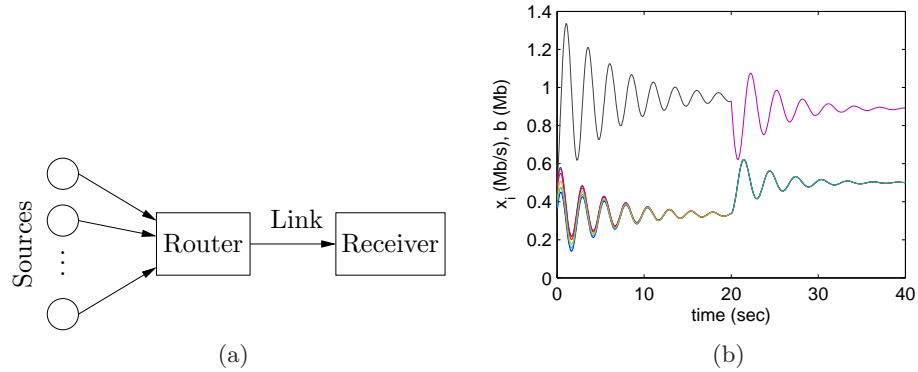


Figure 2.21: Congestion control simulation: (a) Multiple sources attempt to communicate through a router across a single link. (b) Simulation with 6 sources starting random rates, with 2 sources dropping out at $t = 20$ s.

Figure 2.21 shows a simulation of 6 sources communicating across a single link, with two sources dropping out at $T = 1$ s and the remaining courses increasing their rates to compensate. Note that the solutions oscillate before approaching their equilibrium values, but that the transmission rates and buffer size automatically adjust depending on the number of sources.

A good presentation of the ideas behind the control principles for the Internet are given by one of its designers in [Jac88]. The paper [Kel85] is an early effort of analysis of the system. The book [HDPT04] gives many interesting examples of control of computer systems. ∇

Example 2.13 (Consensus protocols in sensor networks). Sensor networks are used in a variety of applications where we want to collect and aggregate information over a region of space using multiple sensors that are connected together via a communications network. Examples include monitoring environmental conditions in a geographical area (or inside a building), monitoring movement of animals or vehicles, or monitoring the resource loading across a group of computers. In many sensor networks the computational resources for the system are distributed along with the sensors and it can be important for the set of distributed agents to reach a consensus about a certain property across the network, such as the average temperature in a region or the average computational load amongst a set of computers.

To illustrate how such a consensus might be achieved, we consider the problem of computing the average value of a set of numbers that are locally available to the individual agents. We wish to design a “protocol” (algorithm) such that all agents will agree on the average value. We consider the

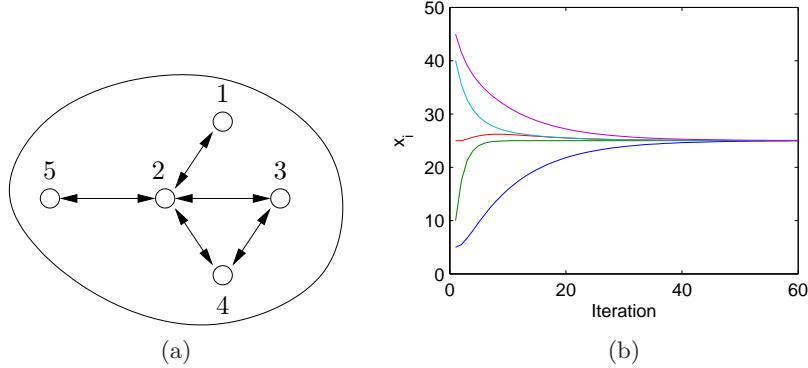


Figure 2.22: Consensus protocols for sensor networks: (a) a simple sensor network with five notes; (b) simulation demonstrating convergence of the network to the average value of the initial conditions.

case in which all agents cannot necessarily communicate with each other directly, although we will assume that the communications network is connected (meaning that no agents are completely isolated from the group). Figure 2.22a shows a simple situation of this type.

We model the connectivity of the sensor network using a graph, with nodes corresponding to the sensors and edges corresponding to the existence of a direct communications link between two nodes. For any such graph, we can build an *adjacency matrix*, where each row and column of the matrix corresponds to a node and a 1 in the respective row and column indicates that the two nodes are connected. For the network shown in Figure 2.22a, the corresponding adjacency matrix is

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 1 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{pmatrix}.$$

We also use the notation \mathcal{N}_i to represent the set of neighbors of a node i . For example, $\mathcal{N}_2 = \{1, 3, 4, 5\}$ and $\mathcal{N}_3 = \{2, 4\}$.

To solve the consensus problem, we let x^i be the state of the i th sensor, corresponding to that sensor's estimate of the average value that we are trying to compute. We initialize the state to the value of the quantity measured by the individual sensor. Our consensus protocol can now be

realized as a local update law of the form

$$x_{k+1}^i = x_k^i + \gamma \sum_{j \in \mathcal{N}_i} (x_k^j - x_k^i). \quad (2.31)$$

This protocol attempts to compute the average by updating the local state of each agent based on the value of its neighbors. The combined dynamics of all agents can be written in the form

$$x_{k+1} = x_k - \gamma(D - A)x_k \quad (2.32)$$

where A is the adjacency matrix and D is a diagonal matrix whose entries correspond to the number of neighbors of the corresponding node. The constant γ describes the rate at which we update our own estimate of the average based on the information from our neighbors. The matrix $L := D - A$ is called the *Laplacian* of the graph.

The equilibrium points of equation (2.32) are the set of states such that $x_{k+1}^* = x_k^*$. It is easy to show that $x^* = \alpha(1, 1, \dots, 1)$ is an equilibrium state for the system, corresponding to each sensor having an identical estimate α for the average. Furthermore, we can show that α is precisely the average value of the initial states. To see this, let

$$W_k = \frac{N}{\sum_{i=1}^n} x_k^i$$

where N is the number of nodes in the sensor network. W_0 is the average of the initial states of the network, which is the average quantity we are trying to compute. W_k is given by the difference equation

$$W_{k+1} = \frac{1}{N} \sum_{i=1}^n x_{k+1}^i = \frac{1}{N} \sum_{i=1}^n \left(x_k^i + \gamma \sum_{j \in \mathcal{N}_i} (x_k^j - x_k^i) \right).$$

Since $i \in \mathcal{N}_j$ implies that $j \in \mathcal{N}_i$, it follows that each term in the second sum occurs twice with opposite sign. Thus we can conclude that $W_{k+1} = W_k$ and hence $W_k = W_0$ for all k , which implies that at the equilibrium point α must be W_0 , the average of the initial states. W is called an *invariant* and the use of invariants is an important technique for verifying correctness of computer programs.

Having shown that the desired consensus state is an equilibrium point for our protocol, we still must show that the algorithm actually converges to this state. Since there can be cycles in the graph, it is possible that the state of the system could get into an “infinite loop” and never converge

to the desired consensus state. A formal analysis requires tools that will be introduced later in the text, but it can be shown that for any given graph, we can always find a γ such that the states of the individual agents converge to the average. A simulation demonstrating this property is shown in Figure 2.22b.

Although we have focused here on consensus to the average value of a set of measurements, other consensus states can be achieved through choice of appropriate feedback laws. Examples include finding the maximum or minimum value in a network, counting the number of nodes in a network, and computing higher order statistical moments of a distributed quantity. ∇

Biological Systems

Biological systems are filled with feedback loops and provide perhaps the richest source of feedback and control examples. The basic problem of homeostasis, in which a quantity such as temperature or blood sugar level is regulated to a fixed value, is but one of the many types of complex feedback interactions that can occur in molecular machines, cells, organisms and ecosystems.

Example 2.14 (Transcriptional regulation). Transcription is the process by which mRNA is generated from a segment of DNA. The promoter region of a gene allows transcription to be controlled by the presence of other proteins, which bind to the promoter region and either repress or activate RNA polymerase (RNAP), the enzyme that produces mRNA from DNA. The mRNA is then translated into a protein according to its nucleotide sequence.

A simple model of the transcriptional regulation process is the use of a Hill function [dJ02, Mur04]. Consider the regulation of a protein A with concentration given by p_A and corresponding mRNA concentration m_A . Let B be a second protein with concentration p_B that represses the production of protein A through transcriptional regulation. The resulting dynamics of p_A and m_A can be written as

$$\begin{aligned} \frac{dm_A}{dt} &= -\tau m_A + \frac{\alpha}{1 + p_B^n} + \alpha_0 \\ \frac{dp_A}{dt} &= \beta(m_A - p_A), \end{aligned} \tag{2.33}$$

where $\alpha + \alpha_0$ is the basal transcription rate, τ represents the rate of degradation of mRNA, α and n are parameters that describe how B represses

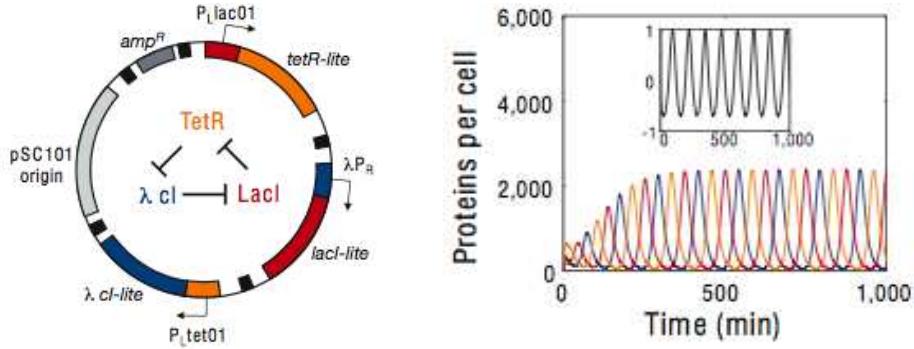


Figure 2.23: The repressilator genetic regulatory network: (a) a schematic diagram of the repressilator, showing the layout of the genes in the plasmid that holds the circuit as well as the circuit diagram (center); (b) simulation of a simple model of the repressilator.

A and β represents both the rate of production of the protein from its corresponding mRNA and also the rate of degradation of A . The parameter α_0 describes the “leakiness” of the promotor and n is called the Hill coefficient and relates to the cooperativity of the promotor. For simplicity we will assume that $\tau = 1$, which corresponds to choosing units of time that correspond to the mRNA decay rate.

A similar model can be used when a protein activates the production of another protein, rather than repressing it. In this case, the equations have the form

$$\begin{aligned} \frac{dm_A}{dt} &= -\tau m_A + \frac{\alpha p_B^n}{1 + p_B^n} + \alpha_0 \\ \frac{dp_A}{dt} &= \beta(m_A - p_A), \end{aligned} \quad (2.34)$$

where the variables are the same as described. Note that in the case of the activator, if p_B is zero then the production rate is α_0 (versus $\alpha + \alpha_0$ for the repressor). As p_B gets large, the second term in the expression for \dot{m}_A approaches 1 and the transcription rate becomes $\alpha + \alpha_0$ (versus α_0 for the repressor). Thus we see that the activator and repressor act in opposite fashion from each other.

As an example of how these models can be used, we consider the model of a “repressilator”, originally due to Elowitz and Leibler [EL00]. The repressilator is a synthetic circuit in which three proteins each repress another in a cycle. This is shown schematically in Figure 2.23a, where the three proteins are tetR, λ cI and LacI. The basic idea of the repressilator is that if tetR

is present then it represses the production of λcI . If λcI is present, then LacI is produced (at the basal transcription rate), which in turn represses TetR. Once TetR is repressed then λcI is no longer repressed and so on. If the dynamics of the circuit are designed properly, the resulting protein concentrations will oscillate.

We can model this system using three copies of equation (2.33), with A and B replaced by the appropriate combination of TetR, cI and LacI. The state of the system is then given by $x = (m_{\text{TetR}}, p_{\text{TetR}}, m_{cI}, p_{cI}, m_{\text{LacI}}, p_{\text{LacI}})$. Figure 2.23b shows the traces of the three protein concentrations for parameters $\alpha_0 = 0$, $\alpha = 50$, $\beta = 0.2$ and $n = 2$ and initial conditions $x(0) = 0.2, 0.1, 0.1, 0.4, 0.3, 0.5$ (from [EG05]). ∇

Example 2.15 (Hodgkin-Huxley equations¹). The dynamics of the membrane potential in a cell is a fundamental mechanism in discussing signaling in cells. The Hodgkin-Huxley equations provide a simple model for studying propagation waves in networks of neurons. The model for a single neuron has the form

$$C \frac{dV}{dt} = -I_{Na} - I_K - I_{leak} + I_{input}$$

where V is the membrane potential, C the capacitance, I_{Na} and I_K the current caused by transport of sodium and potassium across the cell membrane, I_{leak} is a leakage current and I_{input} is the external stimulation of the cell. Each current obeys Ohms law, i.e.

$$I = g(V - E)$$

where g is the conductance and E the equilibrium voltage. The equilibrium voltage is given by Nernst's law

$$E = \frac{RT}{xF} \log(C_{out}/C_{in})$$

where R is Boltzmann's constant, T the absolute temperature, F Faraday's constant, C_{out} and C_{in} the ion concentrations outside and inside the cell. At 20° we have $RT/F = 20$ mV.

The Hodgkin-Huxley model was originally developed as a means to predict the quantitative behavior of the squid giant axon [HH52]. Hodgkin and Huxley shared the 1963 Nobel Prize in Physiology (along with J. C. Eccles) for analysis of the electrical and chemical events in nerve cell discharge. ∇

¹H. R. Wilson, *Spikes, Decisions and Actions—Dynamical Foundations of Neuroscience*. Oxford University Press.

2.5 Further Reading

Modeling is ubiquitous in engineering and science and has a long history in applied mathematics. For example, the Fourier series was introduced in connection with modeling of heat conduction in solids. Models of dynamics have been developed in many different fields, including mechanics [Gol53], heat conduction [CJ59], fluids! [BS60], vehicles [Abk69, Bla91, Ell94], circuit theory [Gui63], acoustics [Ber54] and micromechanical systems [Sen01]. Control theory requires modeling from many different domains and most texts control theory contain several chapters on modeling using ordinary differential equations and difference equations (see, for example, [FPEN05]).

A classic book on modeling of physical systems, especially mechanical, electrical and thermo-fluid systems, is Cannon's *Dynamics of Physical Systems* [Can03]. Two of the authors' favorite books on modeling of biological systems are *Mathematical Biology* by J. D. Murray [Mur04] and *Spikes, Decision and Actions: The Dynamical Foundations of Neuroscience* by H. R. Wilson [Wil99]. For readers interested in learning more about object oriented modeling and Modelica, the edited volume by Tiller [Til01] provides an excellent introduction.

2.6 Exercises

1. Use the equations of motion for a balance system to derive a dynamic model for the inverted pendulum described in Example 2.2 and verify that for small θ they are approximated by equation (2.8).
2. (Second order system identification) Verify that equation (2.20) in Example 2.7 is correct and use this formula and the others in the example to compute the parameters corresponding to the step response in Figure 2.11.
3. (Least squares system identification) Consider a nonlinear differential equation that can be written in the form

$$\frac{dx}{dt} = \sum_{i=1}^M \alpha_i f_i(x)$$

where $f_i(x)$ are known nonlinear functions and α_i are unknown, but constant, parameters. Suppose that we have measurements (or estimates) of the state x at time instants t_1, t_2, \dots, t_N , with $N > M$.

Show that the parameters α_i can be determined by finding the least squares solution to a linear equation of the form

$$H\alpha = b$$

where $\alpha \in \mathbb{R}^M$ is the vector of all parameters and $H \in \mathbb{R}^{N \times M}$ and $b \in \mathbb{R}^N$ are appropriately defined.

4. Consider the following discrete time system

$$\begin{aligned} z_{k+1} &= Az_k + Bu_k \\ y_k &= Cz_k \end{aligned}$$

where

$$z = \begin{pmatrix} z^1 \\ z^2 \end{pmatrix} \quad A = \begin{pmatrix} a_{11} & a_{12} \\ 0 & a_{22} \end{pmatrix} \quad B = \begin{pmatrix} 0 \\ 1 \end{pmatrix} \quad C = \begin{pmatrix} 1 & 0 \end{pmatrix}$$

In this problem, we will explore some of the properties of this discrete time system as a function of the parameters, the initial conditions, and the inputs.

- (a) Assume that the off diagonal element $a_{12} = 0$ and that there is no input, $u = 0$. Write a closed form expression for the output of the system from a nonzero initial condition $z_0 = (z_0^1, z_0^2)$ and give conditions on a_{11} and a_{22} under which the output gets smaller as k gets larger.
- (b) Now assume that $a_{12} \neq 0$ and write a closed form expression for the response of the system from a nonzero initial conditions. Given a condition on the elements of A under which the output gets smaller as k gets larger.
- (c) Write a MATLAB program to plot the output of the system in response to a unit step input, $u[k] = 1$, $k \geq 0$. Plot the response of your system with $z_0 = 0$ and A given by

$$A = \begin{pmatrix} 0.5 & 1 \\ 0 & 0.25 \end{pmatrix}$$

5. Consider the delta-sigma converter in Example 2.10. Propose a way to obtain an estimate of the instantaneous value of the reference signal and its derivative from the pulsed output.

6. Consider the linear ordinary differential equation (2.6). Show that by choosing a state space representation with $x_1 = y$, the dynamics can be written as

$$A = \begin{pmatrix} 0 & 1 & & 0 \\ 0 & \ddots & \ddots & 0 \\ 0 & \dots & 0 & 1 \\ -a_n & -a_{n-1} & & -a_1 \end{pmatrix} \quad B = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{pmatrix}$$

$$C = \begin{pmatrix} 1 & \dots & 0 & 0 \end{pmatrix}$$

This canonical form is called *chain of integrators* form.

Chapter 3

Examples

... Don't apply any model until you understand the simplifying assumptions on which it is based, and you can test their validity. Catch phrase: use only as directed. Don't limit yourself to a single model: More than one model may be useful for understanding different aspects of the same phenomenon. Catch phrase: legalize polygamy."

Saul Golomb in his 1970 paper "Mathematical Models—Uses and Limitations" [Gol70].

In this chapter we present a collection of examples spanning many different fields of science and engineering. These examples will be used throughout the text and in exercises to illustrate different concepts. First time readers may wish to focus only on a few examples with which they have the most prior experience or insight to understand the concepts of state, input, output, and dynamics in a familiar setting.

3.1 Cruise Control

The cruise control system of a car is one of the most common control systems encountered in everyday life. The system attempts to keep the speed of the car constant in spite of disturbances caused by changes in the slope of a road and variations in the wind and road surface. The controller compensates for these unknowns by measuring the speed of the car and adjusting the throttle appropriately.

To model the complete system we start with the block diagram in Figure 3.1. Let v be the speed of the car and v_r the desired (reference) speed. The controller, which typically is of the proportional-integral (PI) type described briefly in Chapter 1, receives the signals v and v_r and generates a

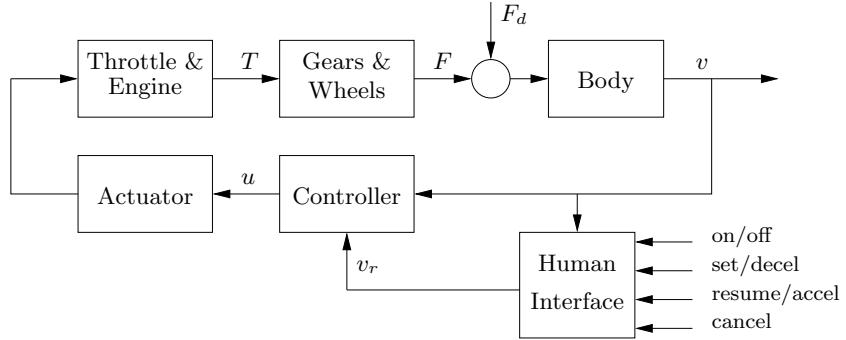


Figure 3.1: Block diagram of a cruise control system for an automobile.

control signal u that is sent to an actuator that controls throttle position. The throttle in turn controls the torque T delivered by the engine, which is then transmitted through gears and the wheels, generating a force F that moves the car. There are disturbance forces F_d due to variations in the slope of the road, the effects of rolling resistance and aerodynamic forces. The cruise controller also has a man-machine interface that allows the driver to set and modify the desired speed. There are also functions that disconnects cruise control when the brake is touched as well as functions to resume cruise control operation.

The system has many individual components—actuator, engine, transmission, wheels and car body—and a detailed model can be very complicated. In spite of this, the model required to design the cruise controller can be quite simple. In essence the model should describe how the car’s speed is influenced by the slope of the road and the control signal u that drives the throttle actuator.

To model the system, it is natural to start with a momentum balance for the car body. Let v be the speed measured in m/s, m the total mass of the car in kg (including passengers), F the force generated by the contact of the wheels with the road, and F_d the disturbance force due to gravity and friction. The equation of motion of the car is simply

$$m \frac{dv}{dt} = F - F_d. \quad (3.1)$$

The force F is generated by the engine, whose torque is proportional to the rate of fuel injection, which is itself proportional to the control signal $0 \leq u \leq 1$ that controls throttle position. The torque also depends on engine speed ω . A simple representation of the torque at full throttle is given by

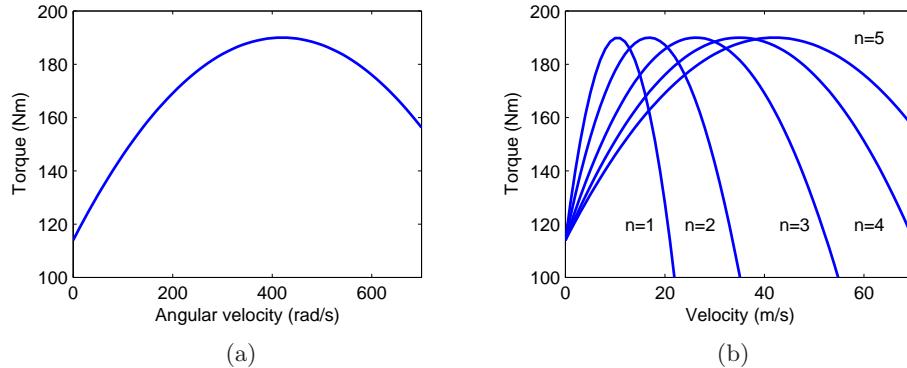


Figure 3.2: Torque curves for typical car engine: (a) torque as a function of the angular velocity of the engine and (b) torque as a function of car speed for different gears.

the torque curve

$$T(\omega) = T_m \left(1 - \beta \left(\frac{\omega}{\omega_m} - 1 \right)^2 \right), \quad (3.2)$$

where the maximum torque T_m is obtained at engine speed ω_m . Typical parameters are $T_m = 190$ Nm, $\omega_m = 420$ rad/sec (about 4000 RPM) and $\beta = 0.4$.

Let n be the gear ratio and r the wheel radius. The engine speed is related to the velocity through the expression

$$\omega = \frac{n}{r}v =: \alpha_n v,$$

and the driving force can be written as

$$F = \frac{nu}{r}T(\omega) = \alpha_n u T(\alpha_n v).$$

Typical values of α_n for gears 1 through 5 are $\alpha_1 = 40$, $\alpha_2 = 25$, $\alpha_3 = 16$, $\alpha_4 = 12$ and $\alpha_5 = 10$. The inverse of α_n has physical interpretation as the *effective wheel radius*. Figure 3.2 shows the torque as function of engine speed and vehicle speed. The figure shows that the effect of the gear is to “flatten” the torque curve so that a torque close to maximum can be obtained almost over the full speed range.

The disturbance force F_d has three major components: F_g , the forces due to gravity; F_r , the forces due to rolling friction; and F_a , the aerodynamic

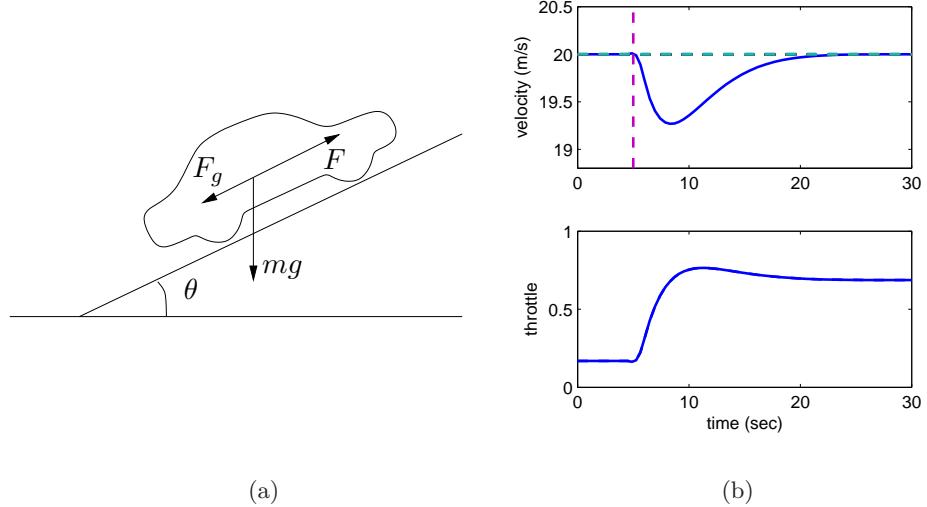


Figure 3.3: Car with cruise control encountering a sloping road: a schematic diagram is shown in (a) and (b) shows the response in speed and throttle when a slope of 4° is encountered. The hill is modeled as a net change in hill angle, θ , of 4 degrees, with a linear change in the angle between $t = 5$ and $t = 6$. The PI controller has proportional gain is $k_p = 0.5$ and the integral gain is $k_i = 0.1$.

drag. Letting the slope of the road be θ , gravity gives the retarding force $F_g = mg \sin \theta$, as illustrated in Figure 3.3a, where $g = 9.8 \text{ m/sec}^2$ is the gravitational constant. A simple model of rolling friction is

$$F_r = mgC_r$$

where C_r is the coefficient of rolling friction; a typical value is $C_r = 0.01$. Finally, the aerodynamic drag is proportional to the square of the speed:

$$F_a = \frac{1}{2}\rho C_d A v^2,$$

where ρ is the density of air, C_d is the shape-dependent aerodynamic drag coefficient and A is the frontal area of the car. Typical parameters are $\rho = 1.3 \text{ kg/m}^3$, $C_d = 0.32$ and $A = 2.4 \text{ m}^2$.

Summarizing, we find that the car can be modeled by

$$m \frac{dv}{dt} = \alpha_n u T(\alpha_n v) - mgC_r - \frac{1}{2}\rho C_d A v^2 - mg \sin \theta, \quad (3.3)$$

where the function T is given by equation (3.2). The model (3.3) is a dynamical system of first order. The state is the car velocity v , which is also

the output. The input is the signal u that controls the throttle position, and the disturbance is the force F_d , which depends on the slope of the road. The system is nonlinear because of the torque curve and the nonlinear character of the aerodynamic drag. There can also be variations in the parameters, e.g. the mass of the car depends on the number of passengers and the load being carried in the car.

We add to this model a feedback controller that attempts to regulate the speed of the car in the presence of disturbances. We shall use a PI (proportional-integral) controller, which has the form

$$u(t) = k_p e(t) + k_i \int_0^t e(\tau) d\tau.$$

This controller can itself be realized as an input/output dynamical system by defining a controller state z and implementing the differential equation

$$\frac{dz}{dt} = v_r - v \quad u = k_p(v_r - v) + k_i z, \quad (3.4)$$

where v_r is the desired (reference) speed. As discussed briefly in the introduction, the integrator (represented by the state z) insures that in steady state the error will be driven to zero, even when there are disturbances or modeling errors. (The design of PI controllers is the subject of Chapter 10.) Figure 3.3b shows the response of the closed loop system, consisting of equations (3.3) and (3.4), when it encounters a hill. The figure shows that even if the hill is so steep so that the throttle changes from 0.17 to almost full throttle, the largest speed error is less than 1 m/s, and the desired velocity is recovered after 20s.

The model (3.3) is essentially a momentum balance for the car. Many approximations were made when deriving it. It may be surprising that such a seemingly complicated system can be described by the simple model (3.3). As we shall see in later chapters, the reason for this is the inherent robustness of feedback systems: even if the model is not perfectly accurate, we can use it to design a controller and make use of the feedback in the controller to manage the uncertainty in the system.

The cruise control system also has a human-machine interface (HMI) that allows the driver to communicate with the system. There are many different ways to implement this system; one version is illustrated in Figure 3.4. The system has four buttons: on-off, set/decelerate, resume/accelerate and cancel. The operation of the system is governed a finite state system and which controls the modes of the PI controller and the reference generator.

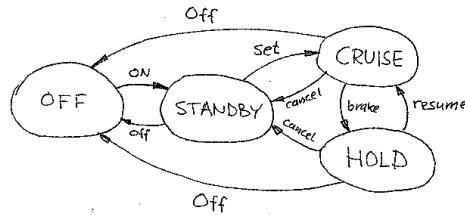


Figure 3.4: Finite state machine for cruise control system.

The controller can operate in two ways: in the normal cruise control mode and in a tracking mode, where the integral is adjusted to match given process inputs and outputs. The tracking mode is introduced to avoid switching transients when the system is controlled manually. The generator for the reference signal has three modes: a normal control mode when the output is controlled by the set/accelerate and resume/decelerate buttons, a tracking mode and a hold mode where the reference is held constant.

To control the overall operation of the controller and reference generator, we use a finite state machine with four states: off, standby, cruise and hold. The states of the controller and the reference generator in the different modes are given in Figure 3.4. The cruise mode is the normal operating mode where the speed can be then be decreased by pushing set/decelerate and increased by pushing the resume/accelerate. When the system is switched on it goes to standby mode. The cruise mode is activated by pushing the set/accelerate button. If the brake is touched or if the gear is changed, the system goes into hold mode and the current velocity is stored in the reference generator. The controller is then switched to tracking mode and the reference generator is switched to hold mode, where it holds the current velocity. Touching the resume button then switches the system to cruise mode. The system can be switched to standby mode from any state by pressing the cancel button.

The PI controller should be designed to have good regulation properties and to give good transient performance when switching between resume and control modes. Implementation of controllers and reference generators will be discussed more fully in Chapter 10. A popular description of cruise control system can be found on the companion web site. Many automotive applications are discussed in detail in [BP96] and [KN00].

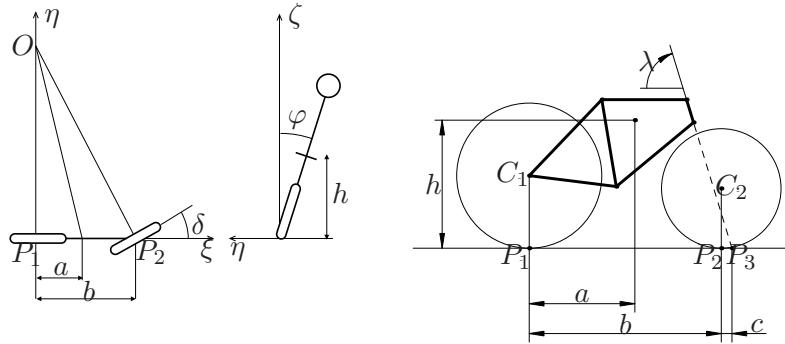


Figure 3.5: Schematic top (left), rear (middle), and side (right) views of a bicycle. The steering angle is δ , the roll angle is φ . The center of mass has height h and on the distance a from a vertical through the contact point P_1 of the rear wheel. The wheel base is b and the trail is c .

3.2 Bicycle Dynamics

The bicycle is an interesting dynamical system system with the feature that one of its key properties is due to a feedback mechanism that is created by a clever design of the front fork. A detailed model of a bicycle is complex because the system has many degrees of freedom and the geometry is complicated. However, a great deal of insight can be obtained from simple models.

To derive the equations of motion we assume that the bicycle rolls on the horizontal xy plane. Introduce a coordinate system that is fixed to the bicycle with the ξ -axis through the contact points of the wheels with the ground, the η -axis horizontal and the ζ -axis vertical, as shown in Figure 3.5. Let v_0 be the velocity of the bicycle at the rear wheel, b the wheel base, φ the tilt angle and δ the steering angle. The coordinate system rotates around the point O with the angular velocity $\omega = v_0\delta/b$, and an observer fixed to the bicycle experiences forces due to the motion of the coordinate system.

The tilting motion of the bicycle is similar to an inverted pendulum, as shown in the rear view in Figure 3.5b. To model the tilt, consider the rigid body obtained when the wheels, the rider and the front fork assembly are fixed to the rear frame. Let m be the total mass of the system, J the moment of inertia of this body with respect to the ξ -axis, and D the product of inertia with respect to the $\xi\zeta$ axes. Furthermore, let the ξ and ζ coordinates of the center of mass be a and h , respectively. We have $J \approx mh^2$ and $D = mah$.

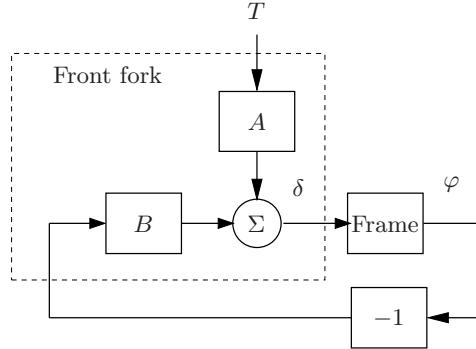


Figure 3.6: Block diagram of the bicycle with a front fork. The steering torque applied to the handlebars is T , the roll angle is φ , and the steering angle δ . Notice that the front fork creates a feedback from the roll angle φ to the steering angle δ that under certain conditions can stabilize the system.

The torques acting on the system are due to gravity and centripetal action. Assuming that the steering angle δ is small, the equation of motion becomes

$$J \frac{d^2\varphi}{dt^2} - \frac{Dv_0}{b} \frac{d\delta}{dt} = mgh \sin \varphi + \frac{mv_0^2 h}{b} \delta, \quad (3.5)$$

The term $mgh \sin \varphi$ is the torque generated by gravity. The terms containing δ and its derivative are the torques generated by steering, with the term $(Dv_0/b) d\delta/dt$ due to inertial forces and the term $(mv_0^2 h/b) \delta$ due to centripetal forces.

The steering angle is influenced by the torque the rider applies to the handle bar. Because of the tilt of the steering axis and the shape of the front fork, the contact point of the front wheel with the road P_2 is behind the axis of rotation of the front wheel assembly, as shown in Figure 3.5. The distance c between the contact point of the front wheel P_2 and the projection of the axis of rotation of the front fork assembly P_3 is called the *trail*. The steering properties of a bicycle depend critically on the trail. A large trail increases stability but make the steering less agile.

A consequence of the design of the front fork is that the steering angle δ is influence both by steering torque T and by the tilt of the frame φ . This means that the bicycle with a front fork is a *feedback system* as illustrated by the block diagram in Figure 3.6. The steering angle δ influences the tilt angle φ and the tilt angle influences the steering angle giving rise to the circular causality that is characteristic for reasoning about feedback. For a front fork with positive trail, the bicycle will steer into the lean creating

a centrifugal force that attempts to diminish the lean. The effect can be verified experimentally by biking on a straight path, creating a lean by tilting the body and observing the steering torque required to keep the bicycle on a straight path when leaning. Under certain conditions, the feedback can actually stabilize the bicycle. A crude empirical model is obtained by assuming that the blocks A and B are static gains k_1 and k_2 respectively:

$$\delta = k_1 T - k_2 \varphi. \quad (3.6)$$

This model neglects the dynamics of the front fork, the tire-road interaction and the fact that the parameters depend on the velocity. A more accurate model is obtained by the rigid body dynamics of the front fork and the frame. Assuming small angles this model becomes

$$M \begin{pmatrix} \ddot{\varphi} \\ \ddot{\delta} \end{pmatrix} + Cv_0 \begin{pmatrix} \dot{\varphi} \\ \dot{\delta} \end{pmatrix} + (K_0 + K_2 v_0^2) \begin{pmatrix} \varphi \\ \delta \end{pmatrix} = \begin{pmatrix} 0 \\ T \end{pmatrix}, \quad (3.7)$$

where the elements of the 2×2 matrices M , C , K_0 and K_2 depend on the geometry and the mass distribution of the bicycle. Even this model is inaccurate because the interaction between tire and road are neglected. Taking this into account requires two additional state variables.

Interesting presentations of the development of the bicycle are given in the books by D. Wilson [Wil04] and Herlihy [Her04]. More details on bicycle modeling is given in the paper [ÅKL05], which has many references. The model (3.7) was presented in a paper by Whipple in 1899 [Whi99].

3.3 Operational Amplifier

The operational amplifier (op amp) is a modern implementation of Black's feedback amplifier. It is a universal component that is widely used for instrumentation, control and communication. It is also a key element in analog computing.

Schematic diagrams of the operational amplifier are shown in Figure 3.7. The amplifier has one inverting input (v_-), one non-inverting input (v_+), and one output (v_{out}). There are also connections for the supply voltages, e_- and e_+ and a zero adjustment (offset null). A simple model is obtained by assuming that the input currents i_- and i_+ are zero and that the output is given by the static relation

$$v_{\text{out}} = \text{sat}_{(v_{\text{min}}, v_{\text{max}})}(k(v_+ - v_-)), \quad (3.8)$$

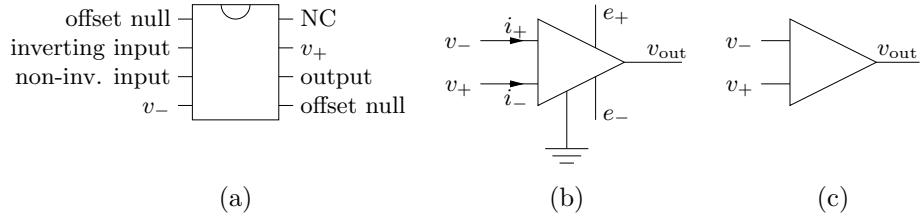


Figure 3.7: An operational amplifier and two schematic diagrams. The figure on the left shows the amplifier pin connections on an integrated circuit chip, the middle figure shows a schematic with all connections, and the diagram on the right shows only the signal connections.

where sat denotes the saturation function

$$\text{sat}_{(a,b)}(x) = \begin{cases} a & \text{if } x < a \\ x & \text{if } a \leq x \leq b \\ b & \text{if } x > b. \end{cases} \quad (3.9)$$

We assume that the gain k is very large, in the range of 10^6 – 10^8 , and the voltages v_{\min} and v_{\max} satisfy

$$e_- \leq v_{\min} < v_{\max} \leq e_+$$

and hence are in the range of the supply voltages. More accurate models are obtained by replacing the saturation function with a smooth function as shown in Figure 3.8. For small input signals the amplifier characteristic (3.8) is linear

$$v_{\text{out}} = k(v_+ - v_-) =: -kv. \quad (3.10)$$

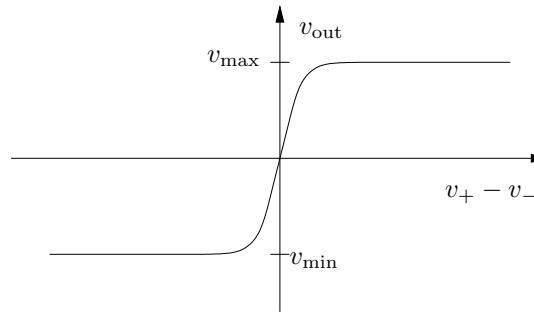


Figure 3.8: Input-output characteristics of an operational amplifier.

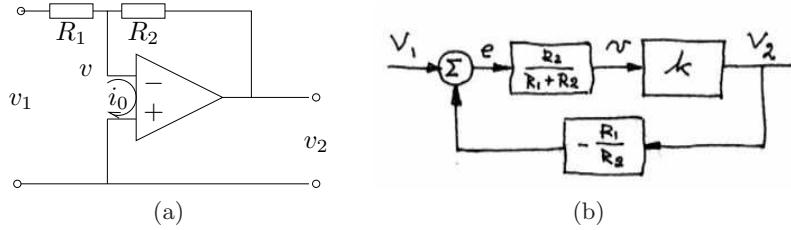


Figure 3.9: Circuit diagram of a stable amplifier based on negative feedback around an operational amplifier (a) and the corresponding block diagram (b).

Since the open loop gain k is very large, the range of input signals where the system is linear is very small.

A simple amplifier is obtained by arranging feedback around the basic operational amplifier as shown in Figure 3.9a. To model the feedback amplifier in the linear range, we assume that the current $i_0 = i_- + i_+$ is zero, and that the gain of the amplifier is so large that the voltage $v = v_- - v_+$ is also zero. It follows from Ohm's law that the currents through resistors R_1 and R_2 are given by

$$\frac{v_1}{R_1} = -\frac{v_2}{R_2}$$

and hence

$$\frac{v_2}{v_1} = -k_{cl} \quad \text{where} \quad k_{cl} = \frac{R_2}{R_1} \quad (3.11)$$

is the closed loop gain of the amplifier.

A more accurate model is obtained by neglecting the current i_0 but assuming that the voltage v is small but not negligible. The current balance then becomes

$$\frac{v_1 - v}{R_1} = \frac{v - v_2}{R_2}. \quad (3.12)$$

Assuming that the amplifier operates in the linear range and using equation (3.10) the gain of the closed loop system becomes

$$k_{cl} = -\frac{v_2}{v_1} = \frac{R_2}{R_1} \frac{1}{1 + \frac{1}{k} \left(1 + \frac{R_2}{R_1} \right)} \quad (3.13)$$

If the open loop gain k of the operational amplifier is large, the closed loop gain k_{cl} is the same as in the simple model given by equation (3.11). Notice that the closed loop gain only depends on the passive components, and that variations in k only have a marginal effect on the closed loop gain. For example if $k = 10^6$ and $R_2/R_1 = 100$, a variation of k by 100% only

gives a variation of 0.01% in the closed loop gain. The drastic reduction in sensitivity is a nice illustration of how feedback can be used to make good systems from bad components. In this particular case, feedback is used to trade high gain and low robustness for low gain and high robustness. Equation (3.13) was the formula that inspired Black when he invented the feedback amplifier.

It is instructive to develop a block diagram for the feedback amplifier in Figure 3.9a. To do this we will represent the pure amplifier with input v and output v_2 as one block. To complete the block diagram we must describe how v depends on v_1 and v_2 . Solving equation (3.12) for v gives

$$v = \frac{R_2}{R_1 + R_2} v_1 + \frac{R_1}{R_1 + R_2} v_2 = \frac{R_2}{R_1 + R_2} \left(v_1 + \frac{R_1}{R_2} v_2 \right),$$

and we obtain the block diagram shown in Figure 3.9b. The diagram clearly shows that the system has feedback and that the gain from v_2 to v is $R_1/(R_1 + R_2)$, which can also be read from the circuit diagram in Figure 3.9a. If the loop is stable and if gain of the amplifier is large it follows that the error e is small and then we find that $v_2 = -(R_2/R_1)v_1$. Notice that the resistor R_1 appears in two blocks in the block diagram. This situation is typical in electrical circuits and it is one reason why block diagrams are not always well suited for some types of physical modeling.

The simple model of the amplifier given by equation (3.10) gives qualitative insight but it neglects the fact that the amplifier is a dynamical system. A more realistic model is

$$\frac{dv_{\text{out}}}{dt} = -av_{\text{out}} - bv. \quad (3.14)$$

The parameter b which has dimensions of frequency is called the gain-bandwidth product of the amplifier.

The operational amplifier is very versatile and many different systems can be built by combining it with resistors and capacitors. Figure 3.10 shows the circuit diagram for analog PI (proportional-integral) controller. To develop a simple model for the circuit we assume that the current i_0 is zero and that the open loop gain k is so large that the input voltage v is negligible. The current i through the capacitor is $i = Cdv_c/dt$, where v_c is the voltage across the capacitor. Since the same current goes through the resistor R_1 we get

$$i = \frac{v_1}{R_1} = C \frac{dv_c}{dt},$$

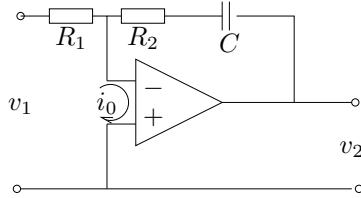


Figure 3.10: Circuit diagram of a PI controller obtained by feedback around an operational amplifier.

which implies that

$$v_c(t) = \frac{1}{C} \int i(t) dt = \frac{1}{R_1 C} \int_0^t v_1(\tau) d\tau.$$

The output voltage is thus given by

$$v_2(t) = -R_2 i - v_c = -\frac{R_2}{R_1} v_1(t) - \frac{1}{R_1 C} \int_0^t v_1(\tau) d\tau,$$

which is the input/output relation for a PI controller.

The development of operational amplifiers is based on the work of Philbrick [Lun05, Phi48] and their usage is described in many textbooks (e.g. [CD75]). Very good information is also available from suppliers [Jun02, Man02].

3.4 Web Server Control

Control is important to ensure proper functioning of web servers, which are key components of the Internet. A schematic picture of a server is shown in Figure 3.11. Requests are arriving, queued and processed by the server, typically on a first-come-first-serve basis. There are typically large variations in arrival rates and service rates. The queue length builds up when the

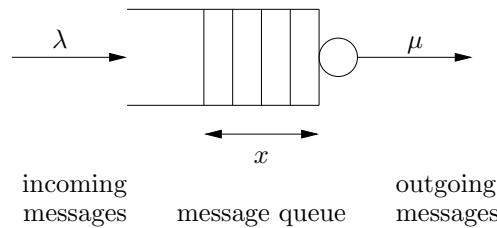


Figure 3.11: Schematic diagram of a web server.

arrival rate is larger than the service rate. When the queue becomes too large, service is denied using some admission control policy.

The system can be modeled in many different ways. One way is to model each incoming request, which leads to an event-based model, where the state is an integer that represents the queue length. The queue changes when a request arrived or a request is served. A discrete time model that captures these dynamics is given by the difference equation

$$x_{k+1} = x_k + u_i - u_o, \quad x \in I$$

where u_i and u_o are *random variables* representing incoming and outgoing requests on the queue. These variables take on the values 0 or 1 with some probability at each time instant. To capture the statistics of the arrival and servicing of messages, we model each of these as a *Poisson process* in which the number of events occurring in a fixed time has a given rate, with the specific timing of events independent of the time since the last event. (The details of random processes are beyond the scope of this text, but can be found in standard texts such as [Pit99].)

The system can also described using a *flow model* by approximating the requests and services by continuous flows and the queue length by a continuous variable. A flow model can be obtained by making probabilistic assumptions on arrival and service rates and computing the average queue length. For example, assuming that the arrival and service rates are Poisson processes with intensities λ and μ it can be shown that the average queue length x is described by the first-order differential equation

$$\frac{dx}{dt} = \lambda u - \mu \frac{x}{x+1}. \quad (3.15)$$

The control variable $0 \leq u \leq 1$ is the fraction of incoming requests that are serviced, giving an effective arrival rate of $u\lambda$. The average time to serve a request is

$$T_s = \frac{x}{\lambda}.$$

If μ , λ and u are constants with $\mu > u\lambda$, the queue length x approaches the steady state value

$$x_{ss} = \frac{u\lambda}{\mu - u\lambda}. \quad (3.16)$$

Figure 3.12a shows the steady state queue length as a function of $\mu - u\lambda$, the effective service rate excess. Notice that the queue length increases rapidly as $\mu - u\lambda$ approaches zero. To have a queue length less than 20 requires $\mu > u\lambda + 0.05$.

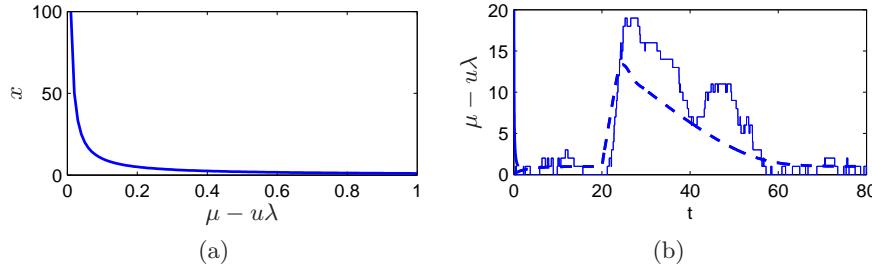


Figure 3.12: The figure on the left shows steady state queue length as a function of $u\lambda - \mu$, and the figure on the right shows the behavior of the queue length when there is a temporary overload in the system. The full line shows a realization of an event based simulation and the dashed line shows the behavior of the flow model (3.15).

Figure 3.12b illustrates the behavior of the server in a typical overload situation. The service rate is $\mu = 1$, while the arrival rate starts at $\lambda = 0.5$. The arrival rate is increased to $\lambda = 4$ at time 20, and it returns to $\lambda = 0.5$ at time 25. The figure shows that the queue builds up quickly and clears very slowly. Since the response time is proportional to queue length, it means that the quality of service is poor for a long period after an overload. The behavior illustrated in Figure 3.12b, which is called the *rush-hour effect*, has been observed in web servers and in many other queuing systems like automobile traffic. Congestion avoidance is a main reason for controlling queues.

The dashed line in Figure 3.12b shows the behavior of the flow model, which describes the average queue length. The simple model captures behavior qualitatively, but since the queue length is short there is significant variability from sample to sample. The behavior shown in Figure 3.12b can be explained quantitatively by observing that the queue length increases at constant rate over large time intervals. It follows from equation (3.15) that the rate of change is approximately 3 messages/second when the queue length builds up at time $t = 20$, and approximately 0.5 messages/second when the queue length decreases after the build up. The time to return to normal is thus approximately 6 times the overload time.

Admission Control

The long delays created by temporary overloads can be reduced by access control. The queue length can be controlled by only admitting a fraction of the incoming requests. Figure 3.13 shows what happens when a simple ad-

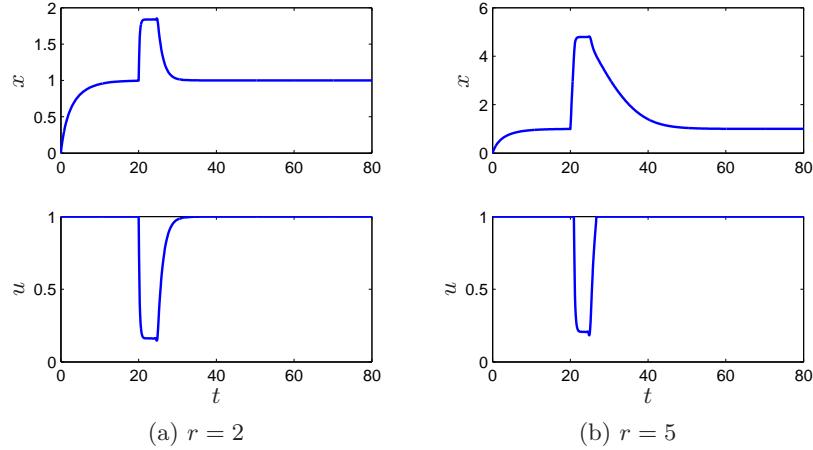


Figure 3.13: Behavior of queue length for a server with admission control when there is a temporary overload in the system. The figure on the left has $r = 2$ and the right figure has $r = 5$, with $k = 1$ in both cases. Compare with a simulation of the uncontrolled system in Figure 3.12b.

mission control strategy is introduced. The feedback used in the simulation is a simple proportional control with saturation described by

$$u = \text{sat}_{(0,1)}(k(r - x)), \quad (3.17)$$

where $\text{sat}_{(a,b)}$ is defined in equation (3.9) and r is the desired (reference) queue length. The feedback gain is $k = 1$, and the saturation ensures that the control variable is in the interval $0 \leq u \leq 1$. Comparing Figures 3.12b and 3.13, we see that simple access control works very well in comparison with the uncontrolled server. The control law ensures that the access is restricted when overload occurs.

The maximum queue length is determined by the reference value r . A low value of r gives a short queue length and the service delay is short, as is clearly seen in Figure 3.13a. A number of customers are, however, denied service. The simulation also indicates that the control problem is not too difficult and that a simple control strategy works quite well. It allows all requests arrived to be serviced if the arrival rate is slow and it restricts admission when the system is overloaded. Admission control is activated when the queue length approaches the value r . Since service time is proportional to queue length, r is a measure of service time.

Notice that the web server control problem we have discussed is not a conventional regulation problem where we wish to keep a constant queue

length. The problem is instead to make sure that the queue length does not become too large when there are many service requests. The key trade-off is to find a good reference value r . A large value gives few rejections but long service time after an overload; a small value guarantees a short service time but more messages will be rejected. The simulation of the simple flow model indicates that the simple admission control strategy works well.

To execute admission control in a real queue, where arrival and departure from the queue are discrete events, we argue as follows. Figure 3.13 shows that all requests are serviced ($u = 1$) except when the system is overloaded, at which point service is reduced significantly. A simple strategy that mimics this for event-based systems is to admit customers as long as the queue length is less than r and deny service for requests if the queue length is greater than r .

Delay Control

An alternative to admission control is *delay control*, where the goal is to keep the delay for serving individual requests constant. An advantage of this approach is that all requests are treated fairly. A block diagram of such a system, with a controller combining feedback u_{fb} and feedforward u_{ff} , is shown in Figure 3.14a. The server delay is estimated based on arriving server requests and queue waiting times of requests that have not been serviced. Feedforward control requires good models and the simple model (3.15) that captures the average behavior of the system is not sufficient.

The control variable is the processing speed u , which can be varied by the changing the number of servers and their processing capacity. It is assumed that u can be regarded as a continuous variable. The delays in serving the requests is the output of the system. An average of past service is easily obtained, but this information is only available with a time delay.

To obtain a better model we consider the situation in Figure 3.14b. A request has just been serviced at time $t = t_k$ and N requests are waiting to be serviced. The average delay of the N requests that are waiting to be serviced is d_k^- , which is a measurable quantity. To predict the additional time required to serve these request we assume that they require the same service time C/u where u is the service rate. The average additional service time for the requests that are processed is then $d_k^+ = (N + 1)C/(2u)$, as indicated in Figure 3.14b. Combining this with the measurable quantity d_k^- we obtain the following estimate of the average service time for the N

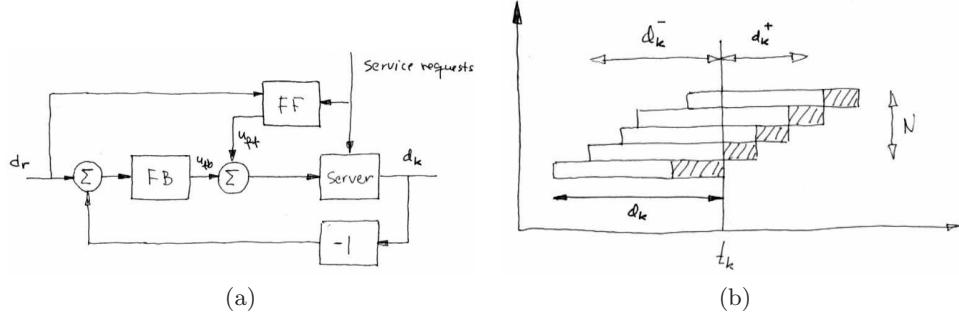


Figure 3.14: The left figure (a) shows a block diagram of a web server system with a controller based on a combination of feedback and feedforward. The right figure (b) shows the history of arrivals and departures of requests. The dashed square indicates the time used to service the requests. The true delay of the request serviced at time t_k is d_k , $d_k^- + d_k^+$ is an estimate of future delays used to calculate the service rate.

requests that are waiting to be serviced

$$d_k = d_k^- + d_k^+ = d_k^- + \frac{(N+1)C}{2u}.$$

Requiring that d_k is equal to the desired delay time d_r , we find that the service rate at instant k should be chosen as

$$u_k = \frac{(N+1)C}{2(d_r - d_k^-)}, \quad (3.18)$$

which is the formula used to calculate the feedforward control signal at time t_k . The control action can be recalculated at each time instant, resulting in a control strategy called *receding horizon control*. The choice of recalculation rate is a compromise because frequent recalculations improves control quality but it also consumes computer resources.

The feedforward is complemented with a feedback controller in the form of a PI controller based on the measured delay at event k . Since the queue dynamics varies with the delay time it is useful to let the parameters of the PI controller depend on the desired delay d_r , an example of *gain scheduling*.

The control algorithm has been tested experimentally on a testbed of PC's connected via Ethernet. One PC was assigned to run the web server, and the others were generating a synthetic workload. The goal of the system was to provide the delay guarantee for that class with as few resources as possible. The input load patterns generated by the clients are

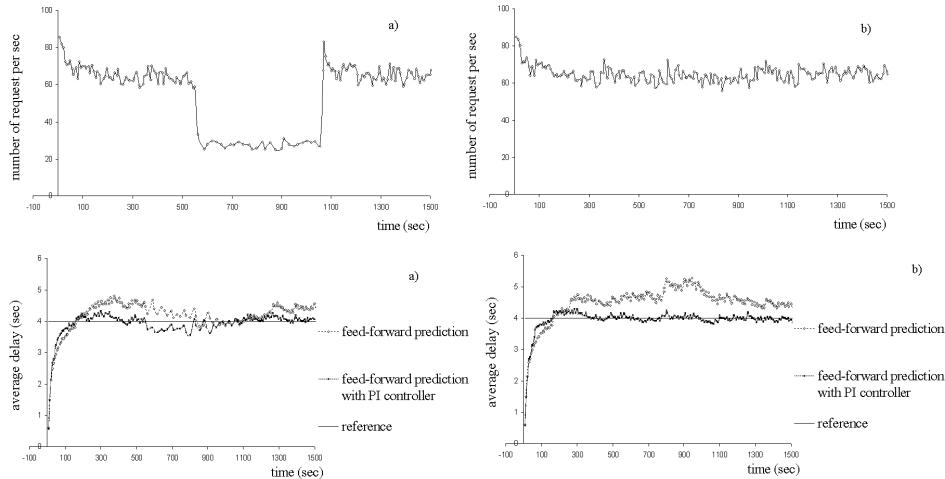


Figure 3.15: Arrival rate (top) and average service delay (bottom) for an experiment with web server control (from [HLA04]).

shown in Figure 3.15. The desired delay for the class was set to $d_r = 4s$ in all experiments. The figure shows that the control algorithm keeps the service time reasonably constant and that the PI controller reduces the variations in delay compared with a pure feedforward controller.

This example illustrates that simple models can give good insight and that nonlinear control strategies are useful. The example also illustrates that continuous time models can be useful for phenomena that are basically discrete. There are also converse examples. Therefore it is a good idea to keep an open mind and master both discrete and continuous time modeling.

The book by Hellerstein et al. [HDPT04] gives many examples of use of feedback in computer systems. The example on delay control is based on the work of Henriksson [HLA04, Hen06].

3.5 Atomic Force Microscope

The 1986 Nobel Prize in Physics was shared by Gerd Binnig and Heinrich Rohrer for their design of the scanning tunneling microscope (SCM). The idea of an SCM is to bring an atomically sharp tip so close to a conducting surface that tunneling occurs. An image is obtained by traversing the tip and measuring the tunneling current as a function of tip position. The image reflects the electron structure of the upper atom-layers of the sample.

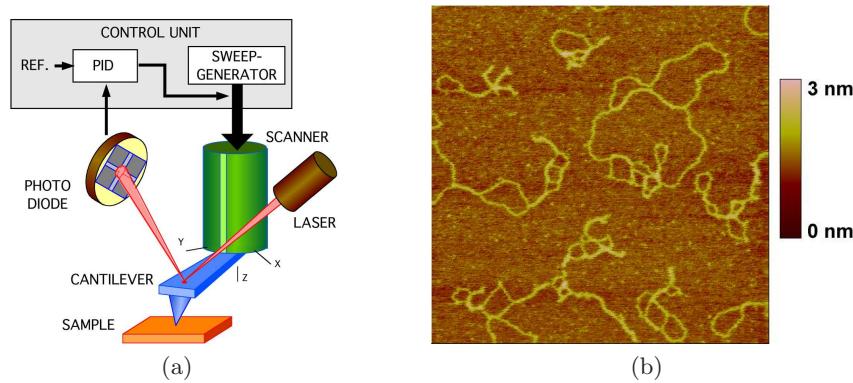


Figure 3.16: Schematic diagram of an atomic force microscope and a sample AFM image of DNA.

This invention has stimulated development of a family of instruments that permit visualization of surface structure at the nanometer scale, including the atomic force microscope (AFM). These instruments are now standard tools for exploring nanoscale structures.

In the atomic force microscope, a sample is probed by a tip on a cantilever which is controlled to exert a constant force on the sample. The control system is essential because it has a direct influence on picture quality and scanning rate. Since the dynamic behavior of the system changes with the properties of the sample, it is necessary to tune the feedback loop, which is currently done manually by adjusting parameters of a PI controller. There are interesting possibilities to make the systems easier to use by introducing automatic tuning and adaptation.

A schematic picture of an atomic force microscope is shown in Figure 3.16a. A micro-cantilever with a tip having a radius of the order of 10 nm is placed close to the sample. The tip can be moved vertically and horizontally using a piezoelectric scanner. Atomic forces bend the cantilever and the cantilever tilt is measured by sensing the deflection of the beam using a photo diode. The signal from the photo diode is amplified and sent to a controller that drives the amplifier for the vertical deflection of the cantilever. By controlling the piezo scanner so that the deflection of the cantilever is constant, the signal driving the vertical deflection of the scanner is a measure of the atomic forces between the cantilever tip and the atoms of the sample. An image of the surface is obtained by scanning the cantilever along the sample. The resolution makes it possible to see the structure of the sample on the atomic scale, as illustrated in Figure 3.16b,

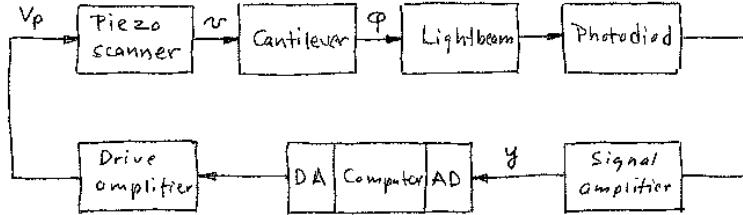


Figure 3.17: Block diagram of the system for vertical positioning of the cantilever.

which shows an AFM image of DNA.

To model the system, we start with the block diagram shown in Figure 3.17, which shows the major components. Signals that are easily accessible are: the voltage V_p that drives the piezo scanner, the input voltage u to its power amplifier and the output voltage y of the signal amplifier for the photo diode. The controller is a PI controller implemented by a computer, which is connected to the system by A/D and D/A converters. The deflection of the cantilever, φ , is also shown.

For a more detailed model we will start with the cantilever, which is at the heart of the system. The micro-cantilever is modeled as a spring-mass-damper system. Let z be the distance from the tip of the cantilever to the sample and let v be the position of the cantilever base. Furthermore let m , k and c be the effective values of mass, spring and damping coefficients. The equation of motion of the cantilever is then

$$m \frac{d^2 z}{dt^2} + c \frac{dz}{dt} + k(z - v) = F, \quad (3.19)$$

where F is the atomic force between the sample and the cantilever tip.

Neutral atoms and molecules are subject to two forces, an attractive van der Waals force, and a repulsion force due to the Pauli exclusion principle. The force between two atoms can be approximately described by the Lennard-Jones potential given by

$$V_{LJ}(z) = A \left(\left(\frac{\sigma}{z} \right)^{12} - \left(\frac{\sigma}{z} \right)^6 \right),$$

where σ is the atom radius and r the distance between the atoms. Approximating the cantilever tip by a sphere with radius R and the sample by a flat surface then integrating the Lennard-Jones potential, the interaction

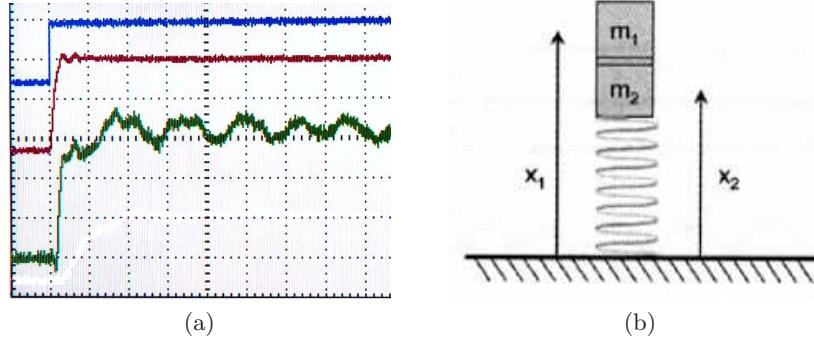


Figure 3.18: Measured step response and model of piezo scanner. The left figure shows a measured step response. The blue signal shows the input is the voltage applied to the drive amplifier (50 mV/div), the red curve is the output of the power amplifier (500 mV/div) and the red curve is the output of the signal amplifier (500 mV/div). The time scale is 25 $\mu\text{s}/\text{div}$. The right figure is a simple mechanical model for the vertical positioner and the piezo crystal.

between the cantilever and the sample can be described by the following potential

$$V(z) = \frac{HR}{6\sigma} \left(\frac{1}{120} \left(\frac{\sigma}{z} \right)^7 - \frac{\sigma}{z} \right),$$

where $H \approx 10^{-19}$ J is the Hamaker constant, and a typical atom radius is $\sigma = 0.4$ nm. The potential has a minimum where the distance between the tip is less than an atom size from the sample and the tip is essentially clamped at the minimum by the atomic forces. The natural frequency of the clamped cantilever is so high that the dynamics of the cantilever can be neglected and we can model the cantilever as a static system. For small deviations, the bending φ of the cantilever is then proportional to the vertical translation of the cantilever.

The piezo scanner gives a deflection that is proportional to the applied voltage, but the system and the amplifiers also have dynamics. Figure 3.18a shows a step response of a scanner from the input voltage u to the drive amplifier to the output voltage y of the signal amplifier for the photo diode. A schematic mechanical representation of the vertical motion of the scanner is shown in Figure 3.18b. The figure shows that the system responds quickly but that there is a poorly damped oscillatory mode caused by the dynamics of the scanner. The instrument designer has two choices, either to accept the oscillation and to have a slow response time or else to design a control

system that can damp the oscillations which gives a faster response and a faster imaging. Damping the oscillations is a significant challenge because there are many oscillatory modes and they can change depending on how the instrument is used. An instrument designer also has the choice to redesign the mechanics so that the resonances occur at higher frequencies.

The book by Sarid [Sar91] gives a broad coverage of atomic force microscopes. The interaction of atoms close to surfaces is fundamental to solid state physics. A good source is Kittel [Kit95] where the Lennard-Jones potential is discussed. Modeling and control of atomic force microscopes are discussed by Schitter [Sch01].

3.6 Drug Administration

The phrase “take two pills three times a day” is a recommendation that we are all familiar with. Behind this recommendation is a solution of an open loop control problem. The key issue is to make sure that the concentration of a medicine in a part of our bodies will be sufficiently high to be effective but not so high that it will cause undesirable side effects. The control action is quantized, *take two pills*, and sampled, *every 8 hours*. The prescriptions can be based on very simple models in terms of empirical tables where the dosage is based on the age and weight of the patient. A more sophisticated administration of medicine is used to keep concentration of insulin and glucose at a right level. In this case the substances are controlled by continuous measurement and injection, and the control schemes are often model based.

Drug administration is clearly a control problem. To do it properly it is necessary to understand how a drug spreads in the body after it is administered. This topic, called *pharmacokinetics*, is now its own discipline and the models used are called *compartment models*. They go back to 1920 when Widmark modeled propagation of alcohol in the body [WT24]. Pharmacokinetics describes how drugs are distributed in different organs of the body. Compartment models are now important for screening of all drugs used by humans. The schematic diagram in Figure 3.19 illustrates the idea of a compartment model. Compartment models are also used in many other fields such as environmental science.

One-Compartment Model

The simplest dynamic model is obtained by assuming that the body behaves like a single compartment: that the drug is spread evenly in the body after

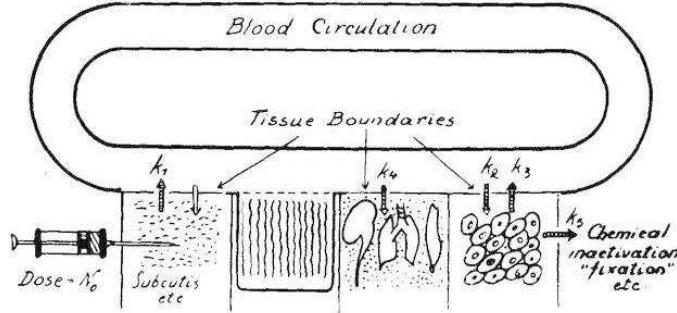


Figure 3.19: Schematic diagram of the circulation system (from Teorell [Teo37]).

it has been administered, and that it is then removed at a rate proportional to the concentration. Let c be the concentration, V the volume and q the outflow rate or the clearance. Converting the description of the system into differential equations, the model becomes

$$V \frac{dc}{dt} = -qc. \quad (3.20)$$

This equation has the solution

$$c(t) = c_0 e^{-qt/V} = c_0 e^{-kt},$$

which shows that the concentration decays exponentially after an injection. The input is introduced implicitly as an initial condition in the model (3.20). The way the input enters the model depends on how the drug is administered. The input can be represented as a mass flow into the compartment where the drug is injected. A pill that is dissolved can also be interpreted as an input in terms of a mass flow rate.

The model (3.20) is called a *a one-compartment model* or a *single pool model*. The parameter q/V is called the elimination rate constant. The simple model is often used in studies where the concentration is measured in the blood plasma. By measuring the concentration at a few times, the initial concentration can be obtained by extrapolation. If the total amount of injected substance is known, the volume V can then be determined as $V = m/c_0$; this volume is called the *the apparent volume of distribution*. This volume is larger than the real volume if the concentration in the plasma is lower than in other parts of the body. The model (3.20) is very simple and there are large individual variations in the parameters. The parameters V and q are often normalized by dividing with the weight of the person.

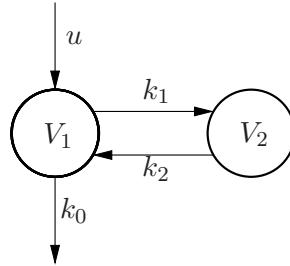


Figure 3.20: Schematic diagram of a model with two compartments.

Typical parameters for aspirin are $V = 0.2 \text{ l/kg}$ and $q = 0.01 \text{ l/h/kg}$. These numbers can be compared with a blood volume of 0.07 l/kg , a plasma volume of 0.05 l/kg and intracellular fluid volume of 0.4 l/kg .

The simple one compartment model gives the gross behavior but it is based on strong simplifications. Improved models can be obtained by considering the body as composed of several compartments. We will work out the details for a system with two compartments.

Two-Compartment Model

Consider the system shown in Figure 3.20, where the compartments are represented as circles and the flows by arrows. We assume that there is perfect mixing in each compartment and that the transport between the compartments are driven by concentration differences. We further assume that a drug with concentration c_0 is injected in compartment 1 at a volume flow rate of u and that the concentration in compartment 2 is the output.

Let x_1 and x_2 be the total mass of the drug in the compartments and let V_1 and V_2 be the volumes of the compartments. A mass balance for the system gives

$$\begin{aligned} \frac{dx_1}{dt} &= q(c_2 - c_1) - q_0 c_1 + c_0 u = q\left(\frac{x_2}{V_2} - \frac{x_1}{V_1}\right) - \frac{q_0}{V_1} c_1 + c_0 u \\ &= -(k_1 + k_0)x_1 + k_2 x_2 + c_0 u \\ \frac{dx_2}{dt} &= q(c_1 - c_2) = q\left(\frac{x_1}{V_1} - \frac{x_2}{V_2}\right) = k_1 x_1 - k_2 x_2 \\ y = c_2 &= \frac{1}{V_2}x_2, \end{aligned}$$

where $k_0 = q_0/V_1$, $k_1 = q/V_1$ and $k_2 = q/V_2$. Introducing matrices, this

model can be written as

$$\begin{aligned}\frac{dx}{dt} &= \begin{pmatrix} -k_0 - k_1 & k_2 \\ k_1 & -k_2 \end{pmatrix} x + \begin{pmatrix} c_0 \\ 0 \end{pmatrix} u \\ y &= \begin{pmatrix} 0 & 1/V_2 \end{pmatrix} x.\end{aligned}\tag{3.21}$$

In this model we have used the total mass of the drug in each compartment as state variables. If we instead choose to use the concentrations as state variables, the model becomes

$$\begin{aligned}\frac{dc}{dt} &= \begin{pmatrix} -k_0 - k_1 & k_1 \\ k_2 & -k_2 \end{pmatrix} c + \begin{pmatrix} b_0 \\ 0 \end{pmatrix} u \\ y &= \begin{pmatrix} 0 & 1 \end{pmatrix} x,\end{aligned}\tag{3.22}$$

where $b_0 = c_0/V_1$. Mass is called an *extensive variable* and concentration is called an *intensive variable*.

The papers by Widmark and Tandberg [WT24] and Teorell [Teo37] are classics. Pharmacokinetics is now an established discipline with many textbooks [Dos68, Jac72, GP82]. Because of its medical importance pharmacokinetics is now an essential component of drug development. Compartment models are also used in other branches of medicine and in ecology. The problem of determining rate coefficients from experimental data is discussed in [BÅ70] and [God83].

3.7 Population Dynamics

Population growth is a complex dynamic process that involves the interaction of one or more species with their environment and the larger ecosystem. The dynamics of population groups are interesting and important in many different areas of social and environmental policy. There are examples where new species have been introduced in new habitats, sometimes with disastrous results. There are also attempts to control population growth both through incentives and through legislation. In this section we describe some of the models that can be used to understand how populations evolve with time and as a function of their environment.

Simple Growth Model

Let x the the population of a species at time t . A simple model is to assume that the birth and death rates are proportional to the total population. This

gives the linear model

$$\frac{dx}{dt} = bx - dx = (b - d)x = rx \quad (3.23)$$

where birth rate b and death rate d are parameters. The model gives an exponential increase if $b > d$ or an exponential decrease if $B < d$. A more realistic model is to assume that the birth rate decreases when the population is large. The following modification of the model (3.23) has this property:

$$\frac{dx}{dt} = rx\left(1 - \frac{x}{x_c}\right) = f(x), \quad (3.24)$$

where x_c is the *carrying capacity* of the environment. The model (3.24) is called the *logistic growth* model.

Predator Prey Models

A more sophisticated model of population dynamics includes the effects of competing populations, where one species may feed on another. This situation, referred to as the *predator prey problem*, was already introduced in Example 2.3, where we developed a discrete time model that captured some of the features of historical records of lynx and hare populations.

In this section, we replace the difference equation model used there with a more sophisticated differential equation model. Let $H(t)$ represent the number of hares (prey) and $L(t)$ represent the number of lynxes (predator). The dynamics of the system are modeled as

$$\begin{aligned} \frac{dH}{dt} &= r_h H \left(1 - \frac{H}{K}\right) - \frac{aHL}{1 + aHT_h} & H \geq 0 \\ \frac{dL}{dt} &= r_l L \left(1 - \frac{L}{kH}\right) & L \geq 0. \end{aligned}$$

In the first equation, r_h represents the growth rate of the hares, K represents the maximum population of hares (in the absence of lynxes), a represents the interaction term that describes how the hares are diminished as a function of the lynx population, and T_h depends is a time constant for prey consumption. In the second equation, r_l represents the growth rate of the lynxes and k represents the fraction of hares versus lynxes at equilibrium. Note that both the hare and lynx dynamics include terms that resemble the logistic growth model (3.24).

Of particular interest are the values at which the population values remain constant, called *equilibrium points*. The equilibrium points for this

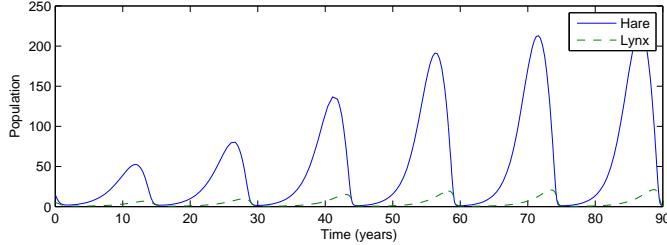


Figure 3.21: A simulation of the predator prey model with $r_h = 0.02$, $K = 500$, $a = 0.03$, $T_h = 5$, $r_l = 0.01$, $k = 0.2$ and time scale chosen to correspond to weeks.

system can be determined by setting the right hand side of the above equations to zero. Letting H_e and L_e represent the equilibrium state, from the second equation we have

$$L_e = kH_e.$$

Substituting this into the first equation, we must solve

$$r_h H_e \left(1 - \frac{H_e}{K} \right) - \frac{akH_e^2}{1 + aH_e T_h} = 0.$$

Multiplying through by the denominator, we get

$$\begin{aligned} 0 &= H_e \cdot \left(r_h \left(1 - \frac{H_e}{K} \right) (1 + aH_e T_h) - akH_e \right) \\ &= H_e \cdot \left(\frac{r_h a T_h}{K} H_e^2 + (ak + r_h/K - r_h a T_h) H_e - r_h \right). \end{aligned}$$

This gives one solution at $H_e = 0$ and a second that can be solved analytically or numerically.

Figure 3.21 shows a simulation of the dynamics starting from a set of population values near the nonzero equilibrium values. We see that for this choice of parameters, the simulation predicts an oscillatory population count for each species, reminiscent of the data shown in Figure 2.6 (page 48).

Fisheries Management

We end this section by discussing a control problem that has had significant impact on international legislation for fishing.

The dynamics of a commercial fishery can be described by the following simple model

$$\frac{dx}{dt} = f(x) - h(x, u), \quad (3.25)$$

where x be the total biomass, $f(x)$ the growth rate and $h(x, u)$ the harvesting rate. The logistic function (3.24) is a simple model for the growth rate and the harvesting can be modeled by

$$h(x, u) = axu, \quad (3.26)$$

where the control variable u is the harvesting effort, and a is a constant. The rate of revenue is

$$g(x, u) = bh(x, u) - cu, \quad (3.27)$$

where b and c are constants representing the price of fish and the cost of fishing. Using equations (3.26) and (3.27) we find that the rate of revenue is

$$g(x, u) = (abx - c)u.$$

In a situation where there are many fishermen and no concern for the environment, it is economic to fish as long as $abx > c$ and there will then be an equilibrium where the biomass is

$$x_\infty = \frac{c}{ab}, \quad (3.28)$$

which is the equilibrium with unrestricted fishing.

Assume that the population is initially at equilibrium at $x(0) = x_c$. The revenue rate with unrestricted fishing is then $(abx_c - c)u$, which can be very large. The fishing effort then naturally increases until the equilibrium (3.28), where the revenue rate is zero.

We can contrast unrestricted fishing with the situation for a single fishery. A typical case is when a country has all fishing rights in a large area. In such a case it is natural to maximize the rate of *sustainable revenue*. This can be accomplished by adding the constraint that the biomass x in equation (3.25) is constant, which implies that

$$f(x) = h(x, u).$$

Solving this equation for u gives

$$u = u_d(x) = \frac{f(x)}{ax}.$$

Inserting the value of u into equation (3.27) gives the following rate of revenue

$$\begin{aligned} g(x) &= bh(x, u_d) - cu_d(x) = \left(b - \frac{c}{ax}\right)f(x) \\ &= rx\left(b - \frac{c}{ax}\right)\left(1 - \frac{x}{x_c}\right) = \frac{r}{x_c}\left(-abx^2 + (c + abx_c)x - cx_c\right). \end{aligned} \quad (3.29)$$

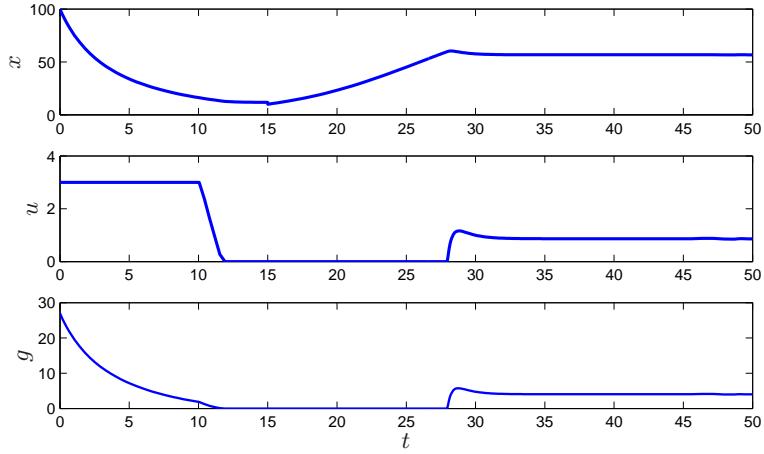


Figure 3.22: Simulation of a fishery. The curves show total biomass x , harvesting rate u and revenue rate g as a function of time t . The fishery is modeled by equations (3.25), (3.26), (3.27) with parameters $x_c = 100$, $a = 0.1$, $b = 1$ and $c = 1$. Initially fishing is unrestricted at rate $u = 3$, at time $t = 15$ fishing is changed to harvesting at a sustainable rate, accomplished by a PI controller with parameters $k = 0.5$ and $k_i = 0.5$.

The rate of revenue has a maximum

$$r_0 = \frac{r(c - abx_c)^2}{4abx_c}, \quad (3.30)$$

for

$$x_0 = \frac{x_c}{2} + \frac{c}{2ab}. \quad (3.31)$$

Figure 3.22 shows a simulation of a fishery. The system is initially in equilibrium with $x = 100$. Fishing begins with constant harvesting rate $u = 3$ at time $t = 0$. The initial revenue rate is large, but it drops rapidly as the population decreases. At time $t = 12$ the revenue rate is practically zero. The fishing policy is changed to a sustainable strategy at time $t = 15$. This is accomplished by using a PI controller where the reference is the optimal sustainable population size $x_0 = 55$, given by equation (3.31). The feedback stops harvesting for a period but the biomass increases rapidly. At time $t = 28$ the harvesting rate increases rapidly and a sustainable steady state is reached in a short time.

Volume I of the two volume set by J. Murray [Mur04] give a broad coverage of population dynamics. Maintaining a sustainable fish population

is a global problem that has created many controversies and conflicts. A detailed mathematical treatment is given in [?]. The mathematical analyses has influenced international agreement on fishing.

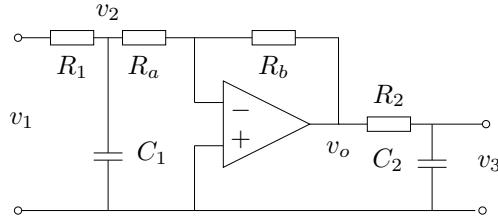
3.8 Exercises

1. Consider the cruise control example described in Section 3.1. Build a simulation that recreates the response to a hill shown in Figure 3.3b and show the effects of increasing and decreasing the mass of the car by 25%. Redesign the controller (using trial and error is fine) so that it returns to the within 10% of the desired speed within 3 seconds of encountering the beginning of the hill.
2. Consider the inverted pendulum model of the bicycle given in Figure 3.6. Assume that the block labeled body is modeled by equation (3.5) and that the front fork is modeled by (3.6). Derive the equations for the closed loop. Show that when $T = 0$ the equation is the same as for a mass spring damper system. Also show that the spring coefficient is negative for low velocities but positive if the velocity is sufficiently large.
3. Show that the dynamics of a bicycle frame given by equation (3.5) can be written in state space form as

$$\begin{aligned} \frac{d}{dt} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} &= \begin{pmatrix} 0 & mgh/J \\ 1 & 0 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \end{pmatrix} u \\ y &= \begin{pmatrix} Dv_0 \\ bJ \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}, \end{aligned}$$

where the input u is the torque applied to the handle bars and the output y is the title angle φ . What do the states x_1 and x_2 represent?

4. Combine the bicycle model given by equation (3.5) and the model for steering kinematics in Example 2.8 to obtain a model that describes the path of the center of mass of the bicycle.
5. Consider the op amp circuit shown below:



Show that the dynamics can be written in state space form as

$$\begin{aligned}\frac{dx}{dt} &= \begin{pmatrix} -\frac{1}{R_1 C_1} - \frac{1}{R_a C_1} & 0 \\ \frac{R_b}{R_a} \frac{1}{R_2 C_2} & -\frac{1}{R_2 C_2} \end{pmatrix} x + \begin{pmatrix} \frac{1}{R_1 C_1} \\ 0 \end{pmatrix} u \\ y &= \begin{pmatrix} 0 & 1 \end{pmatrix} x\end{aligned}$$

where $u = v_1$ and $y = v_3$. (Hint: Use v_2 and v_3 as your state variables.)

6. (Atomic force microscope) A simple model for the vertical motion of the scanner is shown in Figure 3.18b, where the system is approximated with two masses. The mass m_1 is half of the piezo crystal and the mass m_2 is the other half of the piezo crystal and the mass of the support. A simple model is obtained by assuming that the piezo crystal generates a force F between the masses and that there is a damping c in the spring. Let the positions of the center of the masses be x_1 and x_2 , and let the elongation of the piezo stack is $u = x_1 - x_2$. A momentum balance gives the following model for the system.

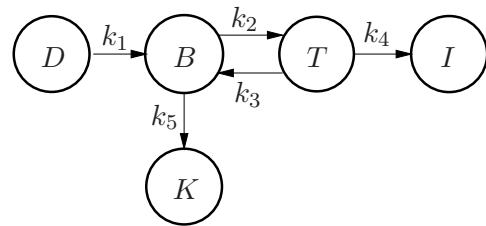
$$\begin{aligned}m_1 \frac{d^2x_1}{dt^2} &= F \\ m_2 \frac{d^2x_2}{dt^2} &= -c \frac{dx_2}{dt} - kx_2 - F \\ u &= x_1 - x_2.\end{aligned}$$

Review the assumptions made in the simplified model. Let the elongation u of the piezo stack be the control variable and the height of the sample x_1 be the output. Show that the relation between x_1 and u is given by

$$(m_2 - m_1) \frac{d^2x_1}{dt^2} + c \frac{dx_1}{dt} + kx_1 = m_1 \frac{d^2u}{dt^2} + c \frac{du}{dt} + ku.$$

Simulate the system and show that the response is qualitatively the same as the one shown in Figure 3.18a. Can the parameters of the model be determined from a step response experiment of the type shown in Figure 3.18a?

7. (Drug administration) Consider the compartment model in Figure 3.20. Assume that there is no outflux, i.e. $k_0 = 0$. Compare the models where the states are masses and concentrations. Compute the steady state solutions for the different cases. Give a physical interpretation of the results.
8. (Drug administration) Show that the model represented by the schematic diagram in Figure 3.19 can be represented by the compartment model shown below:



where compartment D represents the issue where the drug is injected, compartment B represents the blood, compartment T represents tissue where the drug should be active, compartment K the kidney where the drug is eliminated, and I a part of the body where the drug is inactive.

Write a simulation for the system and explore how the amount of the drug in the different compartments develops over time. Relate your observations to your physical intuition and the schematic diagram above. Modify your program so that you can investigate what happens if the drug is injected directly to the blood stream, compartment B , instead of in compartment D .

9. (Drug administration) The metabolism of alcohol in the body has can be modeled by the nonlinear compartment model

$$\begin{aligned} V_b \frac{dc_b}{dt} &= q(c_l - c_b) + q_{iv} \\ V_l \frac{dc_l}{dt} &= q(c_b - c_l) - q_{max} \frac{c_l}{c_0 + c_l} + q_{gi} \end{aligned}$$

where $V_b = 48$ l and $V_l = 0.6$ l are the effective distribution volume of body water and liver water, c_b and c_l the corresponding concentrations of alcohol, q_{iv} and q_{gi} are the injection rates for intravenously and gastrointestinal intake, $q = 1.5$ l/min is the total hepatic blood flow,

$q_{max} = 2.75 \text{ mmol/min}$ and $k_m = 0.1 \text{ mmol}$. Simulate the system and compute the concentration in the blood for oral and intravenous doses of 12 g and 40 g of alcohol.

10. (Population dynamics) Consider the model for logistic growth given by equation (3.24). Show that the maximum growth rate occurs when the size of the population is half of the steady state value.
11. (Population dynamics) Verify the curves in Figure 3.21 by creating a program that integrates the differential equations.

Chapter 4

Dynamic Behavior

Predictability: Does the Flap of a Butterfly's Wings in Brazil set off a Tornado in Texas?

Talk given by Edward Lorenz, December 1972 meeting of the American Association for the Advancement of Science.

In this chapter we give a broad discussion of the behavior of dynamical systems, focused on systems modeled by nonlinear differential equations. This allows us to discuss equilibrium points, stability, limit cycles and other key concepts of dynamical systems. We also introduce some methods for analyzing global behavior of solutions.

4.1 Solving Differential Equations

In the last chapter, we saw that one of the methods of modeling dynamical systems is through the use of ordinary differential equations (ODEs). A state space, input/output system has the form

$$\begin{aligned}\frac{dx}{dt} &= f(x, u) \\ y &= h(x, u),\end{aligned}\tag{4.1}$$

where $x = (x_1, \dots, x_n) \in \mathbb{R}^n$ is the state, $u \in \mathbb{R}^p$ is the input, and $y \in \mathbb{R}^q$ is the output. The smooth maps $f : \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}^n$ and $h : \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}^q$ represent the dynamics and measurements for the system. We will focus in this text on single input, single output (SISO) systems, for which $p = q = 1$.

We begin by investigating systems in which the input has been set to a function of the state, $u = \alpha(x)$. This is one of the simplest types of feedback,

in which the system regulates its own behavior. The differential equations in this case become

$$\frac{dx}{dt} = f(x, \alpha(x)) = F(x). \quad (4.2)$$

In order to understand the dynamic behavior of this system, we need to analyze the features of the solutions of equation (4.2). While in some simple situations we can write down the solutions in analytical form, more often we must rely on computational approaches. We begin by describing the class of solutions for this problem.

Initial Value Problems

We say that $x(t)$ is a *solution* of the differential equation (4.2) on the time interval $t_0 \in \mathbb{R}$ to $t_f \in \mathbb{R}$ if

$$\frac{dx(t)}{dt} = F(x(t)) \quad \text{for all } t_0 \leq t \leq t_f.$$

A given differential equation may have many solutions. We will most often be interested in the *initial value problem*, where $x(t)$ is prescribed at a given time $t_0 \in \mathbb{R}$ and we wish to find a solution valid for all *future* time, $t > t_0$.

We say that $x(t)$ is a solution of the differential equation (4.2) *with initial value* $x_0 \in \mathbb{R}^n$ at $t_0 \in \mathbb{R}$ if

$$x(t_0) = x_0 \quad \text{and} \quad \frac{dx(t)}{dt} = F(x(t)) \quad \text{for all } t_0 \leq t \leq t_f.$$

For most differential equations we will encounter, there is a *unique* solution that is defined for $t_0 \leq t \leq t_f$. The solution may be defined for all time $t \geq t_0$, in which case we take $t_f = \infty$. Because we will primarily be interested in solutions of the initial value problem for ODEs, we will often refer to this simply as the solution of an ODE.

We will usually assume that t_0 is equal to 0. In the case when F is independent of time (as in equation (4.2)), we can do so without loss of generality by choosing a new independent (time) variable, $\tau = t - t_0$ (Exercise 2).

Example 4.1 (Damped oscillator). Consider a damped, linear oscillator, introduced in Example 2.4. The equations of motion for the system are

$$m\ddot{q} + c\dot{q} + kq = 0,$$

where q is the displacement of the oscillator from its rest position. We assume that $c^2 < 4km$, corresponding to a lightly damped system (the

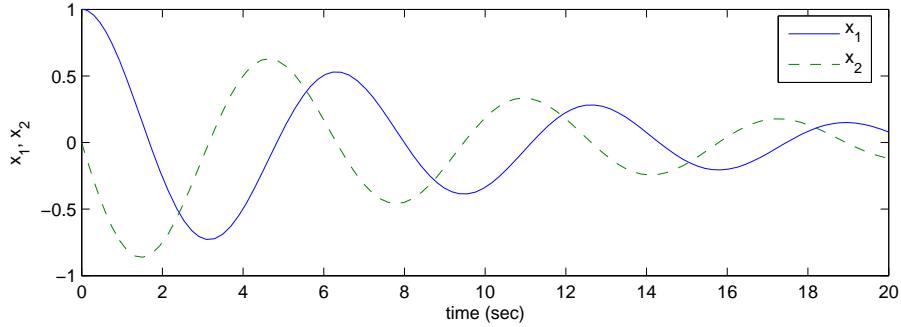


Figure 4.1: Response of the damped oscillator to the initial condition $x_0 = (1, 0)$.

reason for this particular choice will become clear later). We can rewrite this in state space form by setting $x_1 = q$ and $x_2 = \dot{q}$, giving

$$\begin{aligned}\dot{x}_1 &= x_2 \\ \dot{x}_2 &= -\frac{k}{m}x_1 - \frac{c}{m}x_2.\end{aligned}$$

In vector form, the right hand side can be written as

$$F(x) = \begin{pmatrix} x_2 \\ -\frac{k}{m}x_1 - \frac{c}{m}x_2 \end{pmatrix}.$$

The solution to the initial value problem can be written in a number of different ways and will be explored in more detail in Chapter 5. Here we simply assert that the solution can be written as

$$\begin{aligned}x_1(t) &= e^{-\frac{ct}{2m}} \left(x_{10} \cos \omega_d t + \left(\frac{cx_{10} + 2mx_{20}}{2m\omega_d} \right) \sin \omega_d t \right) \\ x_2(t) &= e^{-\frac{ct}{2m}} \left(x_{20} \cos \omega_d t - \left(\frac{2kx_{10} + cx_{20}}{2m\omega_d} \right) \sin \omega_d t \right),\end{aligned}$$

where $x_0 = (x_{10}, x_{20})$ is the initial condition and $\omega_d = \sqrt{4km - c^2}/2m$. This solution can be verified by substituting it into the differential equation. We see that the solution is explicitly dependent on the initial condition and it can be shown that this solution is unique. A plot of the initial condition response is shown in Figure 4.1. We note that this form of the solution only holds for $c^2 - 4km < 0$, corresponding to an “underdamped” oscillator. ∇

Numerical Solutions

One of the benefits of the computer revolution that is that it is very easy to obtain a numerical solution of a differential equation when the initial condition is given. A nice consequence of this is as soon as we have a model in the form of equation (4.2), it is straightforward to generate the behavior of x for different initial conditions, as we saw briefly in the previous chapter.

Modern computing environments such as LabVIEW, MATLAB and Mathematica allow simulation of differential equations as a basic operation. For example, these packages provides several tools for representing, simulating, and analyzing ordinary differential equations of the form in equation (4.2). To define an ODE in MATLAB or LabVIEW, we define a function representing the right hand side of equation (4.2):

```
function xdot = system(t, x)
    xdot(1) = F1(x);
    xdot(2) = F2(x);
    ...

```

Each expression $F_i(x)$ takes a (column) vector x and returns the i th element of the differential equation. The second argument to the function `system`, t , represents the current time and allows for the possibility of time-varying differential equations, in which the right hand side of the ODE in equation (4.2) depends explicitly on time.

ODEs defined in this fashion can be simulated by using the `ode45` command:

```
ode45('file', [0,T], [x10, x20, ..., xn0])
```

The first argument is the name of the function defining the ODE, the second argument gives the time interval over which the simulation should be performed and the final argument gives the vector of initial conditions. Similar capabilities exist in other packages such as Octave and Scilab.

Example 4.2 (Balance system). Consider the balance system given in Example 2.1 and reproduced in Figure 4.2a. Suppose that a coworker has designed a control law that will hold the position of the system steady in the upright position at $p = 0$. The form of the control law is

$$F = -Kx,$$

where $x = (p, \theta, \dot{p}, \dot{\theta}) \in \mathbb{R}^4$ is the state of the system, F is the input, and $K = (k_1, k_2, k_3, k_4)$ is the vector of “gains” for the control law.

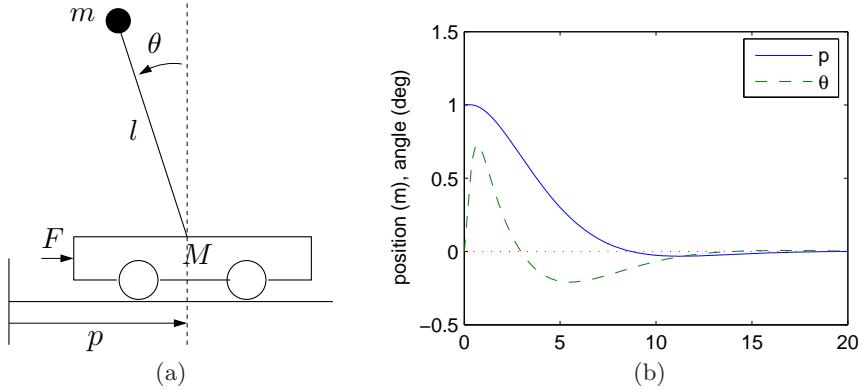


Figure 4.2: Balance system: (a) simplified diagram and (b) initial condition response.

The equations of motion for the system, in state space form, are

$$\begin{aligned} \frac{d}{dt} \begin{pmatrix} p \\ \theta \\ \dot{p} \\ \dot{\theta} \end{pmatrix} &= \begin{pmatrix} \dot{p} \\ \dot{\theta} \\ \frac{-ml \sin \theta \dot{\theta}^2 + mg(ml^2/J_t) \sin \theta \cos \theta - c\dot{p} + u}{M_t - m(ml^2/J_t) \cos^2 \theta} \\ \frac{-ml^2 \sin \theta \cos \theta \dot{\theta}^2 + M_t g l \sin \theta + cl \cos \theta \dot{p} + \gamma \dot{\theta} + l \cos \theta u}{J_t(M_t/m) - m(l \cos \theta)^2} \end{pmatrix} \\ y &= \begin{pmatrix} p \\ \theta \end{pmatrix}, \end{aligned}$$

where $M_t = M + m$ and $J_t = J + ml^2$. We use the following parameters for the system (corresponding roughly to a human being balanced on a stabilizing cart):

$$M = 10 \text{ kg} \quad m = 80 \text{ kg} \quad c = 0.1 \text{ Ns/m}$$

$$J = 100 \text{ kg m}^2/\text{s}^2 \quad l = 1 \text{ m} \quad g = 9.8 \text{ m/s}^2$$

$$K = \begin{pmatrix} -1 & 120 & -4 & 20 \end{pmatrix}$$

This system can now be simulated using MATLAB or a similar numerical tool. The results are shown in Figure 4.2b, with initial condition $x_0 = (1, 0, 0, 0)$. We see from the plot that after an initial transient, the angle and position of the system return to zero (and remain there). ∇

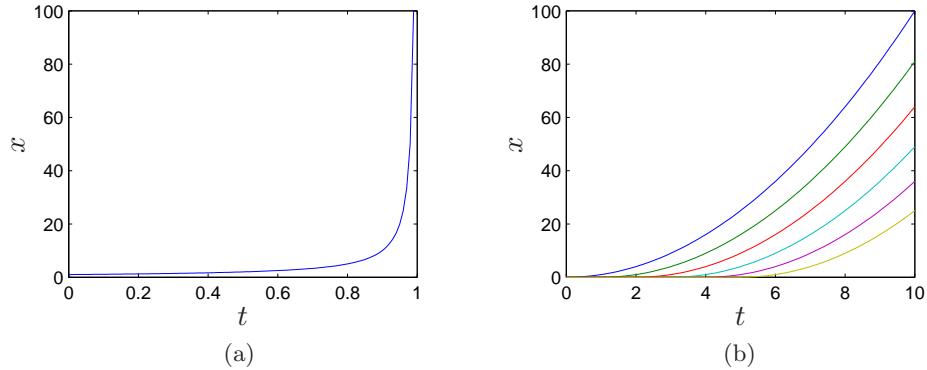


Figure 4.3: Solutions to the differential equations (4.3) and (4.4).



Existence and Uniqueness

Without imposing some conditions on the function F , the differential equation (4.2) may not have a solution for all t , and there is no guarantee that the solution is unique. We illustrate these possibilities with two examples.

Example 4.3 (Finite escape time). Let $x \in \mathbb{R}$ and consider the differential equation

$$\frac{dx}{dt} = x^2 \quad (4.3)$$

with initial condition $x(0) = 1$. By differentiation we can verify that the function

$$x(t) = \frac{1}{1-t} \quad (4.4)$$

satisfies the differential equation and it also satisfies the initial condition. A graph of the solution is given in Figure 4.3a; notice that the solution goes to infinity as t goes to 1. Thus the solution only exists in the time interval $0 \leq t < 1$. ∇

Example 4.4 (No unique solution). Let $x \in \mathbb{R}$ and consider the differential equation

$$\frac{dx}{dt} = \sqrt{x}$$

with initial condition $x(0) = 0$. We can show that the function

$$x(t) = \begin{cases} 0 & \text{if } 0 \leq t \leq a \\ \frac{1}{4}(t-a)^2 & \text{if } t > a \end{cases}$$

satisfies the differential equation for all values of the parameter $a \geq 0$. To see this, we differentiate $x(t)$ to obtain

$$\frac{dx}{dt} = \begin{cases} 0 & \text{if } 0 \leq t \leq a \\ \frac{1}{2}(t-a) & \text{if } t > a \end{cases}$$

and hence $\dot{x} = \sqrt{x}$ for all $t \geq 0$ with $x(0) = 0$. A graph of some of the possible solutions is given in Figure 4.3b. Notice that in this case there are many solutions to the differential equation. ∇

These simple examples show that there may be difficulties even with simple differential equations. Existence and uniqueness can be guaranteed by requiring that the function F has the property that for some fixed $c \in \mathbb{R}$

$$\|F(x) - F(y)\| < c\|x - y\| \quad \text{for all } x, y,$$

which is called *Lipschitz continuity*. A sufficient condition for a function to be Lipschitz is that the Jacobian, $\partial F/\partial x$, is uniformly bounded for all x . The difficulty in Example 4.3 is that the derivative $\partial F/\partial x$ becomes large for large x and the difficulty in Example 4.4 is that the derivative $\partial F/\partial x$ is infinite at the origin.

4.2 Qualitative Analysis

The qualitative behavior of nonlinear systems is important for understanding some of the key concepts of stability in nonlinear dynamics. We will focus on an important class of systems known as planar dynamical systems. These systems have two state variables $x \in \mathbb{R}^2$, allowing their solutions to be plotted in the (x_1, x_2) plane. The basic concepts that we describe hold more generally and can be used to understand dynamical behavior in higher dimensions.

Phase Portraits

A convenient way to understand the behavior of dynamical systems with state $x \in \mathbb{R}^2$ is to plot the *phase portrait* of the system, briefly introduced in Chapter 2. We start by introducing the concept of a vector field. For a system of ordinary differential equations

$$\frac{dx}{dt} = F(x),$$

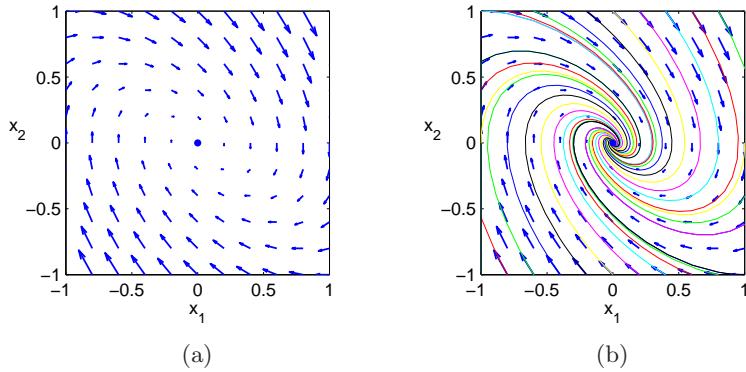


Figure 4.4: Vector field plot (a) and phase portrait (b) for a damped oscillator. This plots were produced using the `phaseplot` command in MATLAB.

the right hand side of the differential equation defines at every $x \in \mathbb{R}^n$ a velocity $F(x) \in \mathbb{R}^n$. This velocity tells us how x changes and can be represented as a vector $F(x) \in \mathbb{R}^n$. For planar dynamical systems, we can plot these vectors on a grid of points in the plane and obtain a visual image of the dynamics of the system, as shown in Figure 4.4a.

A phase portrait is constructed by plotting the flow of the vector field corresponding to the planar dynamical system. That is, for a set of initial conditions, we plot the solution of the differential equation in the plane \mathbb{R}^2 . This corresponds to following the arrows at each point in the phase plane and drawing the resulting trajectory. By plotting the resulting trajectories for several different initial conditions, we obtain a phase portrait, as shown in Figure 4.4b.

Phase portraits give us insight into the dynamics of the system by showing us the trajectories plotted in the (two dimensional) state space of the system. For example, we can see whether all trajectories tend to a single point as time increases or whether there are more complicated behaviors as the system evolves. In the example in Figure 4.4, corresponding to a damped oscillator, we see that for all initial conditions the system approaches the origin. This is consistent with our simulation in Figure 4.1 (also for a damped oscillator), but it allows us to infer the behavior for all initial conditions rather than a single initial condition. However, the phase portrait does not readily tell us the rate of change of the states (although this can be inferred from the length of the arrows in the vector field plot).

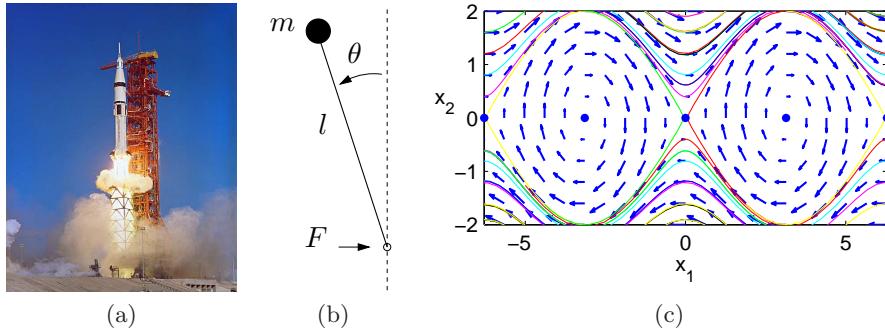


Figure 4.5: An inverted pendulum: (a) motivating application, a Saturn rocket; (b) a simplified diagram of the model; (c) phase portrait. In the phase portrait, the equilibrium points are marked by solid dots along the $x_2 = 0$ line.

Equilibrium Points

An *equilibrium point* of a dynamical system represents a stationary condition for the dynamics. We say that a state x_e is an equilibrium point for a dynamical system

$$\frac{dx}{dt} = F(x)$$

if $F(x_e) = 0$. If a dynamical system has an initial condition $x(0) = x_e$ then it will stay at the equilibrium point: $x(t) = x_e$ for all $t \geq 0$.¹

Equilibrium points are one of the most important features of a dynamical system since they define the states corresponding to constant operating conditions. A dynamical system can have zero, one or more equilibrium points.

Example 4.5 (Inverted pendulum). Consider the inverted pendulum in Figure 4.5, which is a portion of the balance system we considered in Chapter 2. The inverted pendulum is a simplified version of the problem of stabilizing a rocket: by applying forces at the base of the rocket, we seek to keep the rocket stabilized in the upright position. The state variables are the angle $\theta = x_1$ and the angular velocity $d\theta/dt = x_2$, the control variable is the acceleration u of the pivot, and the output is the angle θ .

For simplicity we ignore any damping ($\gamma = 0$) and assume that $mgl/J_t = 1$ and $ml/J_t = 1$, where $J_t = J + ml^2$, so that the dynamics (equation (2.8))

¹We take $t_0 = 0$ from here on.

become

$$\begin{aligned}\frac{dx}{dt} &= \begin{pmatrix} x_2 \\ \sin x_1 + u \cos x_1 \end{pmatrix} \\ y &= x_1.\end{aligned}\tag{4.5}$$

This is a nonlinear time-invariant system of second order.

The equilibrium points for the system are given by

$$x_e = \begin{pmatrix} 0 \\ \pm n\pi \end{pmatrix}$$

where $n = 0, 1, 2, \dots$. The equilibrium points for n even correspond to the pendulum pointing up and those for n odd correspond to the pendulum hanging down. A phase portrait for this system (without corrective inputs) is shown in Figure 4.5c. The phase plane shown in the figure is $\mathbb{R} \times \mathbb{R}$, which results in our model having an infinite number of equilibria, corresponding to $0, \pm\pi, \pm 2\pi, \dots$ ∇

Limit Cycles

Nonlinear systems can exhibit very rich behavior. Consider the differential equation

$$\begin{aligned}\frac{dx_1}{dt} &= -x_2 - x_1(1 - x_1^2 - x_2^2) \\ \frac{dx_2}{dt} &= x_1 - x_2(1 - x_1^2 - x_2^2).\end{aligned}\tag{4.6}$$

The phase portrait and time domain solutions are given in Figure 4.6. The figure shows that the solutions in the phase plane converge to a circular trajectory. In the time domain this corresponds to an oscillatory solution. Mathematically the circle is called a *limit cycle*. More formally, we call a solution $x(t)$ a limit cycle of period $T > 0$ if $x(t + T) = x(t)$ for all $t \in \mathbb{R}$.

Example 4.6 (Predator prey). Consider the predator prey example introduced in Section 3.7. The dynamics for the system are given by

$$\begin{aligned}\frac{dH}{dt} &= r_h H \left(1 - \frac{H}{K}\right) - \frac{aHL}{1 + aHT_h} \quad H \geq 0 \\ \frac{dL}{dt} &= r_l L \left(1 - \frac{L}{kH}\right) \quad L \geq 0.\end{aligned}$$

The phase portrait for this system is shown in Figure 4.7. In addition to the two equilibrium points, we see a limit cycle in the diagram. This limit cycle

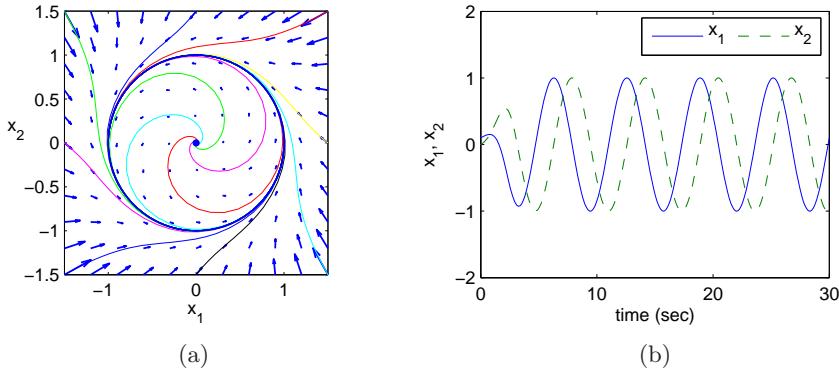


Figure 4.6: Phase portrait and time domain simulation for a system with a limit cycle.

is *attracting* or *stable* since initial conditions near the limit cycle approach it as time increases. It divides the phase space into two different regions: one inside the limit cycle in which the size of the population oscillations growth with time (until they rich the limit cycle) and one outside the limit cycle in which they decay. ∇

There are methods for determining limit cycles for second order systems, but for general higher order systems we have to resort to computational analysis. Computer algorithms find limit cycles by searching for periodic trajectories in state space that satisfy the dynamics of the system. In many situations, stable limit cycles can be found by simulating the system with different initial conditions.

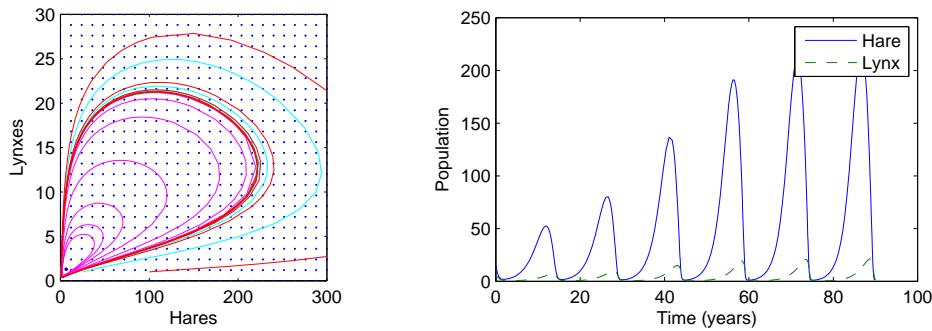


Figure 4.7: Phase portrait and time domain simulation for the predator prey system.

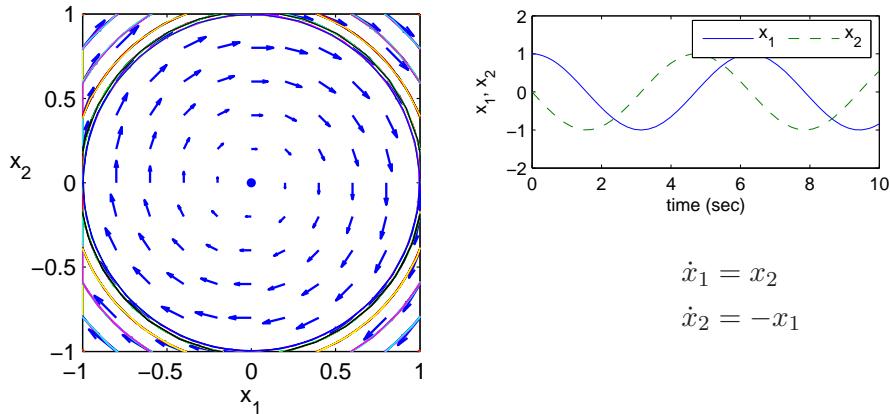


Figure 4.8: Phase portrait and time domain simulation for a system with a single stable equilibrium point.

4.3 Stability

The stability of an equilibrium point determines whether or not solutions nearby the equilibrium point remain nearby, get closer, or move further away.

Definitions

An equilibrium point is *stable* if initial conditions that start near an equilibrium point stay near that equilibrium point. Formally, we say that an equilibrium point x_e is stable if for all $\epsilon > 0$, there exists an $\delta > 0$ such that

$$\|x(0) - x_e\| < \delta \implies \|x(t) - x_e\| < \epsilon \quad \text{for all } t > 0.$$

Note that this definition does not imply that $x(t)$ gets closer to x_e as time increases, but just that it stays nearby. Furthermore, the value of δ may depend on ϵ , so that if we wish to stay very close to the equilibrium point, we may have to start very, very close ($\delta \ll \epsilon$). This type of stability is sometimes called stability “in the sense of Lyapunov”. If a system is stable in the sense of Lyapunov and the trajectories don’t converge to the equilibrium point, we say that the equilibrium point is *neutrally stable*.

An example of a neutrally stable equilibrium point is shown in Figure 4.8. From the phase portrait, we see that if we start near the equilibrium then we stay near the equilibrium. Indeed, for this example, given any ϵ that

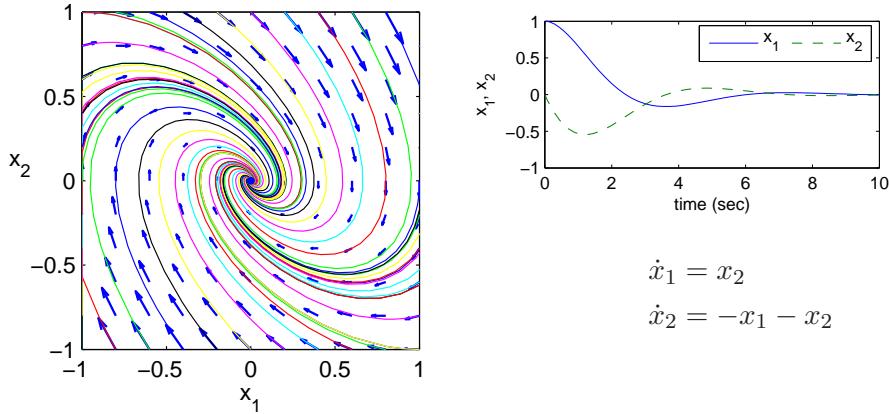


Figure 4.9: Phase portrait and time domain simulation for a system with a single asymptotically stable equilibrium point.

defines the range of possible initial conditions, we can simply choose $\delta = \epsilon$ to satisfy the definition of stability.

An equilibrium point x_e is (locally) *asymptotically stable* if it is stable in the sense of Lyapunov and also $x(t) \rightarrow x_e$ as $t \rightarrow \infty$ for $x(t)$ sufficiently close to x_e . This corresponds to the case where all nearby trajectories converge to the equilibrium point for large time. Figure 4.9 shows an example of an asymptotically stable equilibrium point. Note from the phase portraits that not only do all trajectories stay near the equilibrium point at the origin, but they all approach the origin as t gets large (the directions of the arrows on the phase plot show the direction in which the trajectories move).

An equilibrium point is *unstable* if it is not stable. More specifically, we say that an equilibrium point is unstable if given some $\epsilon > 0$, there does not exist a $\delta > 0$ such that if $\|x(0) - x_e\| < \delta$ then $\|x(t) - x_e\| < \epsilon$ for all t . An example of an unstable equilibrium point is shown in Figure 4.10.

The definitions above are given without careful description of their domain of applicability. More formally, we define an equilibrium point to be *locally* stable (or asymptotically stable) if it is stable for all initial conditions $x \in B_r(x_e)$ where

$$B_r(x_e) = \{x : \|x - x_e\| < r\}$$

is a ball of radius r around x_e and $r > 0$. A system is globally stable if it is stable for all $r > 0$. Systems whose equilibrium points are only locally stable can have interesting behavior away from equilibrium points, as we explore in the next section.

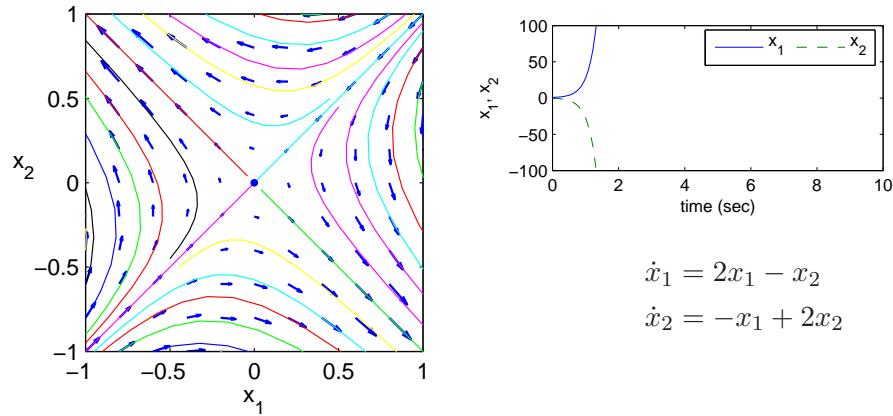


Figure 4.10: Phase portrait and time domain simulation for a system with a single unstable equilibrium point.

For planar dynamical systems, equilibrium points have been assigned names based on their stability type. An asymptotically stable equilibrium point is called a *sink* or sometimes an *attractor*. An unstable equilibrium point can either be a *source*, if all trajectories lead away from the equilibrium point, or a *saddle*, if some trajectories lead to the equilibrium point and others move away (this is the situation pictured in Figure 4.10). Finally, an equilibrium point which is stable but not asymptotically stable (such as the one in Figure 4.8) is called a *center*.

Example 4.7 (Damped inverted pendulum). Consider the damped inverted pendulum introduced Example 2.2. The equations of motion are

$$\frac{d}{dt} \begin{pmatrix} \theta \\ \dot{\theta} \end{pmatrix} = \begin{pmatrix} \dot{\theta} \\ \frac{mgl}{J_t} \sin \theta - \frac{\gamma}{J_t} \dot{\theta} + \frac{l}{J_t} \cos \theta u \end{pmatrix} \quad (4.7)$$

A phase diagram for the system is shown in Figure 4.11. The equilibrium point at $x = (0, 0)$ is a locally unstable equilibrium point (corresponding to the inverted position). The equilibrium points at $x = (\pm\pi, 0)$ correspond to locally asymptotically stable equilibrium points. An example of locally stable (but not asymptotically) stable points is the undamped pendulum, shown in Figure 4.5 on page 119.

It is much more natural to describe the pendulum in terms of an angle φ and an angular velocity. The phase space is then a manifold $S^1 \times \mathbb{R}$, where S^1 represents the unit circle. Using this description, the dynamics evolve on a cylinder and there are only two equilibria, as shown in Figure 4.11c. ∇

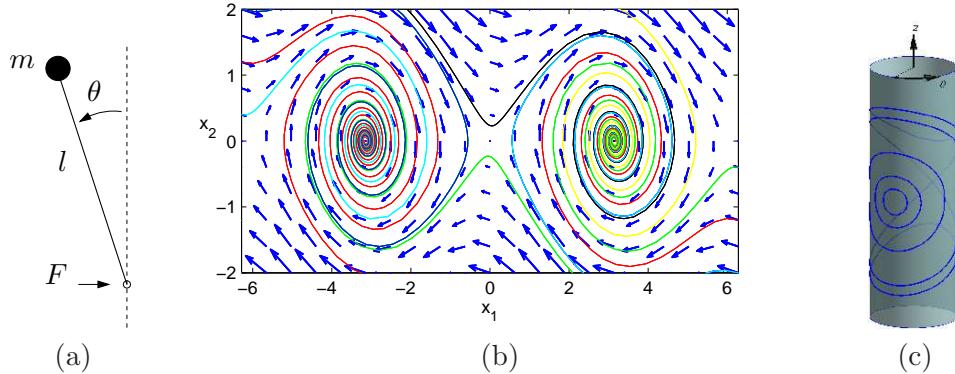


Figure 4.11: Phase portrait for a damped inverted pendulum: (a) diagram of the inverted pendulum system; (b) phase portrait with $\theta \in [2\pi, 2\pi]$; (c) phase portrait with θ periodic.

Example 4.8 (Congestion control). The model for congestion control in a network consisting of a single computer connected to a router, introduced in Example 2.12, is given by

$$\begin{aligned}\frac{dx}{dt} &= -b \frac{x^2}{2} + (b_{\max} - b) \\ \frac{db}{dt} &= x - c,\end{aligned}$$

where x is the transmission rate from the source and b is the buffer size of the router. The phase portrait is shown in Figure 4.12 for two different parameter values. In each case we see that the system converges to an equilibrium point in which the full capacity of the link is used and the router buffer is not at capacity. The horizontal and vertical lines on the plots correspond to the router buffer limit and link capacity limits. When the system is operating outside these bounds, packets are being lost.

We see from the phase portrait that the equilibrium point at

$$x^* = c \quad b^* = \frac{2b_{\max}}{2 + c^2},$$

is stable, since all initial conditions result in trajectories that converge to this point. Note also that some of the trajectories cross outside of the region where $x > 0$ and $b > 0$, which is not possible in the actual system; this shows some of the limits of this model away from the equilibrium points. A more accurate model would use additional nonlinear elements in the model to insure that the quantities in the model always stayed positive. ∇

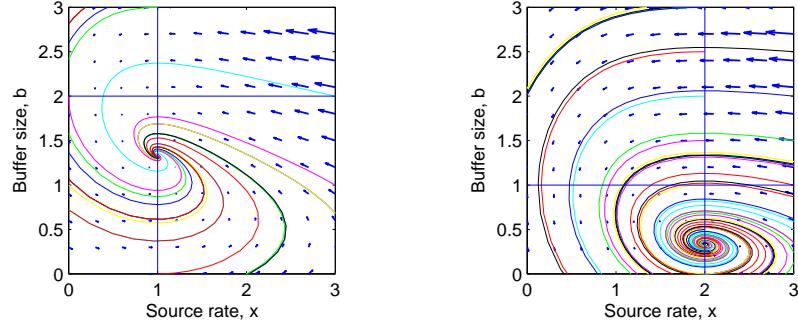


Figure 4.12: Phase portraits for a congestion control protocol running with a single source computer: (a) with router buffer size $b_{\max} = 2$ Mb and link capacity $c = 1$ Mb/sec and (b) router buffer size $b_{\max} = 1$ Mb and link capacity $c = 2$ Mb/sec.

Stability Analysis via Linear Approximation

An important feature of differential equations is that it is often possible to determine the local stability of an equilibrium point by approximating the system by a linear system. We shall explore this concept in more detail later, but the following examples illustrates the basic idea.

Example 4.9 (Inverted pendulum). Consider again the inverted pendulum, whose dynamics are given by

$$\frac{dx}{dt} = \begin{pmatrix} x_2 \\ \frac{mgl}{J_t} \sin x_1 - \frac{\gamma}{J_t} x_2 + \frac{l}{J_t} \cos x_1 u \end{pmatrix}$$

$$y = x_1,$$

where we have defined the state as $x = (\theta, \dot{\theta})$. We first consider the equilibrium point at $x = (0, 0)$, corresponding to the straight up position. If we assume that the angle $\theta = x_1$ remains small, then we can replace $\sin x_1$ with x_1 and $\cos x_1$ with 1, which gives the approximate system

$$\frac{dx}{dt} = \begin{pmatrix} x_2 \\ \frac{mgl}{J_t} x_1 - \frac{\gamma}{J_t} x_2 + \frac{l}{J_t} u \end{pmatrix} \quad (4.8)$$

$$y = x_1.$$

Intuitively, this system should behave similarly to the more complicated model as long as x_1 is small. In particular, it can be verified that the system (4.5) is unstable by plotting the phase portrait or computing the eigenvalues of the system matrix (as described in the next chapter).

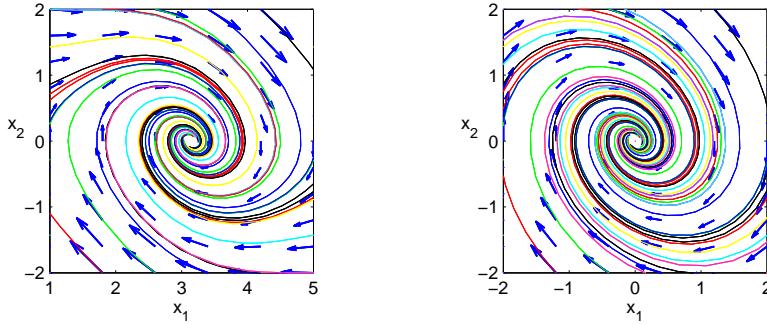


Figure 4.13: Comparison between the phase portraits for the full nonlinear systems (left) and its linear approximation around the origin (right).

We can also approximate the system around the stable equilibrium point at $x = (\pi, 0)$. In this case we have to expand $\sin x_1$ and $\cos x_1$ around $x_1 = \pi$, according to the expansions

$$\sin(\pi + \theta) = -\sin \theta \approx -\theta \quad \cos(\pi + \theta) = \cos(\theta) \approx 1.$$

If we define $z_1 = x_1 - \pi$ and $z_2 = x_2$, the resulting approximate dynamics are given by

$$\begin{aligned} \frac{dx}{dt} &= \begin{pmatrix} z_2 \\ -\frac{mgl}{J_t}z_1 - \frac{\gamma}{J_t}z_2 + \frac{l}{J_t}u \end{pmatrix} \\ y &= z_1. \end{aligned} \tag{4.9}$$

Note that $z = (0, 0)$ is the equilibrium point for this system and that it has the same basic form as the dynamics shown in Figure 4.9. Figure 4.13 shows the phase portraits for the original system and the approximate system around the corresponding equilibrium points. Note that they are very similar (although not exactly the same). More generally, it can be shown that if a linear approximation has either asymptotically stable or unstable equilibrium point, then the local stability of the original system must be the same. ∇

The fact that a linear model can sometimes be used to study the behavior of a nonlinear system near an equilibrium point is a powerful one. Indeed, we can take this even further and use local linear approximations of a nonlinear system to design a feedback law that keeps the system near its equilibrium point (design of dynamics). By virtue of the fact that the closed loop dynamics have been chosen to stay near the equilibrium, we can

even use the linear approximation to design the feedback that ensures this condition is true!



Lyapunov Functions

A powerful tool for determining stability is the use of Lyapunov functions. A *Lyapunov function* $V : \mathbb{R}^n \rightarrow \mathbb{R}$ is an energy-like function that can be used to determine stability of a system. Roughly speaking, if we can find a non-negative function that always decreases along trajectories of the system, we can conclude that the minimum of the function is a stable equilibrium point (locally).

To describe this more formally, we start with a few definitions. We say that a continuous function $V(x)$ is *positive definite* if $V(x) > 0$ for all $x \neq 0$ and $V(0) = 0$. We will often write this as $V(x) \succ 0$. Similarly, a function is *negative definite* if $V(x) < 0$ for all $x \neq 0$ and $V(0) = 0$. We say that a function $V(x)$ is *positive semidefinite* if $V(x)$ can be zero at points other than $x = 0$ but otherwise $V(x)$ is strictly positive. We write this as $V(x) \succeq 0$ and define negative semi-definite functions analogously.

To illustrate the difference between a positive definite function and a positive semi-definite function, suppose that $x \in \mathbb{R}^2$ and let

$$V_1(x) = x_1^2 \quad V_2(x) = x_1^2 + x_2^2.$$

Both V_1 and V_2 are always non-negative. However, it is possible for V_1 to be zero even if $x \neq 0$. Specifically, if we set $x = (0, c)$ where $c \in \mathbb{R}$ is any non-zero number, then $V_1(x) = 0$. On the other hand, $V_2(x) = 0$ if and only if $x = (0, 0)$. Thus $V_1(x) \succeq 0$ and $V_2(x) \succ 0$.

We can now characterize the stability of a system

$$\frac{dx}{dt} = F(x) \quad x \in \mathbb{R}^n.$$

Theorem 4.1. *Let $V(x)$ be a non-negative function on \mathbb{R}^n and let \dot{V} represent the time derivative of V along trajectories of the system dynamics:*

$$\frac{dV(x)}{dt} = \frac{\partial V}{\partial x} \frac{dx}{dt} = \frac{\partial V}{\partial x} F(x).$$

Let $B_r = B_r(0)$ be a ball of radius r around the origin. If there exists $r > 0$ such that $\dot{V} \leq 0$ for all $x \in B_r$, then $x = 0$ is locally stable in the sense of Lyapunov. If $\dot{V} < 0$ in B_r , then $x = 0$ is locally asymptotically stable.

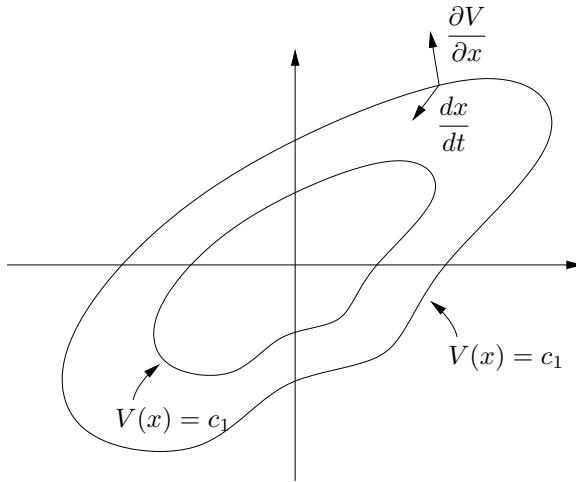


Figure 4.14: Geometric illustration of Lyapunov's stability theorem. The dashed ellipses correspond to level sets of the Lyapunov function; the solid line is a trajectory of the system.

If V satisfies one of the conditions above, we say that V is a (local) *Lyapunov function* for the system. These results have a nice geometric interpretation. The level curves for a positive definite function are closed contours as shown in Figure 4.14. The condition that $\dot{V}(x)$ is negative simply means that the vector field points towards lower level curves. This means that the trajectories move to smaller and smaller values of V and, if $\dot{V} \prec 0$, then x must approach 0.

A slightly more complicated situation occurs if $\dot{V}(x) \preceq 0$. In this case it is possible that $\dot{V}(x) = 0$ when $x \neq 0$ and hence x could stop decreasing in value. The following example illustrates these two cases.

Example 4.10. Consider the second order system

$$\begin{aligned}\frac{dx_1}{dt} &= -ax_1 \\ \frac{dx_2}{dt} &= -bx_1 - cx_2.\end{aligned}$$

Suppose first that $a, b, c > 0$ and consider the Lyapunov function candidate

$$V(x) = \frac{1}{2}x_1^2 + \frac{1}{2}x_2^2.$$

Taking the derivative of V and substituting the dynamics, we have

$$\frac{dV(x)}{dt} = -ax_1^2 - bx_1x_2 - cx_2^2.$$

To check whether this is negative definite, we complete the square by writing

$$\frac{dV}{dt} = -a(x_1 + \frac{b}{a}x_2)^2 - (c - \frac{b^2}{a})x_2^2.$$

Clearly $\dot{V} \prec 0$ if $a > 0$ and $(c - \frac{b^2}{a}) > 0$.

Suppose now that $a, b, c > 0$ and $c = b^2/a$. Then the derivative of the Lyapunov function becomes

$$\frac{dV}{dt} = -a(x_1 + \frac{b}{a}x_2)^2 \leq 0.$$

This function is not negative definite since if $x_1 = -\frac{b}{a}x_2$ then $\dot{V} = 0$ but $x \neq 0$. Hence we cannot include asymptotic stability, but we *can* say the system is stable (in the sense of Lyapunov).

The fact that \dot{V} is not negative definite does not mean that this system is not asymptotically stable. As we shall see in Chapter 5, we can check stability of a linear system by looking at the eigenvalues of the dynamics matrix for the model

$$\frac{dx}{dt} = \begin{pmatrix} -a & 0 \\ -b & -c \end{pmatrix} x.$$

By inspection (since the system is lower triangular), the eigenvalues are $\lambda_1 = -a < 0$ and $\lambda_2 = -c < 0$, and hence the system can be shown to be asymptotically stable.

To demonstrate asymptotic stability using Lyapunov functions, we must try a different Lyapunov function candidate. Suppose we try

$$V(x) = \frac{1}{2}x_1^2 + \frac{1}{2}(x_2 - \frac{b}{c-a}x_1)^2.$$

It is easy to show that $V(x) \succ 0$ since $V(x) \geq 0$ for all x and $V(x) = 0$ implies that $x_1 = 0$ and $x_2 - \frac{b}{c-a}x_1 = x_2 = 0$. We now check the time derivative of V :

$$\begin{aligned} \frac{dV(x)}{dt} &= x_1\dot{x}_1 + (x_2 - \frac{b}{c-a}x_1)(\dot{x}_2 - \frac{b}{c-a}\dot{x}_1) \\ &= -ax_1^2 + (x_2 - \frac{b}{c-a}x_1)(-bx_1 - cx_2 + \frac{b}{c-a}x_1) \\ &= -ax_1^2 - c(x_2 - \frac{b}{c-a}x_1)^2. \end{aligned}$$

We see that $\dot{V} \prec 0$ as long as $c \neq a$ and hence we can show stability except for this case (explored in more detail in the exercises). ∇

As this example illustrates, Lyapunov functions are not unique and hence we can use many different methods to find one. It turns out that Lyapunov functions can always be found for any stable system (under certain conditions) and hence one knows that if a system is stable, a Lyapunov function exists (and vice versa). Recent results using “sum of squares” methods have provided systematic approaches for finding Lyapunov systems [PPP02]. Sum of squares techniques can be applied to a broad variety of systems, including systems whose dynamics are described by polynomial equations as well as “hybrid” systems, which can have different models for different regions of state space.

Lyapunov Functions for Linear Systems



For a linear dynamical system of the form

$$\dot{x} = Ax$$

it is possible to construct Lyapunov functions in a systematic manner. To do so, we consider quadratic functions of the form

$$V(x) = x^T Px$$

where $P \in \mathbb{R}^{n \times n}$ is a symmetric matrix ($P = P^T$). The condition that $V \succ 0$ is equivalent to the condition that P is a *positive definite* matrix:

$$x^T Px > 0 \quad \text{for all } x \neq 0,$$

which we write as $P > 0$. It can be shown that if P is symmetric and positive definite then all of its eigenvalues are real and positive.

Given a candidate Lyapunov function, we can now compute its derivative along flows of the system:

$$\frac{dV}{dt} = \frac{\partial V}{\partial x} \frac{dx}{dt} = x^T (A^T P + PA)x.$$

The requirement that $\dot{V} \prec 0$ (for asymptotic stability) becomes a condition that the matrix $Q = A^T P + PA$ be *negative definite*:

$$x^T Q x < 0 \quad \text{for all } x \neq 0.$$

Thus, to find a Lyapunov function for a linear system it is sufficient to choose a $Q < 0$ and solve the *Lyapunov equation*:

$$A^T P + PA = Q.$$

This is a linear equation in the entries of P and hence it can be solved using linear algebra. The following examples illustrate its use.

Example 4.11. Consider the linear system from Example 4.10, for which we have

$$A = \begin{pmatrix} -a & 0 \\ -b & -c \end{pmatrix} \quad P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}.$$

We choose $Q = -I \in \mathbb{R}^{2 \times 2}$ and the corresponding Lyapunov equation is

$$\begin{pmatrix} -a & -b \\ 0 & -c \end{pmatrix} \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} + \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} \begin{pmatrix} -a & 0 \\ -b & -c \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

and solving for the elements of P yields

$$P = \begin{pmatrix} \frac{b^2+ac+c^2}{2a^2c+2ac^2} & \frac{-b}{2c(a+c)} \\ \frac{-b}{2c(a+c)} & \frac{1}{2} \end{pmatrix}$$

or

$$V(x) = \frac{b^2 + ac + c^2}{2a^2c + 2ac^2}x_1^2 - \frac{b}{c(a+c)}x_1x_2 + \frac{1}{2}x_2^2.$$

It is easy to verify that $P > 0$ (check its eigenvalues) and by construction $\dot{P} = -I < 0$. Hence the system is asymptotically stable. ∇

This same technique can also be used for searching for Lyapunov functions for nonlinear systems. If we write

$$\frac{dx}{dt} = f(x) =: Ax + \tilde{f}(x),$$

where $\tilde{f}(x)$ contains terms that are second order and higher in the elements of x , then we can find a Lyapunov function for the linear portion of the system and check to see if this is a Lyapunov function for the full nonlinear system. The following example illustrates the approach.

Example 4.12 (Congestion control). Consider the congestion control problem described in Example 4.8, where we used phase portraits to demonstrate stability of the equilibrium points under different parameter values. We now wish to consider the general set of equations (from Example 2.12):

$$\begin{aligned} \frac{dx_i}{dt} &= -b\frac{x_i^2}{2} + (b_{\max} - b) \\ \frac{db}{dt} &= \sum_{i=1}^N x_i - c, \end{aligned}$$

The equilibrium points are given by

$$x_i^* = \frac{c}{N} \quad \text{for all } i \quad b^* = \frac{2N^2 b_{\max}}{2N^2 + c^2},$$

To check for stability, we search for an appropriate Lyapunov function. For notational simplicity, we choose $N = 3$. It will also be convenient to rewrite the dynamics about the equilibrium point by choosing variables

$$z = \begin{pmatrix} z_1 \\ z_2 \\ z_3 \end{pmatrix} = \begin{pmatrix} x_1 - x_1^* \\ x_2 - x_2^* \\ b - b^* \end{pmatrix}.$$

The dynamics written in terms of z become

$$\frac{d}{dt} \begin{pmatrix} z_1 \\ z_2 \\ z_3 \end{pmatrix} = \begin{pmatrix} -\frac{b^*(z_1+c)z_1}{N^2} - \left(1 + \frac{(2c+Nz_1)^2}{2N^2}\right) \\ -\frac{b^*(z_2+c)z_2}{2} - \left(1 + \frac{(2c+Nz_2)^2}{2N^2}\right) \\ z_1 + z_2 \end{pmatrix} =: F(z)$$

and $z = 0$ is an equilibrium point for the transformed system.

We now write $F(z)$ as a linear portion plus higher order terms:

$$\begin{aligned} F(z) &= \begin{pmatrix} -\frac{b^*c}{N}z_1 - \frac{c^2+2N^2}{2N^2}z_3 \\ -\frac{b^*c}{N}z_2 - \frac{c^2+2N^2}{2N^2}z_3 \\ z_1 + z_2 \end{pmatrix} + \begin{pmatrix} -\frac{b^*}{2}z_1^2 \frac{z_1(2c+Nz_1)z_3}{2N} \\ -\frac{b^*}{2}z_2^2 \frac{z_2(2c+Nz_2)z_3}{2N} \\ z_1 + z_2 \end{pmatrix} \\ &= \begin{pmatrix} -\frac{b^*c}{N} & 0 & -\frac{c^2+2N^2}{2N^2} \\ 0 & -\frac{b^*c}{N} & -\frac{c^2+2N^2}{2N^2} \\ 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \\ z_3 \end{pmatrix} + \begin{pmatrix} -\frac{b^*}{2}z_1^2 \frac{z_1(2c+Nz_1)z_3}{2N} \\ -\frac{b^*}{2}z_2^2 \frac{z_2(2c+Nz_2)z_3}{2N} \\ z_1 + z_2 \end{pmatrix}. \end{aligned}$$

To find a candidate Lyapunov function, we solve the equation

$$A^T P + P A = Q$$

where A is the linear portion of F and $Q < 0$. Choosing $Q = -I \in \mathbb{R}^{3 \times 3}$, we obtain

$$P = \begin{pmatrix} \frac{c^2 N + 3N^3}{2b^* c^3 + 4b^* c N^2} & \frac{N^3}{2b^* c^3 + 4b^* c N^2} & \frac{N^2}{2c^2 + 4N^2} \\ \frac{N^3}{2b^* c^3 + 4b^* c N^2} & \frac{c^2 N + 3N^3}{2b^* c^3 + 4b^* c N^2} & \frac{N^2}{2c^2 + 4N^2} \\ \frac{N^2}{2c^2 + 4N^2} & \frac{N^2}{2c^2 + 4N^2} & \frac{c^2 N + 4N^3}{4b^* c N} + \frac{b^* c N}{2c^2 + 4N^2} \end{pmatrix}$$

We now check to see if this is a Lyapunov function for the original system:

$$\begin{aligned}\dot{V} &= \frac{\partial V}{\partial x} \frac{dx}{dt} = (z^T A^T + \tilde{F}^T(z))Pz + z^T P(Az + \tilde{F}(z)) \\ &= z^T (A^T P + PA)z + \tilde{F}^T(z)Pz + z^T P\tilde{F}(z).\end{aligned}$$

Note that all terms in \tilde{F} are quadratic or higher order in z and hence it follows that $\tilde{F}^T(z)Pz$ and $z^T P\tilde{F}(z)$ consist of terms that are at least third order in z . It follows that if z is sufficiently close to zero then the cubic and higher order terms will be smaller than the quadratic terms. Hence, sufficiently close to $z = 0$, $\dot{V} \prec 0$. ∇

This technique for proving local stability of a nonlinear system by looking at the linearization about an equilibrium point is a general one that we shall return to in Chapter 5.



Krasovskii-Lasalle Invariance Principle

For general nonlinear systems, especially those in symbolic form, it can be difficult to find a function $V \succ 0$ whose derivative is strictly negative definition ($\dot{V} \prec 0$). The Krasovskii-Lasalle theorem enables us to conclude asymptotic stability of an equilibrium point under less restrictive conditions, namely in the case that $\dot{V} \preceq 0$, which is often much easier to construct. However, it applies only to time-invariant or periodic systems.

We will deal with the time-invariant case and begin by introducing a few more definitions. We denote the solution trajectories of the time-invariant system

$$\frac{dx}{dt} = F(x) \quad (4.10)$$

as $x(t; x_0, t_0)$, which is the solution of equation (4.10) at time t starting from x_0 at t_0 . We write $x(\cdot; x_0, t_0)$ for the set of all points lying along the trajectory.

Definition 4.1 (ω limit set). The ω limit set of a trajectory $x(\cdot; x_0, t_0)$ is the set of all points $z \in \mathbb{R}^n$ such that there exists a strictly increasing sequence of times t_n such that

$$s(t_n; x_0, t_0) \rightarrow z$$

as $n \rightarrow \infty$.

Definition 4.2 (Invariant set). The set $M \subset \mathbb{R}^n$ is said to be an *invariant set* if for all $y \in M$ and $t_0 \geq 0$, we have

$$x(t; y, t_0) \in M \quad \text{for all } t \geq t_0.$$

It may be proved that the ω limit set of every trajectory is closed and invariant. We may now state the Krasovskii-Lasalle principle.

Theorem 4.2 (Krasovskii-Lasalle principle). *Let $V : \mathbb{R}^n \rightarrow \mathbb{R}$ be a locally positive definite function such that on the compact set $\Omega_r = \{x \in \mathbb{R}^n : V(x) \leq r\}$ we have $\dot{V}(x) \leq 0$. Define*

$$S = \{x \in \Omega_r : \dot{V}(x) = 0\}.$$

As $t \rightarrow \infty$, the trajectory tends to the largest invariant set inside S ; i.e., its ω limit set is contained inside the largest invariant set in S . In particular, if S contains no invariant sets other than $x = 0$, then 0 is asymptotically stable.

A global version of the preceding theorem may also be stated. An application of the Krasovskii-Lasalle principle is given in the following example.

Example 4.13 (Damped spring mass system). Consider a damped spring mass system with dynamics

$$m\ddot{q} + c\dot{q} + kq = 0.$$

A natural candidate for a Lyapunov function is the total energy of the system, given by

$$V = \frac{1}{2}m\dot{q}^2 + \frac{1}{2}kq^2.$$

The derivative of this function along trajectories of the system is

$$\dot{V} = m\dot{q}\ddot{q} + kq\dot{q} = -c\dot{q}.$$

This function is only negative semi-definite and hence we cannot conclude asymptotic stability using Theorem 4.1. However, note that $\dot{V} = 0$ implies that $\dot{q} = 0$. If we define

$$S = \{(q, \dot{q}) : \dot{q} = 0\}$$

then we can compute the largest invariant set inside S . For this set, we must have $\dot{q}(t) = 0$ for all t and hence $\ddot{q}(t) = 0$ as well.

Using the dynamics of the system, we see that if $\dot{q}(t) = 0$ and $\ddot{q}(t) = 0$ then $\dot{q}(t) = 0$ as well. hence the largest invariant set inside S is $(q, \dot{q}) = 0$

and we can use the Krasovskii-Lasalle principle to conclude that the origin is asymptotically stable. Note that we have not made use of Ω_r in this argument; for this example we have $\dot{V}(x) \leq 0$ for any state and hence we can choose r arbitrarily large. ∇



4.4 Parametric and Non-Local Behavior

Most of the tools that we have explored are focused on the local behavior of a fixed system near an equilibrium point. In this section we briefly introduce some concepts regarding the global behavior of nonlinear systems and the dependence of the behavior on parameters in the system model.

Regions of attraction

To get some insight into the behavior of a nonlinear system we can start by finding the equilibrium points. We can then proceed to analyze the local behavior around the equilibria. The behavior of a system near an equilibrium point is called the *local* behavior of the system.

The solutions of the system can be very different far away from this equilibrium point. This is seen, for example, in the inverted pendulum in Example 4.7. The downward hanging equilibrium point is stable, with small oscillations that eventually converge to the origin. But far away from this equilibrium point there are trajectories for which the pendulum swings around the top multiple times, giving very long oscillations that are topologically different than those near the origin.

To better understand the dynamics of the system, we can examine the set of all initial conditions that converge to a given asymptotically stable equilibrium point. This set is called the *region of attraction* for the equilibrium point. An example is shown in Figure 4.15. In general, computing regions of attraction is extremely difficult. However, even if we cannot determine the region of attraction, we can often obtain patches around the stable equilibria that are attracting. This gives partial information about the behavior of the system.

One method for approximating the region of attraction is through the use of Lyapunov functions. Suppose that V is a local Lyapunov function for a system around an equilibrium point x_0 . Let Γ_r be set on which $V(x)$ has value less than c ,

$$\Gamma_r = \{x \in \mathbb{R}^n : V(x) \leq r\},$$

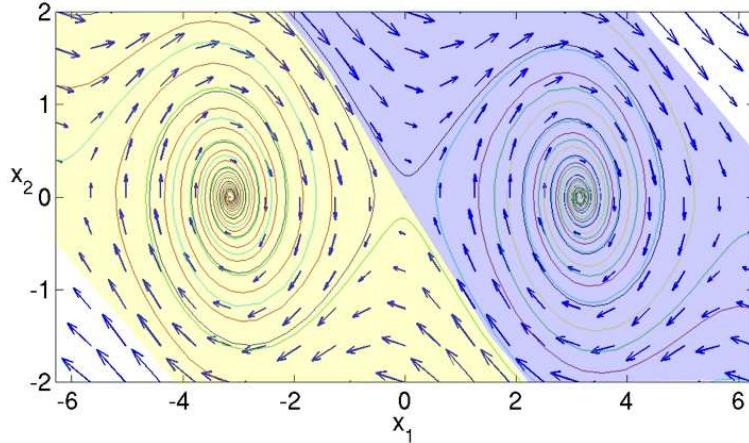


Figure 4.15: Phase portrait for an inverted pendulum with damping. Shaded regions indicate the regions of attraction for the two stable equilibrium points.

and suppose that $\dot{V}(x) \leq 0$ for all $x \in \Gamma_r$, with equality only at the equilibrium point x_0 . Then Γ_r is inside the region of attraction of the equilibrium point. Since this approximation depends on the Lyapunov function and the choice of Lyapunov function is not unique, it can sometimes be a very conservative estimate.

The Lyapunov tests that we derived for checking stability were local in nature. That is, we asked that a Lyapunov function satisfy $V > 0$ and $\dot{V} < 0$ for $x \in B_r$. If it turns out that the conditions on the Lyapunov function are satisfied for all $x \in \mathbb{R}^n$, then it can be shown that the region of attraction for the equilibrium point is the entire state space and the equilibrium point is said to be *globally* stable.

Bifurcations

Another very important property of nonlinear systems is how their behavior changes as the parameters governing the dynamics change. We can study this in the context of models by exploring how the location of equilibrium points and their stability, regions of attraction and other dynamic phenomena such as limit cycles vary based on the values of the parameters in the model.

Consider a family of differential equations

$$\frac{dx}{dt} = F(x, \mu), \quad x \in \mathbb{R}^n, \mu \in \mathbb{R}^k, \quad (4.11)$$

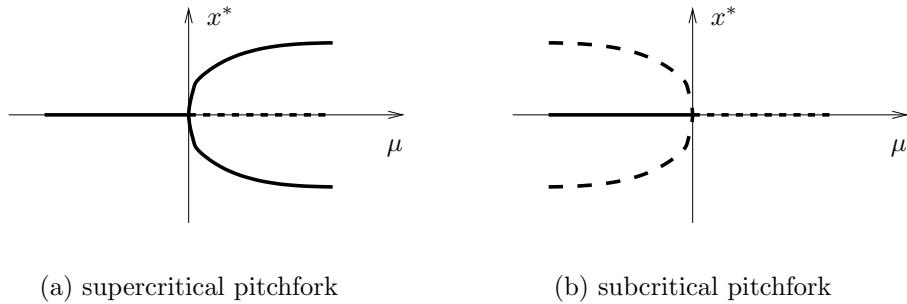


Figure 4.16: Pitchfork bifurcation.

where x is the state and μ is a set of parameters that describe the family of equations. The equilibrium solutions satisfy

$$F(x, \mu) = 0$$

and as μ is varied, the corresponding solutions $x_e(\mu)$ vary. We say that the system (4.11) has a *bifurcation* at $\mu = \mu^*$ if the behavior of the system changes qualitatively at μ^* . This can occur either due to a change in stability type or a change in the number of solutions at a given value of μ . The following examples illustrate some of the basic concepts.

Example 4.14 (Simple exchange of stability). Consider the scalar dynamical system

$$\dot{x} = \mu x.$$

This system has a bifurcation at $\mu = 0$ since the stability of the system changes from asymptotically stable (for $\mu < 0$) to neutrally stable ($\mu = 0$) to unstable (for $\mu > 0$). ∇

This type of bifurcation is very common in control systems when a system changes from being stable to unstable when a parameter is changed.

Example 4.15 (Pitchfork bifurcation). Consider the scalar dynamical system

$$\dot{x} = \mu x - x^3.$$

The equilibrium values of x are plotted in Figure 4.16a, with solid lines representing stable equilibria and dashed lines representing unstable equilibria. As illustrated in the figure, the number and type of the solutions changes at $\mu = 0$ and hence we say there is a bifurcation at $\mu = 0$.

Note that the sign of the cubic term determines whether the bifurcation generates a stable branch (called a *supercritical* bifurcation and shown in Figure 4.16a) or an unstable branch (called a *subcritical* bifurcation and shown in Figure 4.16b). ∇

Bifurcations provide a tool for studying how systems evolve as operating parameters change and are particularly useful in the study of stability of differential equations. To illustrate how bifurcations arise in the context of feedback systems, we consider the predator prey system introduced earlier.

Example 4.16 (Predator prey). Consider the predator prey system described in Section 3.7. The dynamics of the system is given by

$$\begin{aligned} \frac{dH}{dt} &= r_h H \left(1 - \frac{H}{K}\right) - \frac{aHL}{1 + aHT_h} \\ \frac{dL}{dt} &= r_l L \left(1 - \frac{L}{kH}\right), \end{aligned} \quad (4.12)$$

where H and L are the number of hares (prey) and lynxes (predators), and r_h , r_l , K , k , a and T_h are parameters that model a given predator prey system (described in more detail in Section 3.7). The system has an equilibrium point at $H_e > 0$ and $L_e > 0$ that can be solved for numerically.

To explore how the parameters of the model affect the behavior of the system, we choose to focus on two specific parameters of interest: r_l , the growth rate of the lynxes, and T_h , the time constant for prey consumption. Figure 4.17a is a numerically computed *parametric stability diagram* showing the regions in the chosen parameter space for which the equilibrium point is stable (leaving the other parameters at their nominal values). We see from this figure that for certain combinations of r_l and T_h we get a stable equilibrium point while at other values this equilibrium point is unstable.

Figure 4.17b shows a numerically computed *bifurcation diagram* for the system. In this plot, we choose one parameter to vary (T_h) and then plot the equilibrium value of one of the states (L) on the vertical axis. The remaining parameters are set to their nominal values. A solid line indicates that the equilibrium point is stable; a dashed line indicates that the equilibrium point is unstable. Note that the stability in the bifurcation diagram matches that in the parametric stability diagram for $r_l = 0.01$ (the nominal value) and T_h varying from 0 to 20. For the predator prey system, when the equilibrium point is unstable, the solution converges to a stable limit cycle. The amplitude of this limit cycle is shown using the dot-dashed line in Figure 4.17b. ∇

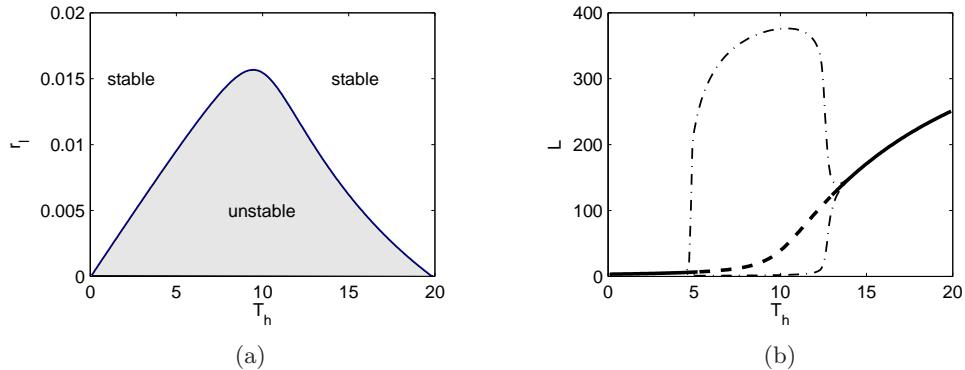


Figure 4.17: Bifurcation analysis of the predator-prey system: (a) parametric stability diagram showing the regions in parameter space for which the system is stable; (b) bifurcation diagram showing the location and stability of the equilibrium point as a function of T_h . The dotted lines indicate the upper and lower bounds for the limit cycle at that parameter value (computed via simulation). The nominal values of the parameters in the model are $r_h = 0.02$, $K = 500$, $a = 0.03$, $T_h = 5$, $r_l = 0.01$ and $k = 0.2$.

Parametric stability diagrams and bifurcation diagrams can provide valuable insights into the dynamics of a nonlinear system. It is usually necessary to carefully choose the parameters that one plots, including combining the natural parameters of the system to eliminate extra parameters when possible.

Control of bifurcations via feedback

Now consider a family of control systems

$$\dot{x} = F(x, u, \mu), \quad x \in \mathbb{R}^n, u \in \mathbb{R}^m, \mu \in \mathbb{R}^k, \quad (4.13)$$

where u is the input to the system. We have seen in the previous sections that we can sometimes alter the stability of the system by choice of an appropriate feedback control, $u = \alpha(x)$. We now investigate how the control can be used to change the bifurcation characteristics of the system. As in the previous section, we rely on examples to illustrate the key points. A more detailed description of the use of feedback to control bifurcations can be found in the work of Abed and co-workers [LA96].

A simple case of bifurcation control is when the system can be *stabilized* near the bifurcation point through the use of feedback. In this case, we

can completely eliminate the bifurcation through feedback, as the following simple example shows.

Example 4.17 (Stabilization of the pitchfork bifurcation). Consider the subcritical pitchfork example from the previous section, with a simple additive control:

$$\dot{x} = \mu x + x^3 + u.$$

Choosing the control law $u = -kx$, we can stabilize the system at the nominal bifurcation point $\mu = 0$ since $\mu - k < 0$ at this point. Of course, this only shifts the bifurcation point and so k must be chosen larger than the maximum value of μ that can be achieved.

Alternatively, we could choose the control law $u = -kx^3$ with $k > 1$. This changes the sign of the cubic term and changes the pitchfork from a subcritical bifurcation to a supercritical bifurcation. The stability of the $x = 0$ equilibrium point is not changed, but the system operating point moves slowly away from zero after the bifurcation rather than growing without bound. ∇

4.5 Further Reading

The field of dynamical systems has a rich literature that characterizes the possible features of dynamical systems and describes how parametric changes in the dynamics can lead to topological changes in behavior. A very readable introduction to dynamical systems is given by Strogatz [Sto94]. More technical treatments include Guckenheimer and Holmes [GH83] and Wiggins [Wig90]. For students with a strong interest in mechanics, the text by Marsden and Ratiu [MR94] provides a very elegant approach using tools from differential geometry. Finally, very nice treatments of dynamical systems methods in biology are given by Wilson [Wil99] and Ellner and Guckenheimer [EG05].

There is a large literature on Lyapunov stability theory. We highly recommend the very comprehensive treatment by Khalil [Kha92].

4.6 Exercises

1. Consider the cruise control system described in Section 3.1. Plot the phase portrait for the combined vehicle dynamics and PI compensator with $k = 1$ and $k_i = 0.5$.

2. Show that if we have a solution of the differential equation (4.1) given by $x(t)$ with initial condition $x(t_0) = x_0$, then $\tilde{x}(\tau) = x(t - t_0) - x_0$ is a solution of the differential equation

$$\frac{d\tilde{x}}{d\tau} = F(\tilde{x})$$

with initial condition $\tilde{x}(0) = 0$.



3. We say that an equilibrium point $x^* = 0$ is an *exponentially stable* equilibrium point of (4.2) if there exist constants $m, \alpha > 0$ and $\epsilon > 0$ such that

$$\|x(t)\| \leq me^{-\alpha(t-t_0)} \|x(t_0)\| \quad (4.14)$$

for all $\|x(t_0)\| \leq \epsilon$ and $t \geq t_0$. Prove that an equilibrium point is exponentially stable if and only if there exists an $\epsilon > 0$ and a function $V(x, t)$ that satisfies

$$\begin{aligned} \alpha_1 \|x\|^2 &\leq V(x, t) \leq \alpha_2 \|x\|^2 \\ \left. \frac{dV}{dt} \right|_{\dot{x}=f(x,t)} &\leq -\alpha_3 \|x\|^2 \\ \left\| \frac{\partial V}{\partial x}(x, t) \right\| &\leq \alpha_4 \|x\| \end{aligned}$$

for some positive constants $\alpha_1, \alpha_2, \alpha_3, \alpha_4$, and $\|x\| \leq \epsilon$.

4. Consider the asymptotically stable system

$$\frac{dx}{dt} = \begin{pmatrix} -\lambda & 0 \\ b & -\lambda \end{pmatrix} x,$$

where $\lambda > 0$. Find a Lyapunov function for the system that proves asymptotic stability.

Chapter 5

Linear Systems

Few physical elements display truly linear characteristics. For example the relation between force on a spring and displacement of the spring is always nonlinear to some degree. The relation between current through a resistor and voltage drop across it also deviates from a straight-line relation. However, if in each case the relation is ?reasonably? linear, then it will be found that the system behavior will be very close to that obtained by assuming an ideal, linear physical element, and the analytical simplification is so enormous that we make linear assumptions wherever we can possibly do so in good conscience.

R. Cannon, *Dynamics of Physical Systems*, 1967 [Can03].

In Chapters 2–4 we considered the construction and analysis of differential equation models for physical systems. We placed very few restrictions on these systems other than basic requirements of smoothness and well-posedness. In this chapter we specialize our results to the case of linear, time-invariant, input/output systems. This important class of systems is one for which a wealth of analysis and synthesis tools are available, and hence it has found great utility in a wide variety of applications.

5.1 Basic Definitions

We have seen several examples of linear differential equations in the examples of the previous chapters. These include the spring mass system (damped oscillator) and the operational amplifier in the presence of small (non-saturating) input signals. More generally, many physical systems can be modeled very accurately by linear differential equations. Electrical circuits are one example of a broad class of systems for which linear models can be used effectively. Linear models are also broadly applicable in mechani-

cal engineering, for example as models of small deviations from equilibria in solid and fluid mechanics. Signal processing systems, including digital filters of the sort used in CD and MP3 players, are another source of good examples, although often these are best modeled in discrete time (as described in more detail in the exercises).

In many cases, we *create* systems with linear input/output response through the use of feedback. Indeed, it was the desire for linear behavior that led Harold S. Black, who invented the negative feedback amplifier, to the principle of feedback as a mechanism for generating amplification. Almost all modern single processing systems, whether analog or digital, use feedback to produce linear or near-linear input/output characteristics. For these systems, it is often useful to represent the input/output characteristics as linear, ignoring the internal details required to get that linear response.

For other systems, nonlinearities cannot be ignored if one cares about the global behavior of the system. The predator prey problem is one example of this; to capture the oscillatory behavior of the coupled populations we must include the nonlinear coupling terms. However, if we care about what happens near an equilibrium point, it often suffices to approximate the nonlinear dynamics by their local *linearization*, as we already explored briefly in Section 4.3. The linearization is essentially an approximation of the nonlinear dynamics around the desired operating point.

Linearity

We now proceed to define linearity of input/output systems more formally. Consider a state space system of the form

$$\begin{aligned}\frac{dx}{dt} &= f(x, u) \\ y &= h(x, u),\end{aligned}\tag{5.1}$$

where $x \in \mathbb{R}^n$, $u \in \mathbb{R}^p$ and $y \in \mathbb{R}^q$. As in the previous chapters, we will usually restrict ourselves to the single input, single output case by taking $p = q = 1$. We also assume that all functions are smooth and that for a reasonable class of inputs (e.g., piecewise continuous functions of time) that the solutions of equation (5.1) exist for all time.

It will be convenient to assume that the origin $x = 0$, $u = 0$ is an equilibrium point for this system ($\dot{x} = 0$) and that $h(0, 0) = 0$. Indeed, we can do so without loss of generality. To see this, suppose that $(x_e, u_e) \neq (0, 0)$ is an equilibrium point of the system with output $y_e = h(x_e, u_e) \neq 0$. Then

we can define a new set of states, inputs, and outputs

$$\tilde{x} = x - x_e \quad \tilde{u} = u - u_e \quad \tilde{y} = y - y_e$$

and rewrite the equations of motion in terms of these variables:

$$\begin{aligned} \frac{d}{dt}\tilde{x} &= f(\tilde{x} + x_e, \tilde{u} + u_e) &=: \tilde{f}(\tilde{x}, \tilde{u}) \\ \tilde{y} &= h(\tilde{x} + x_e, \tilde{u} + u_e) - y_e &=: \tilde{h}(\tilde{x}, \tilde{u}). \end{aligned}$$

In the new set of variables, we have that the origin is an equilibrium point with output 0, and hence we can carry our analysis out in this set of variables. Once we have obtained our answers in this new set of variables, we simply have to remember to “translate” them back to the original coordinates (through a simple set of additions).

Returning to the original equations (5.1), now assuming without loss of generality that the origin is the equilibrium point of interest, we write the output $y(t)$ corresponding to initial condition $x(0) = x_0$ and input $u(t)$ as $y(t; x_0, u)$. Using this notation, a system is said to be a *linear input/output system* if the following conditions are satisfied:

- (i) $y(t; \alpha x_1 + \beta x_2, 0) = \alpha y(t; x_1, 0) + \beta y(t; x_2, 0)$
- (ii) $y(t; \alpha x_0, \delta u) = \alpha y(t; x_0, 0) + \delta y(t; 0, u)$
- (iii) $y(t; 0, \delta u_1 + \gamma u_2) = \delta y(t; 0, u_1) + \gamma y(t; 0, u_2).$

Thus, we define a system to be linear if the outputs are jointly linear in the initial condition response and the forced response. Property (ii) is the usual decomposition of a system response into the homogeneous response ($u = 0$) and the particular response ($x_0 = 0$). Property (iii) is the formal definition of the the *principle of superposition* illustrated in Figure 5.1.

Example 5.1 (Scalar system). Consider the first order differential equation

$$\begin{aligned} \frac{dx}{dt} &= ax + u \\ y &= x \end{aligned}$$

with $x(0) = x_0$. Let $u_1 = A \sin \omega_1 t$ and $u_2 = B \cos \omega_2 t$. The homogeneous solution the ODE is

$$x_h(t) = e^{at} x_0$$

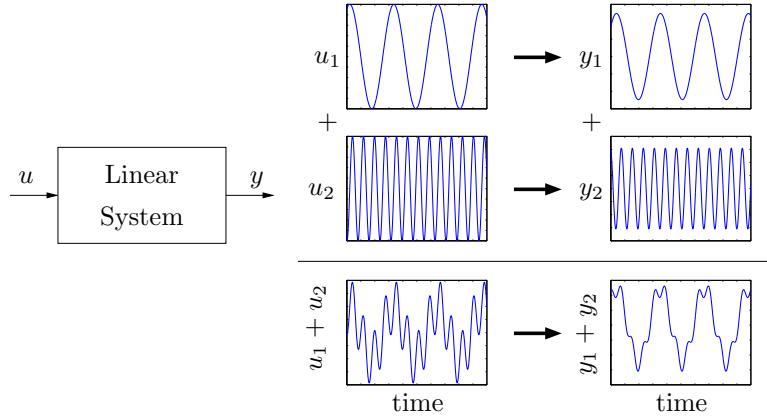


Figure 5.1: Illustration of the principle of superposition. The output corresponding to $u_1 + u_2$ is the sum of the outputs y_1 and y_2 due to the individual inputs.

and the two particular solutions are

$$\begin{aligned}x_1(t) &= -A \frac{-\omega_1 e^{at} + \omega_1 \cos \omega_1 t + a \sin \omega_1 t}{a^2 + \omega_1^2} \\x_2(t) &= B \frac{a e^{at} - a \cos \omega_2 t + \omega_2 \sin \omega_2 t}{a^2 + \omega_2^2}.\end{aligned}$$

Suppose that we now choose $x(0) = \alpha x_0$ and $u = u_1 + u_2$. Then the resulting solution is

$$\begin{aligned}x(t) &= e^{at} \left(\alpha x(0) + \frac{A \omega_1}{a^2 + \omega_1^2} + \frac{B a}{a^2 + \omega_2^2} \right) \\&\quad - A \frac{\omega_1 \cos \omega_1 t + a \sin \omega_1 t}{a^2 + \omega_1^2} + B \frac{-a \cos \omega_2 t + \omega_2 \sin \omega_2 t}{a^2 + \omega_2^2}\end{aligned}\quad (5.2)$$

(to see this, substitute the equation in the differential equation). Thus, the properties of a linear system are satisfied for this particular set of initial conditions and inputs. ∇

We now consider a differential equation of the form

$$\begin{aligned}\frac{dx}{dt} &= Ax + Bu \\y &= Cx + Du,\end{aligned}\quad (5.3)$$

where $A \in \mathbb{R}^{n \times n}$ is a square matrix, $B \in \mathbb{R}^n$ is a column vector of length n , C is a row vector of width n and D is a scalar. (In the case of a multi-input systems, B , C and D becomes a matrices of appropriate dimension.)

Equation (5.3) is a system of linear, first order, differential equations with input u , state x and output y . We now show that this system is a linear input/output system, in the sense described above.

Proposition 5.1. *The differential equation (5.3) is a linear input/output system.*

Proof. Let $x_{h1}(t)$ and $x_{h2}(t)$ be the solutions of the linear differential equation (5.3) with input $u(t) = 0$ and initial conditions $x(0) = x_{01}$ and x_{02} , respectively, and let $x_{p1}(t)$ and $x_{p2}(t)$ be the solutions with initial condition $x(0) = 0$ and inputs $u_1(t), u_2(t) \in \mathbb{R}$. It can be verified by substitution that the solution of equation (5.3) with initial condition $x(0) = \alpha x_{01} + \beta x_{02}$ and input $u(t) = \delta u_1 + \gamma u_2$ and is given by

$$x(t) = (\alpha x_{h1}(t) + \beta x_{h2}(t)) + (\delta x_{p1}(t) + \gamma x_{p2}(t)).$$

The corresponding output is given by

$$y(t) = (\alpha y_{h1}(t) + \beta y_{h2}(t)) + (\delta y_{p1}(t) + \gamma y_{p2}(t)).$$

By appropriate choices of α, β, δ and γ , properties (i)–(iii) can be verified. \square

As in the case of linear differential equations in a single variable, we define the solution $x_h(t)$ with zero input as the *homogeneous* solution and the solution $x_p(t)$ with zero initial condition as the *particular* solution. Figure 5.2 illustrates how these the homogeneous and particular solutions can be superposed to form the complete solution.

It is also possible to show that if a system is input/output linear in the sense we have described, that it can always be represented by a state space equation of the form (5.3) through appropriate choice of state variables.

Time Invariance

Time invariance is another important concept that is can be used to describe a system whose properties do not change with time. More precisely, if the input $u(t)$ gives output $y(t)$, then if we shift the time at which the input is applied by a constant amount a , $u(t+a)$ gives the output $y(t+a)$. Systems that are linear and time-invariant, often called LTI systems, have the interesting property that their response to an arbitrary input is completely characterized by their response to step inputs or their response to short “impulses”.

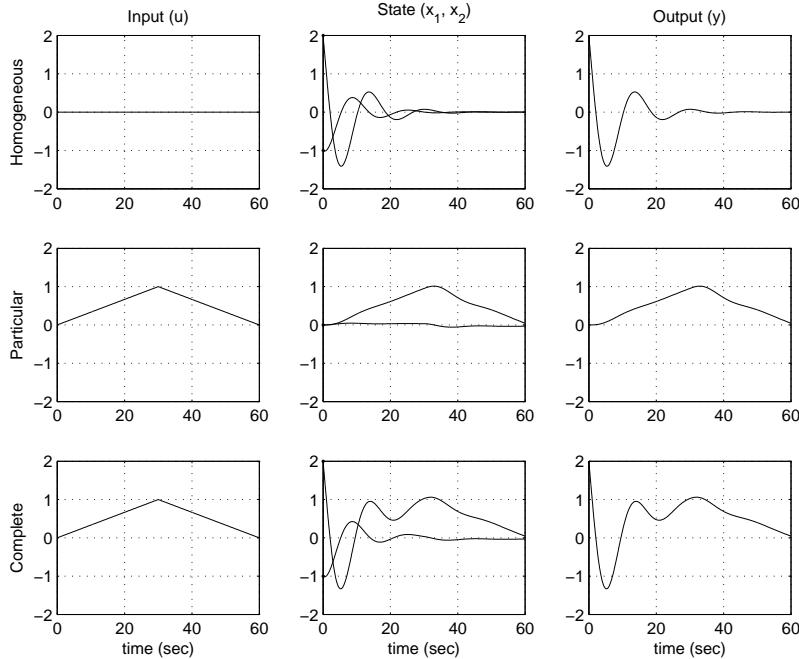


Figure 5.2: Superposition of homogeneous and particular solutions. The first row shows the input, state and output corresponding to the initial condition response. The second row shows the same variables corresponding to zero initial condition, but nonzero input. The third row is the complete solution, which is the sum of the two individual solutions.

We will first compute the response to a piecewise constant input. Assume that the system is initially at rest and consider the piecewise constant input shown in Figure 5.3a. The input has jumps at times t_k and its values after the jumps are $u(t_k)$. The input can be viewed as a combination of steps: the first step at time t_0 has amplitude $u(t_0)$, the second step at time t_1 has amplitude $u(t_1) - u(t_0)$, etc.

Assuming that the system is initially at an equilibrium point (so that the initial condition response is zero), the response to the input can then be obtained by superimposing the responses to a combination of step inputs. Let $H(t)$ be the response to a unit step applied at time t . The response to the first step is then $H(t - t_0)u(t_0)$, the response to the second step is

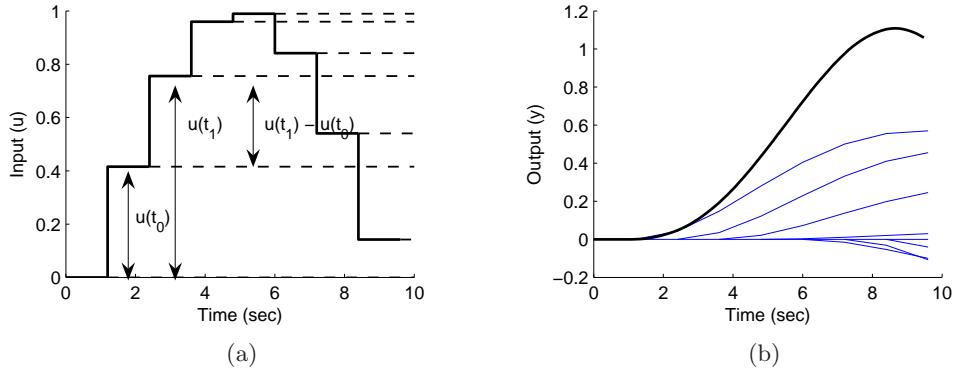


Figure 5.3: Response to piecewise constant inputs: (a) a piecewise constant signal can be represented as a sum of step signals; (b) the resulting output is the sum of the individual outputs.

$H(t - t_1)(u(t_1) - u(t_0))$, and we find that the complete response is given by

$$\begin{aligned} y(t) &= H(t - t_0)u(t_0) + H(t - t_1)(u(t_1) - u(t_0)) + \dots \\ &= (H(t) - H(t - t_1))u(t_0) + (H(t - t_1) - H(t - t_2))u(t_1) \\ &= \sum_{n=0}^{\infty} (H(t - t_n) - H(t - t_{n+1}))u(t_n) \\ &= \sum_{n=0}^{\infty} \frac{H(t - t_n) - H(t - t_{n+1})}{t_{n+1} - t_n} (t_{n+1} - t_n)u(t_n). \end{aligned}$$

An example of this computation is shown in Figure 5.3b.

The response to a continuous input signal is obtained by taking the limit as $t_{n+1} - t_n \rightarrow 0$, which gives

$$y(t) = \int_0^\infty H'(\tau)u(\tau)d\tau, \quad (5.4)$$

where H' is the derivative of the step response, which is also called the *impulse response*. The response of a linear time-invariant system to any input can thus be computed from the step response. We will derive equation (5.4) in a slightly different way in the next section.

5.2 The Convolution Equation

Equation (5.4) shows that the input response of a linear system can be written as an integral over the inputs $u(\tau)$. In this section we derive a more

general version of this formula, which shows how to compute the output of a linear system based on its state space representation.

The Matrix Exponential

Although we have shown that the solution of a linear set of differential equations defines a linear input/output system, we have not fully computed the solution of the system. We begin by considering the homogeneous response corresponding to the system

$$\frac{dx}{dt} = Ax. \quad (5.5)$$

For the *scalar* differential equation

$$\dot{x} = ax \quad x \in \mathbb{R}, a \in \mathbb{R}$$

the solution is given by the exponential

$$x(t) = e^{at}x(0).$$

We wish to generalize this to the vector case, where A becomes a matrix.

We define the *matrix exponential* as the infinite series

$$e^X = I + X + \frac{1}{2}X^2 + \frac{1}{3!}X^3 + \cdots = \sum_{k=0}^{\infty} \frac{1}{k!}X^k, \quad (5.6)$$

where $X \in \mathbb{R}^{n \times n}$ is a square matrix and I is the $n \times n$ identity matrix. We make use of the notation

$$X^0 = I \quad X^2 = XX \quad X^n = X^{n-1}X,$$

which defines what we mean by the “power” of a matrix. Equation (5.6) is easy to remember since it is just the Taylor series for the scalar exponential, applied to the matrix X . It can be shown that the series in equation (5.6) converges for any matrix $X \in \mathbb{R}^{n \times n}$ in the same way that the normal exponential is defined for any scalar $a \in \mathbb{R}$.

Replacing X in equation (5.6) by At where $t \in \mathbb{R}$ we find that

$$e^{At} = I + At + \frac{1}{2}A^2t^2 + \frac{1}{3!}A^3t^3 + \cdots = \sum_{k=0}^{\infty} \frac{1}{k!}A^kt^k,$$

and differentiating this expression with respect to t gives

$$\frac{d}{dt}e^{At} = A + At + \frac{1}{2}A^3t^2 + \dots = A \sum_{k=0}^{\infty} \frac{1}{k!} A^k t^k = Ae^{At}. \quad (5.7)$$

Multiplying by $x(0)$ from the right we find that $x(t) = e^{At}x(0)$ is the solution to the differential equation (5.5) with initial condition $x(0)$. We summarize this important result as a theorem.

Theorem 5.2. *The solution to the homogeneous system of differential equation (5.5) is given by*

$$x(t) = e^{At}x(0).$$

Notice that the form of the solution is exactly the same as for scalar equations.

The form of the solution immediately allows us to see that the solution is linear in the initial condition. In particular, if x_{h1} is the solution to equation (5.5) with initial condition $x(0) = x_{01}$ and x_{h2} with initial condition x_{02} , then the solution with initial condition $x(0) = \alpha x_{01} + \beta x_{02}$ is given by

$$x(t) = e^{At}(\alpha x_{01} + \beta x_{02}) = (\alpha e^{At}x_{01} + \beta e^{At}x_{02}) = \alpha x_{h1}(t) + \beta x_{h2}(t).$$

Similarly, we see that the corresponding output is given by

$$y(t) = Cx(t) = \alpha y_{h1}(t) + \beta y_{h2}(t),$$

where y_{h1} and y_{h2} are the outputs corresponding to x_{h1} and x_{h2} .

We illustrate computation of the matrix exponential by three examples.

Example 5.2 (Double integrator). A very simple linear system that is useful for understanding basic concepts is the second order system given by

$$\begin{aligned}\ddot{q} &= u \\ q &= q.\end{aligned}$$

This system system is called a *double integrator* because the input u is integrated twice to determine the output y .

In state space form, we write $x = (q, \dot{q})$ and

$$\frac{dx}{dt} = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} x + \begin{pmatrix} 0 \\ 1 \end{pmatrix} u.$$

The dynamics matrix of a double integrator is

$$A = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix}$$

and we find by direct calculation that $A^2 = 0$ and hence

$$e^{At} = \begin{pmatrix} 1 & t \\ 0 & 1 \end{pmatrix}.$$

Thus the homogeneous solution ($u = 0$) for the double integrator is given by

$$\begin{aligned} x(t) &= \begin{pmatrix} x_1(0) + tx_2(0) \\ x_2(0) \end{pmatrix} \\ y(t) &= x_1(0) + tx_2(0). \end{aligned}$$

∇

Example 5.3 (Undamped oscillator). A simple model for an oscillator, such as the spring mass system with zero damping, is

$$m\ddot{q} + kq = u.$$

Putting the system into state space form, the dynamics matrix for this system is

$$A = \begin{pmatrix} 0 & 1 \\ -\frac{k}{m} & 0 \end{pmatrix}$$

We have

$$e^{At} = \begin{pmatrix} \cos \omega_0 t & \frac{1}{\omega_0} \sin \omega_0 t \\ -\omega_0 \sin \omega_0 t & \cos \omega_0 t \end{pmatrix} \quad \omega_0 = \sqrt{\frac{k}{m}},$$

and the solution is then given by

$$x(t) = e^{At}x(0) = \begin{pmatrix} \cos \omega_0 t & \frac{1}{\omega_0} \sin \omega_0 t \\ -\omega_0 \sin \omega_0 t & \cos \omega_0 t \end{pmatrix} \begin{pmatrix} x_1(0) \\ x_2(0) \end{pmatrix}.$$

This solution can be verified by differentiation:

$$\begin{aligned} \frac{d}{dt}x(t) &= \begin{pmatrix} -\omega_0 \sin \omega_0 t & \cos \omega_0 t \\ -\omega_0^2 \cos \omega_0 t & -\omega_0 \sin \omega_0 t \end{pmatrix} \begin{pmatrix} x_1(0) \\ x_2(0) \end{pmatrix} \\ &= \begin{pmatrix} 0 & 1 \\ -\omega_0^2 & 0 \end{pmatrix} \begin{pmatrix} \cos \omega_0 t & \frac{1}{\omega_0} \sin \omega_0 t \\ -\omega_0 \sin \omega_0 t & \cos \omega_0 t \end{pmatrix} \begin{pmatrix} x_1(0) \\ x_2(0) \end{pmatrix} = Ax(t). \end{aligned}$$

If the damping c is nonzero, the solution is more complicated, but the matrix exponential can be shown to be

$$e^{At} = e^{\frac{-ct}{2m}} \begin{pmatrix} \frac{e^{\omega_d t} + e^{-\omega_d t}}{2} + \frac{e^{\omega_d t} - e^{-\omega_d t}}{2\sqrt{c^2 - 4km}} & \frac{e^{\omega_d t} - e^{-\omega_d t}}{\sqrt{c^2 - 4km}} \\ -\frac{ke^{\omega_d t} - ke^{-\omega_d t}}{\sqrt{c^2 - 4km}} & \frac{e^{\omega_d t} + e^{-\omega_d t}}{2} - \frac{ce^{\omega_d t} - ce^{-\omega_d t}}{2\sqrt{c^2 - 4km}}, \end{pmatrix}$$

where $\omega_d = \sqrt{c^2 - 4km}/2m$. Note that ω_d can either be real or complex, but in the case it is complex the combinations of terms will always yield a positive value for the entry in the matrix exponential. ∇

Example 5.4 (Diagonal system). Consider a diagonal matrix

$$A = \begin{pmatrix} \lambda_1 & & 0 \\ & \lambda_2 & \\ 0 & & \ddots & & \lambda_n \end{pmatrix}$$

The k th power of At is also diagonal,

$$(At)^k = \begin{pmatrix} \lambda_1^k t^k & & 0 \\ & \lambda_2^k t^k & \\ 0 & & \ddots & & \lambda_n^k t^k \end{pmatrix}$$

and it follows from the series expansion that the matrix exponential is given by

$$e^{At} = \begin{pmatrix} e^{\lambda_1 t} & & 0 \\ & e^{\lambda_2 t} & \\ 0 & & \ddots & & e^{\lambda_n t} \end{pmatrix}.$$

∇

Eigenvalues and Modes

The initial condition response of a linear system can be written in terms of a matrix exponential involving the dynamics matrix A . The properties of the matrix A therefore determine the resulting behavior of the system. Given a

matrix $A \in \mathbb{R}^{n \times n}$, recall that λ is an eigenvalue of A with eigenvector v if λ and v satisfy

$$Av = \lambda v.$$

In general λ and v may be complex valued, although if A is real-valued then for any eigenvalue λ , its complex conjugate λ^* will also be an eigenvalue (with v^* as the corresponding eigenvector).

Suppose first that λ and v are a real-valued eigenvalue/eigenvector pair for A . If we look at the solution of the differential equation for $x(0) = v$, it follows from the definition of the matrix exponential that

$$e^{At}v = (I + At + \frac{1}{2}A^2t^2 + \dots)v = (v + \lambda tv + \frac{\lambda^2 t^2}{2}v + \dots)v = e^{\lambda t}v.$$

The solution thus lies in the subspace spanned by the eigenvector. The eigenvalue λ describes how the solution varies in time and is often called a *mode* of the system. If we look at the individual elements of the vectors x and v , it follows that

$$\frac{x_i(t)}{x_j(t)} = \frac{v_i}{v_j},$$

and hence the ratios of the components of the state x are constants. The eigenvector thus gives the “shape” of the solution and is also called a *mode shape* of the system.

Figure 5.4 illustrates the modes for a second order system. Notice that the state variables have the same sign for the slow mode $\lambda = -0.08$ and different signs for the fast mode $\lambda = -0.62$.

The situation is a little more complicated when the eigenvalues of A are complex. Since A has real elements, the eigenvalues and the eigenvectors are complex conjugates

$$\lambda = \sigma \pm j\omega \quad \text{and} \quad v = u \pm jw,$$

which implies that

$$u = \frac{v + v^*}{2} \quad w = \frac{v - v^*}{2j}.$$

Making use of the matrix exponential, we have

$$e^{At}v = e^{\lambda t}(u + jw) = e^{\sigma t}((u \cos \omega t - w \sin \omega t) + j(u \sin \omega t + w \cos \omega t)),$$

which implies

$$\begin{aligned} e^{At}u &= \frac{1}{2}(e^{At}v + e^{At}v^*) = ue^{\sigma t} \cos \omega t - we^{\sigma t} \sin \omega t \\ e^{At}w &= \frac{1}{2j}(e^{At}v - e^{At}v^*) = ue^{\sigma t} \sin \omega t + we^{\sigma t} \cos \omega t. \end{aligned}$$

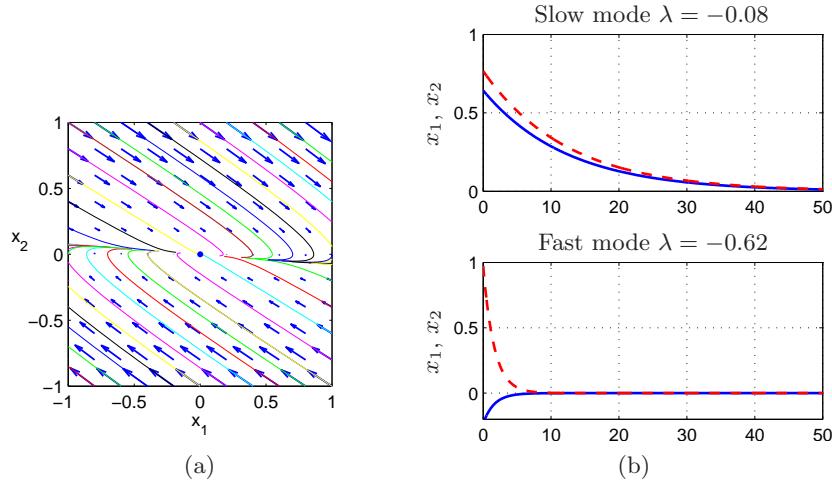


Figure 5.4: Illustration of the notion of modes for a second order system with real eigenvalues. The left figure (a) shows the phase plane and the modes corresponds to solutions that start on the eigenvectors. The time functions are shown in (b). The ratios of the states are also computed to show that they are constant for the modes.

A solution with initial conditions in the subspace spanned by the real part u and imaginary part v of the eigenvector will thus remain in that subspace. The solution will be logarithmic spiral characterized by σ and ω . We again call λ a mode of the system and v the mode shape.

If a matrix A has a n distinct eigenvalues $\lambda_1, \dots, \lambda_n$, then the initial condition response can be written as a linear combination of the modes. To see this, suppose for simplicity that we have all real eigenvalues with corresponding unit eigenvectors v_1, \dots, v_n . From linear algebra, these eigenvectors are linearly independent and we can write the initial condition $x(0)$ as

$$x(0) = \alpha_1 v_1 + \alpha_2 v_2 + \cdots + \alpha_n v_n.$$

Using linearity, the initial condition response can be written as

$$x(t) = \alpha_1 e^{\lambda_1 t} v_1 + \alpha_2 e^{\lambda_2 t} v_2 + \cdots + \alpha_n e^{\lambda_n t} v_n.$$

Thus, the response is a linear combination the modes of the system, with the amplitude of the individual modes growing or decaying as $e^{\lambda_i t}$. The case for distinct complex eigenvalues follows similarly (the case for non-distinct eigenvalues is more subtle and is described in the section on the Jordan form, below).

Linear Input/Output Response

We now return to the general input/output case in equation (5.3), repeated here:

$$\begin{aligned}\frac{dx}{dt} &= Ax + Bu \\ y &= Cx + Du.\end{aligned}\tag{5.8}$$

Using the matrix exponential, the solution to equation (5.8) can be written as follows.

Theorem 5.3. *The solution to the linear differential equation (5.8) is given by*

$$x(t) = e^{At}x(0) + \int_0^t e^{A(t-\tau)}Bu(\tau)d\tau.\tag{5.9}$$

Proof. To prove this, we differentiate both sides and use the property (5.7) of the matrix exponential. This gives

$$\frac{dx}{dt} = Ae^{At}x(0) + \int_0^t Ae^{A(t-\tau)}Bu(\tau)d\tau + Bu(t) = Ax + Bu,$$

which proves the result. Notice that the calculation is essentially the same as for proving the result for a first order equation. \square

It follows from equations (5.8) and (5.9) that the input/output relation for a linear system is given by

$$y(t) = Ce^{At}x(0) + \int_0^t Ce^{A(t-\tau)}Bu(\tau)d\tau + Du(t).\tag{5.10}$$

It is easy to see from this equation that the output is jointly linear in both the initial conditions and the state: this follows from the linearity of matrix/vector multiplication and integration.

Equation (5.10) is called the *convolution equation* and it represents the general form of the solution of a system of coupled linear differential equations. We see immediately that the dynamics of the system, as characterized by the matrix A , play a critical role in both the stability and performance of the system. Indeed, the matrix exponential describes *both* what happens when we perturb the initial condition and how the system responds to inputs.



Another interpretation of the convolution equation can be given using the

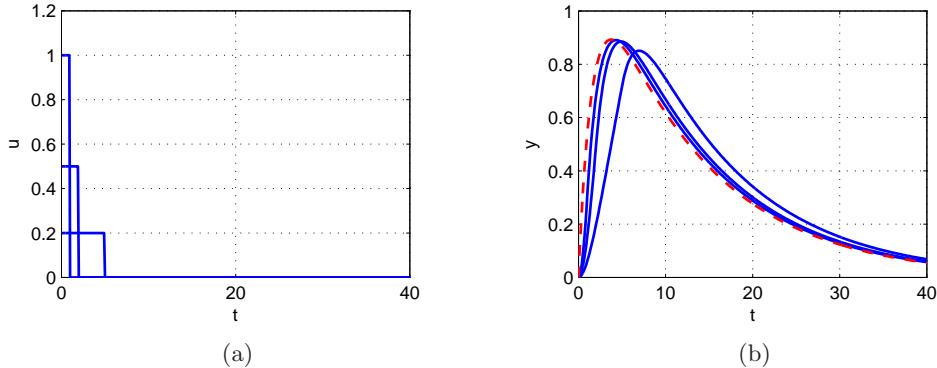


Figure 5.5: (a) Pulses of width 5, 2 and 1, each with total area equal to 1. (b) The pulse responses (solid) and impulse response (dashed) for a linear system with eigenvalues $\lambda = \{-0.08, -0.62\}$.

concept of the *impulse response* of a system. Consider the application of an input signal $u(t)$ given by the following equation:

$$u(t) = p_\epsilon(t) = \begin{cases} 0 & t < 0 \\ 1/\epsilon & 0 \leq t < \epsilon \\ 0 & t \geq \epsilon. \end{cases} \quad (5.11)$$

This signal is a “pulse” of duration ϵ and amplitude $1/\epsilon$, as illustrated in Figure 5.5a. We define an *impulse*, $\delta(t)$, to be the limit of this signal as $\epsilon \rightarrow 0$:

$$\delta(t) = \lim_{\epsilon \rightarrow 0} p_\epsilon(t). \quad (5.12)$$

This signal, sometimes called a *delta function*, is not physically achievable but provides a convenient abstraction for understanding the response of a system. Note that the integral of an impulse is a unit step function, sometimes written as $1(t)$:

$$\begin{aligned} 1(t) &= \int_0^t \delta(\tau) d\tau = \int_0^t \lim_{\epsilon \rightarrow 0} p_\epsilon(\tau) d\tau & t > 0 \\ &= \lim_{\epsilon \rightarrow 0} \int_0^t p_\epsilon(\tau) d\tau = \lim_{\epsilon \rightarrow 0} \int_0^\epsilon 1/\epsilon d\tau = 1 & t > 0 \end{aligned}$$

In particular, the integral of an impulse over an arbitrarily short period of time is identically 1.

We define the *impulse response* of a system, $h(t)$, to be the output corresponding to an impulse as its input:

$$h(t) = \int_0^t Ce^{A(t-\tau)} B \delta(\tau) d\tau = Ce^{At} B, \quad (5.13)$$

where the second equality follows from the fact that $\delta(t)$ is zero everywhere except the origin and its integral is identically one. We can now write the convolution equation in terms of the initial condition response and the convolution of the impulse response and the input signal,

$$y(t) = Ce^{At} x(0) + \int_0^t h(t-\tau) u(\tau) d\tau. \quad (5.14)$$

One interpretation of this equation, explored in Exercise 6, is that the response of the linear system is the superposition of the response to an infinite set of shifted impulses whose magnitude is given by the input, $u(t)$. Note that the second term in this equation is identical to equation (5.4) and it can be shown that the impulse response is formally equivalent to the derivative of the step response.

The use of pulses as an approximation of the impulse response provides a mechanism for identifying the dynamics of a system from data. Figure 5.5b shows the pulse responses of a system for different pulse widths. Notice that the pulse responses approaches the impulse response as the pulse width goes to zero. As a general rule, if the fastest eigenvalue of a stable system has real part $-\lambda_{\max}$, then a pulse of length ϵ will provide a good estimate of the impulse response if $\epsilon\lambda_{\max} < 1$. Note that for Figure 5.5, a pulse width of $\epsilon = 1$ s gives $\epsilon\lambda_{\max} = 0.62$ and the pulse response is very close to the impulse response.

Coordinate Changes

The components of the input vector u and the output vector y are unique physical signals, but the state variables depend on the coordinate system chosen to represent the state. The choice of coordinates affects the values of the matrices A , B and C that are used in the model. (The direct term D is not affecting since it maps inputs to outputs.) We now investigate some of the consequences of changing coordinate systems.

Introduce new coordinates z by the transformation $z = Tx$, where T is an invertible matrix. It follows from equation (5.3) that

$$\begin{aligned} \frac{dz}{dt} &= T(Ax + Bu) = TAT^{-1}z + TBu = \tilde{A}z + \tilde{B}u \\ y &= Cx + DU = CT^{-1}z + Du = \tilde{C}z + Du. \end{aligned}$$

The transformed system has the same form as equation (5.3) but the matrices A , B and C are different:

$$\tilde{A} = TAT^{-1}, \quad \tilde{B} = TB, \quad \tilde{C} = CT^{-1}, \quad \tilde{D} = D. \quad (5.15)$$

As we shall see in several places later in the text, there are often special choices of coordinate systems that allow us to see a particular property of the system, hence coordinate transformations can be used to gain new insight into the dynamics.

We can also compare the solution of the system in transformed coordinates to that in the original state coordinates. We make use of an important property of the exponential map,

$$e^{TST^{-1}} = Te^S T^{-1},$$

which can be verified by substitution in the definition of the exponential map. Using this property, it is easy to show that

$$x(t) = T^{-1}z(t) = T^{-1}e^{\tilde{A}t}Tx(0) + T^{-1} \int_0^t e^{\tilde{A}(t-\tau)} \tilde{B}u(\tau) d\tau.$$

From this form of the equation, we see that if it is possible to transform A into a form \tilde{A} for which the matrix exponential is easy to compute, we can use that computation to solve the general convolution equation for the untransformed state x by simple matrix multiplications. This technique is illustrated in the next section.

Example 5.5 (Modal form). Suppose that A has n real, distinct eigenvalues, $\lambda_1, \dots, \lambda_n$. It follows from matrix linear algebra that the corresponding eigenvectors v_1, \dots, v_n are linearly independent and form a basis for \mathbb{R}^n . Suppose that we transform coordinates according to the rule

$$x = Mz \quad M = \begin{pmatrix} v_1 & v_2 & \cdots & v_n \end{pmatrix}.$$

Setting $T = M^{-1}$, it is easy to show that

$$\tilde{A} = TAT^{-1} = M^{-1}AM = \begin{pmatrix} \lambda_1 & & & 0 \\ & \lambda_2 & & \\ & & \ddots & \\ 0 & & & \lambda_n \end{pmatrix}.$$

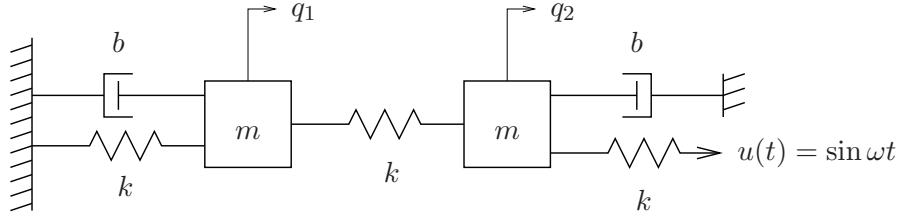


Figure 5.6: Coupled spring mass system.

To see this, note that if we multiple $M^{-1}AM$ by the basis elements

$$e_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \quad e_2 = \begin{pmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \quad \dots \quad e_n = \begin{pmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 1 \end{pmatrix}$$

we get precisely $\lambda_i e_i$, which is the same as multiplying the diagonal form by the canonical basis elements. Since this is true for each e_i , $i = 1, \dots, n$ and since the these vectors form a basis for \mathbb{R}^n , the transformed matrix must be in the given form. This is precisely the diagonal form of Example 5.4, which is also called the *modal form* for the system. ∇

Example 5.6 (Coupled mass spring system). Consider the coupled mass spring system shown in Figure 5.6. The input to this system is the sinusoidal motion of the end of rightmost spring and the output is the position of each mass, q_1 and q_2 . The equations of motion for the system are given by

$$\begin{aligned} m_1 \ddot{q}_1 &= -2kq_1 - c\dot{q}_1 + kq_2 \\ m_2 \ddot{q}_2 &= kq_1 - 2kq_2 - c\dot{q}_2 + ku \end{aligned}$$

In state-space form, we define the state to be $x = (q_1, q_2, \dot{q}_1, \dot{q}_2)$ and we can rewrite the equations as

$$\dot{x} = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -\frac{2k}{m} & \frac{k}{m} & -\frac{c}{m} & 0 \\ \frac{k}{m} & -\frac{2k}{m} & 0 & -\frac{c}{m} \end{pmatrix} x + \begin{pmatrix} 0 \\ 0 \\ 0 \\ \frac{k}{m} \end{pmatrix} u.$$

This is a coupled set of four differential equations and quite difficult to solve in analytical form.

We now define a transformation $z = Tx$ that puts this system into a simpler form. Let $z_1 = \frac{1}{2}(q_1 + q_2)$, $z_2 = \dot{z}_1$, $z_3 = \frac{1}{2}(q_1 - q_2)$ and $z_4 = \dot{z}_3$, so that

$$z = Tx = \frac{1}{2} \begin{pmatrix} 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 \end{pmatrix} x.$$

Using the coordinate transformations described above (or simple substitution of variables, which is equivalent), we can write the system in the z coordinates as

$$\dot{z} = \begin{pmatrix} 0 & 1 & 0 & 0 \\ -\frac{k}{m} & -\frac{c}{m} & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & -\frac{3k}{m} & -\frac{c}{m} \end{pmatrix} z + \begin{pmatrix} 0 \\ \frac{k}{2m} \\ 0 \\ -\frac{k}{2m} \end{pmatrix} u.$$

Note that the resulting matrix equations are block diagonal and hence decoupled. We can thus solve for the solutions by computing the two sets of second order system represented by the states (z_1, z_2) and (z_3, z_4) . Indeed, the functional form of each set of equations is identical to that of a single spring mass system (Section 2.1).

Once we have solved the two sets of independent second order equations, we can recover the dynamics in the original coordinates by inverting the state transformation and writing $x = T^{-1}z$. We can also determine the stability of the system by looking at the stability of the independent second order systems (Exercise 1). ∇

5.3 Stability and Performance

The special form of a linear system and its solution through the convolution equation allow us to analytically solve for the stability of equilibrium points and input/output performance properties.

Stability of Linear Systems

For a linear system, the stability of the equilibrium point at the origin can be determined by looking at the eigenvalues of the stability matrix A :

$$\lambda(A) = \{s \in \mathbb{C} : \det(sI - A) = 0\}.$$

We use the notation λ_i for the i th eigenvalue of A , so that $\lambda_i \in \lambda(A)$.

The easiest class of linear systems to analyze are those whose system matrices are in diagonal form. In this case, the dynamics have the form

$$\begin{aligned}\frac{dx}{dt} &= \begin{pmatrix} \lambda_1 & & & 0 \\ & \lambda_2 & & \\ & & \ddots & \\ 0 & & & \lambda_n \end{pmatrix} x + \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{pmatrix} u \\ y &= \begin{pmatrix} \gamma_1 & \gamma_2 & \cdots & \gamma_n \end{pmatrix} x + Du.\end{aligned}$$

Using Example 5.4, it is easy to show that the state trajectories for this system are independent of each other, so that we can write the solution in terms of n individual systems

$$\dot{x}_i = \lambda_i x_i + \beta_i u.$$

Each of these scalar solutions is of the form

$$x_i(t) = e^{\lambda_i t} x(0) + \int_0^t e^{\lambda_i(t-\tau)} \beta_i u(\tau) d\tau.$$

If we consider the stability of the system when $u = 0$, we see that the equilibrium point $x_e = 0$ is stable if $\lambda_i \leq 0$ and asymptotically stable if $\lambda_i < 0$.

Very few systems are diagonal, but some systems can be transformed into diagonal form via coordinate transformations. One such class of systems is those for which the dynamics matrix has distinct (non-repeating) eigenvalues, as outlined in Example 5.5. In this case it is possible to find a matrix T such that the matrix TAT^{-1} and the transformed system is in diagonal form, with the diagonal elements equal to the eigenvalues of the original matrix A . We can reason about the stability of the original system by noting that $x(t) = T^{-1}z(t)$ and so if the transformed system is stable (or asymptotically stable) then the original system has the same type stability.

For more complicated systems, we make use of the following theorem, proved in the next section:

Theorem 5.4. *The system*

$$\dot{x} = Ax$$

is asymptotically stable if and only if all eigenvalues of A all have strictly negative real part and is unstable if any eigenvalue of A has strictly positive real part.

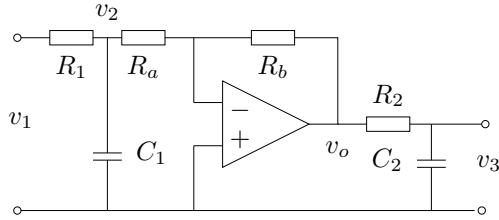


Figure 5.7: Active filter circuit using an operational amplifier.

Example 5.7 (Active filter). Consider the op amp circuit shown in Figure 5.7. There are two energy storage elements, the capacitors C_1 and C_2 . We choose their voltages, v_2 and v_3 , as states. The dynamics for the system (Chapter 3, Exercise 5) are given by

$$\begin{aligned}\dot{x} &= \begin{pmatrix} -\frac{1}{R_1 C_1} - \frac{1}{R_a C_1} & 0 \\ \frac{R_b}{R_a} \frac{1}{R_2 C_2} & -\frac{1}{R_2 C_2} \end{pmatrix} x + \begin{pmatrix} \frac{1}{R_1 C_1} \\ 0 \end{pmatrix} u \\ y &= \begin{pmatrix} 0 & 1 \end{pmatrix} x,\end{aligned}$$

where $u = v_1$ and $y = v_3$. The eigenvalues of the dynamics matrix, A , are

$$\lambda_1 = -\frac{1}{R_1 C_1} - \frac{1}{R_a C_1} \quad \lambda_2 = -\frac{1}{R_2 C_2}.$$

Assuming all capacitances and resistances are positive, these eigenvalues are both real and negative, and hence the equilibrium point at $x = 0$ is asymptotically stable. This implies, in particular, that if no input voltage is applied, the voltages around the system will all converge to zero as $t \rightarrow \infty$.

▽

Jordan Form



Some matrices with equal eigenvalues cannot be transformed to diagonal form. They can however be transformed to the Jordan form. In this form the dynamics matrix has the eigenvalues along the diagonal. When there are equal eigenvalues there may be ones appearing in the super diagonal indicating that there is coupling between the states.

More specifically, we define a matrix to be in *Jordan form* if it can be

written as

$$J = \begin{pmatrix} J_1 & 0 & \cdots & 0 \\ 0 & J_2 & & 0 \\ 0 & \cdots & \ddots & 0 \\ 0 & \cdots & & J_k \end{pmatrix} \quad \text{where} \quad J_i = \begin{pmatrix} \lambda_i & 1 & 0 & \cdots & 0 \\ 0 & \lambda_i & 1 & & 0 \\ \vdots & & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & \lambda_i & 1 \\ 0 & \cdots & 0 & 0 & \lambda_i \end{pmatrix}. \quad (5.16)$$

Each matrix J_i is called a *Jordan block* and λ_i for that block corresponds to an eigenvalue of J .

Theorem 5.5 (Jordan decomposition). *Any matrix $A \in \mathbb{R}^{n \times n}$ can be transformed into Jordan form with the eigenvalues of A determining λ_i in the Jordan form.*

Proof. See any standard text on linear algebra, such as Strang [Str88]. \square

Converting a matrix into Jordan form can be very complicated, although MATLAB can do this conversion for numerical matrices using the `Jordan` function. The structure of the resulting Jordan form is particularly interesting since there is no requirement that the individual λ_i 's be unique, and hence for a given eigenvalue we can have one or more Jordan blocks of different size. We say that a Jordan block J_i is *trivial* if J_i is a scalar (1×1 block).

Once a matrix is in Jordan form, the exponential of the matrix can be computed in terms of the Jordan blocks:

$$e^J = \begin{pmatrix} e^{J_1} & 0 & \cdots & 0 \\ 0 & e^{J_2} & & 0 \\ 0 & \cdots & \ddots & 0 \\ 0 & \cdots & & e^{J_k} \end{pmatrix} \quad (5.17)$$

This follows from the block diagonal form of J . The exponentials of the Jordan blocks can in turn be written as

$$e^{J_i t} = \begin{pmatrix} e^{\lambda_i t} & t e^{\lambda_i t} & \frac{t^2}{2!} e^{\lambda_i t} & \cdots & \frac{t^{n-1}}{(n-1)!} e^{\lambda_i t} \\ 0 & e^{\lambda_i t} & t e^{\lambda_i t} & \cdots & \frac{t^{n-2}}{(n-2)!} e^{\lambda_i t} \\ & & e^{\lambda_i t} & \ddots & \\ & & & \ddots & t e^{\lambda_i t} \\ 0 & & & & e^{\lambda_i t} \end{pmatrix} \quad (5.18)$$

When there are multiple eigenvalues, the invariant subspaces representing the modes correspond to the Jordan blocks of the matrix A . Note that λ may be complex, in which case the transformation T that converts a matrix into Jordan form will also be complex. When λ has a non-zero imaginary component, the solutions will have oscillatory components since

$$e^{\sigma+j\omega t} = e^{\sigma t}(\cos \omega t + j \sin \omega t).$$

We can now use these results to prove Theorem 5.4.

Proof of Theorem 5.4. Let $T \in \mathbb{C}^{n \times n}$ be an invertible matrix that transforms A into Jordan form, $J = TAT^{-1}$. Using coordinates $z = Tx$, we can write the solution $z(t)$ as

$$z(t) = e^{Jt}z(0).$$

Since any solution $x(t)$ can be written in terms of a solution $z(t)$ with $z(0) = Tx(0)$, it follows that it is sufficient to prove the theorem in the transformed coordinates.

The solution $z(t)$ can be written as a combination of the elements of the matrix exponential and from equation (5.18) these elements all decay to zero for arbitrary $z(0)$ if and only if $\operatorname{Re} \lambda_i < 0$. Furthermore, if any λ_i has positive real part, then there exists an initial condition $z(0)$ such that the corresponding solution increases without bound. Since we can scale this initial condition to be arbitrarily small, it follows that the equilibrium point is unstable if any eigenvalue has positive real part. \square

The existence of a canonical form allows us to prove many properties of linear systems by changing to a set of coordinates in which the A matrix is in Jordan form. We illustrate this in the following proposition, which follows along the same lines as the proof of Theorem 5.4.

Proposition 5.6. *Suppose that the system*

$$\dot{x} = Ax$$

has no eigenvalues with strictly positive real part and one or more eigenvalues with zero real part. Then the system is stable if and only if the Jordan blocks corresponding to each eigenvalue with zero real part are scalar (1×1) blocks.

Proof. Exercise 3. \square

Input/Output Response

So far, this chapter has focused on the stability characteristics of a system. While stability is often a desirable feature, stability alone may not be sufficient in many applications. We will want to create feedback systems that quickly react to changes and give high performance in measurable ways.

We return now to the case of an input/output state space system

$$\begin{aligned}\frac{dx}{dt} &= Ax + Bu \\ y &= Cx + Du,\end{aligned}\tag{5.19}$$

where $x \in \mathbb{R}^n$ is the state and $u, y \in \mathbb{R}$ are the input and output. The general form of the solution to equation (5.19) is given by the convolution equation:

$$y(t) = Ce^{At}x(0) + \int_0^t Ce^{A(t-\tau)}Bu(\tau)d\tau + Du(t).$$

We see from the form of this equation that the solution consists of an initial condition response and an input response.

The input response, corresponding to the second term in the equation above, itself consists of two components—the transient response and steady state response. The transient response occurs in the first period of time after the input is applied and reflects the mismatch between the initial condition and the steady state solution. The steady state response is the portion of the output response that reflects the long term behavior of the system under the given inputs. For inputs that are periodic, the steady state response will often also be periodic. An example of the transient and steady state response is shown in Figure 5.8.

Step Response

A particularly common form of input is a *step input*, which represents an abrupt change in input from one value to another. A *unit step* is defined as

$$u = 1(t) = \begin{cases} 0 & t = 0 \\ 1 & t > 0. \end{cases}$$

The *step response* of the system (5.3) is defined as the output $y(t)$ starting from zero initial condition (or the appropriate equilibrium point) and given a *step input*. We note that the step input is discontinuous and hence is not

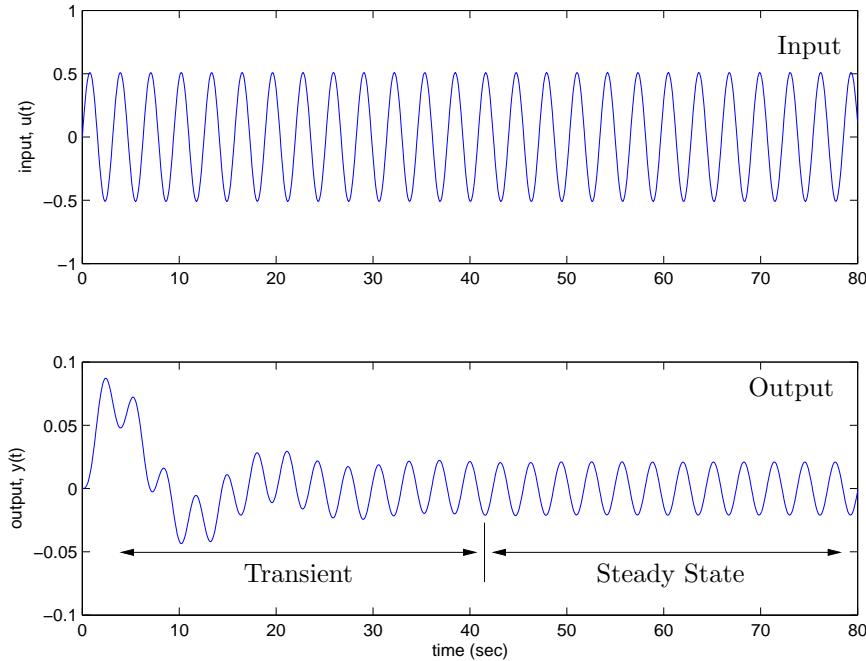


Figure 5.8: Transient versus steady state response. The top plot shows the input to a linear system and the bottom plot the corresponding output. The output signal initially undergoes a transient before settling into its steady state behavior.

physically implementable. However, it is a convenient abstraction that is widely used in studying input/output systems.

We can compute the step response to a linear system using the convolution equation. Setting $x(0) = 0$ and using the definition of the step input above, we have

$$\begin{aligned} y(t) &= \int_0^t C e^{A(t-\tau)} B u(\tau) d\tau + D u(t) \\ &= \int_0^t C e^{A(t-\tau)} B d\tau + D \quad t > 0. \end{aligned}$$

If A has eigenvalues with negative real part (implying that the origin is a stable equilibrium point in the absence of any input), then we can rewrite the solution as

$$y(t) = \underbrace{C A^{-1} e^{At} B}_{\text{transient}} + \underbrace{D - C A^{-1} B}_{\text{steady state}} \quad t > 0. \quad (5.20)$$

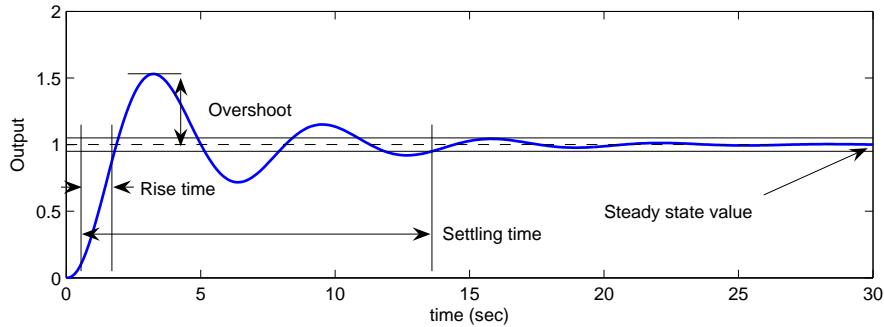


Figure 5.9: Sample step response

The first term is the transient response and decays to zero as $t \rightarrow \infty$. The second term is the steady state response and represents the value of the output for large time.

A sample step response is shown in Figure 5.9. Several terms are used when referring to a step response:

Steady state value The steady state value, y_{ss} , of a step response is the final level of the output, assuming it converges.

Rise time The rise time, T_r , is the amount of time required for the signal to go from 10% of its final value to 90% of its final value. It is possible to define other limits as well, but in this book we shall use these percentages unless otherwise indicated.

Overshoot The overshoot, M_p , is the percentage of the final value by which the signal initially rises above the final value. This usually assumes that future values of the signal do not overshoot the final value by more than this initial transient, otherwise the term can be ambiguous.

Settling time The settling time, T_s , is the amount of time required for the signal to stay within 5% of its final value for all future times. The settling time is also sometimes defined as reaching 1% or 2% of the final value (see Exercise 5).

In general these performance measures can depend on the amplitude of the input step, but for linear systems it can be shown that the quantities defined above are independent of the size of the step.

Frequency Response

The frequency response of an input/output system measures the way in which the system responds to a sinusoidal excitation on one of its inputs. As we have already seen for linear systems, the particular solution associated with a sinusoidal excitation is itself a sinusoid at the same frequency. Hence we can compare the magnitude and phase of the output sinusoid to the input. More generally, if a system has a sinusoidal output response at the same frequency as the input forcing, we can speak of the frequency response of the system.

To see this in more detail, we must evaluate the convolution equation (5.10) for $u = \cos \omega t$. This turns out to be a very messy computation, but we can make use of the fact that the system is linear to simplify the derivation. In particular, we note that

$$\cos \omega t = \frac{1}{2} (e^{j\omega t} + e^{-j\omega t}).$$

Since the system is linear, it suffices to compute the response of the system to the complex input $u(t) = e^{st}$ and we can always reconstruct the input to a sinusoid by averaging the responses corresponding to $s = j\omega t$ and $s = -j\omega t$.

Applying the convolution equation to the input $u = e^{st}$, we have

$$\begin{aligned} y(t) &= \int_0^t C e^{A(t-\tau)} B e^{s\tau} d\tau + D e^{st} \\ &= \int_0^t C e^{A(t-\tau)+sI\tau} B d\tau + D e^{st} \\ &= e^{At} \int_0^t C e^{(sI-A)\tau} B d\tau + D e^{st}. \end{aligned}$$

If we assume that none of the eigenvalues of A are equal to $s = \pm j\omega$, then the matrix $sI - A$ is invertible and we can write (after some algebra)

$$y(t) = \underbrace{C e^{At} \left(x(0) - (sI - A)^{-1} B \right)}_{\text{transient}} + \underbrace{\left(D + C(sI - A)^{-1} B \right) e^{st}}_{\text{steady state}}.$$

Notice that once again the solution consists of both a transient component and a steady state component. The transient component decays to zero if the system is asymptotically stable and the steady state component is proportional to the (complex) input $u = e^{st}$.

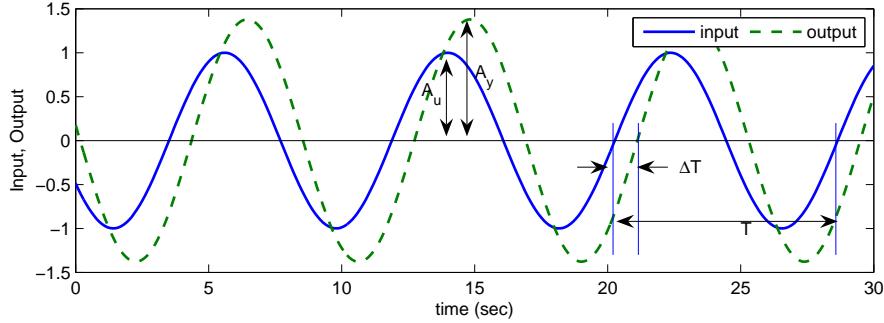


Figure 5.10: Frequency response, showing gain and phase. The phase lag is given by $\theta = -2\pi\Delta T/T$.

We can simplify the form of the solution slightly further by rewriting the steady state response as

$$y_{ss} = M e^{j\theta} e^{st} = M e^{(st+j\theta)}$$

where

$$M e^{j\theta} = C(sI - A)^{-1}B + D \quad (5.21)$$

and M and θ represent the magnitude and phase of the complex number $D + C(sI - A)^{-1}B$. When $s = j\omega$, we say that M is the *gain* and θ is the *phase* of the system at a given forcing frequency ω . Using linearity and combining the solutions for $s = +j\omega$ and $s = -j\omega$, we can show that if we have an input $u = A_u \sin(\omega t + \psi)$ and output $y = A_y \sin(\omega t + \varphi)$, then

$$\text{gain}(\omega) = \frac{A_y}{A_u} = M \quad \text{phase}(\omega) = \varphi - \psi = \theta.$$

If the phase is positive, we say that the output “leads” the input, otherwise we say it “lags” the input.

A sample frequency response is illustrated in Figure 5.10. The solid line shows the input sinusoid, which has amplitude 1. The output sinusoid is shown as a dashed line, and has a different amplitude plus a shifted phase. The gain is the ratio of the amplitudes of the sinusoids, which can be determined by measuring the height of the peaks. The phase is determined by comparing the ratio of the time between zero crossings of the input and output to the overall period of the sinusoid:

$$\theta = -2\pi \cdot \frac{\delta T}{T}.$$

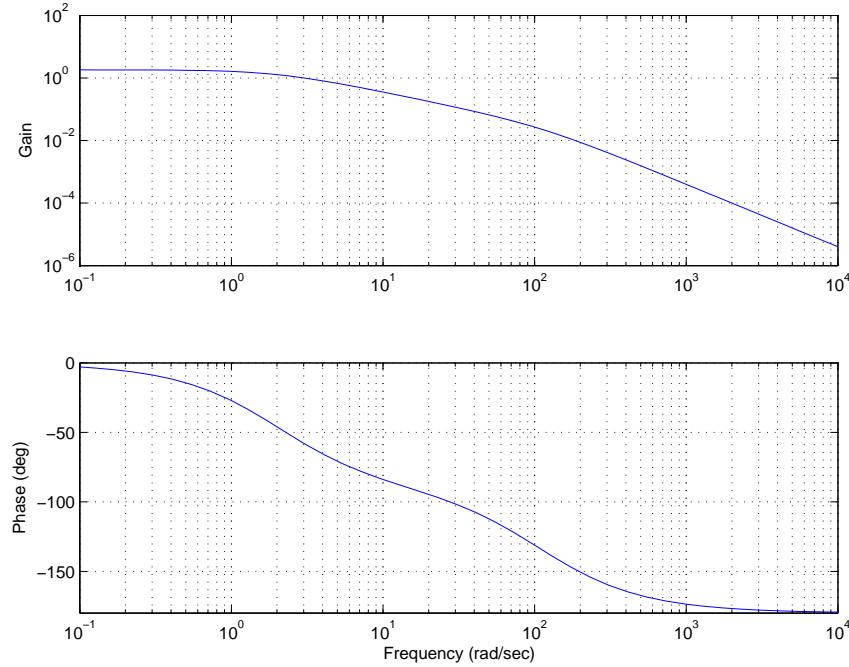


Figure 5.11: Frequency response for the active filter from Example 5.7. The upper plot shows the magnitude as a function of frequency (on a log-log scale) and the lower plot shows the phase (on a log-linear scale).

Example 5.8 (Active filter). Consider the active filter presented in Example 5.7. The frequency response for the system can be computed using equation (5.21):

$$M e^{j\theta} = C(sI - A)^{-1}B + D = \frac{R_b/R_a}{(1 + R_2C_2s)(\frac{R_1+R_a}{R_a} + R_1C_1s)} \quad s = j\omega.$$

The magnitude and phase are plotted in Figure 5.11 for $R_a = 1k\Omega$, $R_b = 100 k\Omega$, $R_1 = 100\Omega$, $R_2 = 5k\Omega$ and $C_1 = C_2 = 100 \mu\text{F}$. ∇

The gain at frequency $\omega = 0$ is called the *zero frequency gain* of the system and corresponds to the ratio between a constant input and the steady output:

$$M_0 = CA^{-1}B + D.$$

Note that the zero frequency gain is only well defined if A is invertible (and, in particular, if it does not have eigenvalues at 0). It is also important to note that the zero frequency gain is only a relevant quantity when a system is

stable about the corresponding equilibrium point. So, if we apply a constant input $u = r$ then the corresponding equilibrium point

$$x_e = -A^{-1}Br$$

must be stable in order to talk about the zero frequency gain. (In electrical engineering, the zero frequency gain is often called the “DC gain”. DC stands for “direct current” and reflects the common separation of signals in electrical engineering into a direct current (zero frequency) term and an alternating current (AC) term.)

5.4 Second Order Systems

One class of systems that occurs frequently in the analysis and design of feedback systems is second order, linear differential equations. Because of their ubiquitous nature, it is useful to apply the concepts of this chapter to that specific class of systems and build more intuition about the relationship between stability and performance.

The canonical second order system is a differential equation of the form

$$\begin{aligned}\ddot{q} + 2\zeta\omega_0\dot{q} + \omega_0^2 q &= ku \\ y &= q.\end{aligned}\tag{5.22}$$

In state space form, this system can be represented as

$$\begin{aligned}\dot{x} &= \begin{pmatrix} 0 & 1 \\ -\omega_0^2 & -2\zeta\omega_0 \end{pmatrix} x + \begin{pmatrix} 0 \\ k \end{pmatrix} u \\ y &= \begin{pmatrix} 1 & 0 \end{pmatrix} x\end{aligned}\tag{5.23}$$

The eigenvalues of this system are given by

$$\lambda = -\zeta\omega_0 \pm \sqrt{\omega_0^2(\zeta^2 - 1)}$$

and we see that the origin is a stable equilibrium point if $\omega_0 > 0$ and $\zeta > 0$. Note that the eigenvalues are complex if $\zeta < 1$ and real otherwise. Equations (5.22) and (5.23) can be used to describe many second order systems, including a damped spring mass system and an active filter, as shown in the examples below.

The form of the solution depends on the value of ζ , which is referred to as the *damping factor* for the system. If $\zeta > 1$, we say that the system is

overdamped and the natural response ($u = 0$) of the system is given by

$$y(t) = \frac{\beta x_{10} + x_{20}}{\beta - \alpha} e^{-\alpha t} - \frac{\alpha x_{10} + x_{20}}{\beta - \alpha} e^{-\beta t}$$

where $\alpha = \omega_0(\zeta + \sqrt{\zeta^2 - 1})$ and $\beta = \omega_0(\zeta - \sqrt{\zeta^2 - 1})$. We see that the response consists of the sum of two exponentially decaying signals. If $\zeta = 1$ then the system is *critically damped* and solution becomes

$$y(t) = e^{-\zeta\omega_0 t} (x_{10} + (x_{20} + \zeta\omega_0 x_{10})t).$$

Note that this is still asymptotically stable as long as $\omega_0 > 0$, although the second term in the solution is increasing with time (but more slowly than the decaying exponential that multiplies it).

Finally, if $0 < \zeta < 1$, then the solution is oscillatory and equation (5.22) is said to be *underdamped*. The parameter ω_0 is referred to as the natural frequency of the system, stemming from the fact that for small ζ , the eigenvalues of the system are approximately $\lambda = -\zeta \pm j\omega_0$. The natural response of the system is given by

$$y(t) = e^{-\zeta\omega_0 t} \left(x_{10} \cos \omega_d t + \left(\frac{\zeta\omega_0}{\omega_d} x_{10} + \frac{1}{\omega_d} x_{20} \right) \sin \omega_d t \right),$$

where $\omega_d = \omega_0 \sqrt{1 - \zeta^2}$. For $\zeta \ll 1$, $\omega_d \approx \omega_0$ defines the oscillation frequency of the solution and ζ gives the damping rate relative to ω_0 .

Because of the simple form of a second order system, it is possible to solve for the step and frequency responses in analytical form. The solution for the step response depends on the magnitude of ζ :

$$\begin{aligned} y(t) &= \frac{k}{\omega_0^2} \left(1 - e^{-\zeta\omega_0 t} \cos \omega_d t + \frac{\zeta}{\sqrt{1 - \zeta^2}} e^{-\zeta\omega_0 t} \sin \omega_d t \right) & \zeta < 1 \\ y(t) &= \frac{k}{\omega_0^2} (1 - e^{-\omega_0 t} (1 + \omega_0 t)) & \zeta = 1 \\ y(t) &= \frac{k}{\omega_0^2} \left(1 - e^{-\omega_0 t} - \frac{1}{2(1 + \zeta)} e^{\omega_0(1 - 2\zeta)t} \right) & \zeta > 1, \end{aligned} \tag{5.24}$$

where we have taken $x(0) = 0$. Note that for the lightly damped case ($\zeta < 1$) we have an oscillatory solution at frequency ω_d , sometimes called the damped frequency.

The step responses of systems with $k = \omega^2$ and different values of ζ are shown in Figure 5.12, using a scaled time axis to allow an easier comparison.

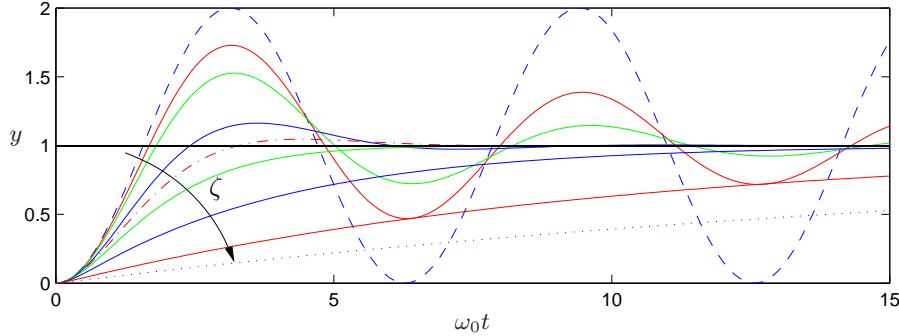


Figure 5.12: Normalized step responses h for the system (5.23) for $\zeta = 0$ (dashed), 0.1, 0.2, 0.5, 0.707 (dash dotted), 1, 2, 5 and 10 (dotted).

The shape of the response is determined by ζ and the speed of the response is determined by ω_0 (including in the time axis scaling): the response is faster if ω_0 is larger. The step responses have an overshoot of

$$M_p = \begin{cases} e^{-\pi\zeta/\sqrt{1-\zeta^2}} & \text{for } |\zeta| < 1 \\ 0 & \text{for } \zeta \geq 1. \end{cases} \quad (5.25)$$

For $\zeta < 1$ the maximum overshoot occurs at

$$t_{max} = \frac{\pi}{\omega_0 \sqrt{1 - \zeta^2}}. \quad (5.26)$$

The maximum decreases and is shifted to the right when ζ increases and it becomes infinite for $\zeta = 1$, when the overshoot disappears.

The frequency response can also be computed explicitly and is given by

$$Me^{j\theta} = \frac{\omega_0^2}{(j\omega)^2 + 2\zeta\omega_0(j\omega) + \omega_0^2} = \frac{\omega_0^2}{\omega_0^2 - \omega^2 + 2j\zeta\omega_0\omega}.$$

A graphical illustration of the frequency response is given in Figure 5.13. Notice the resonance peak that increases with decreasing ζ . The peak is often characterized by its *Q-value*, defined as $Q = 1/2\zeta$.

Example 5.9 (Damped spring mass). The dynamics for a damped spring mass system are given by

$$m\ddot{q} + c\dot{q} + kq = u,$$

where m is the mass, q is the displacement of the mass, c is the coefficient of viscous friction, k is the spring constant and u is the applied force. We

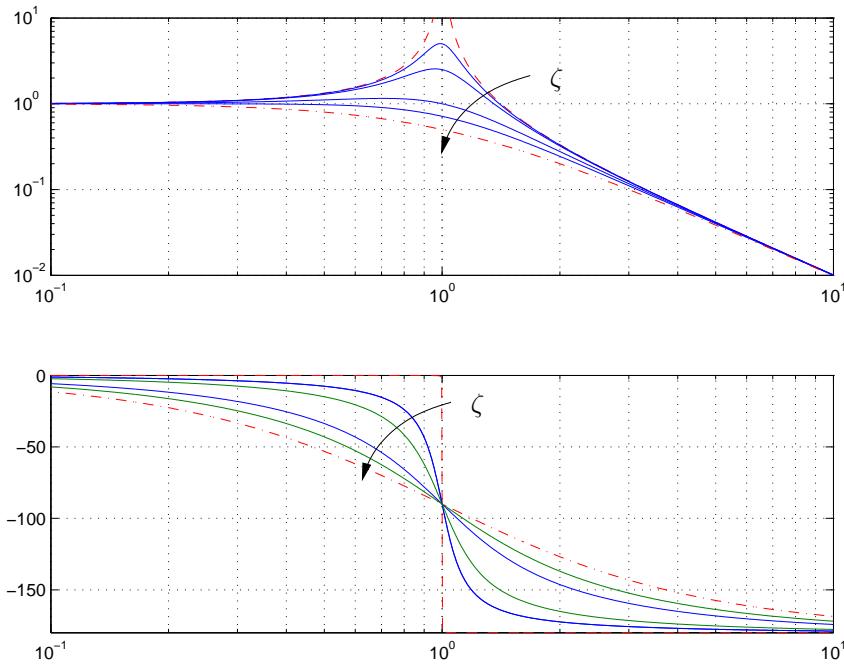


Figure 5.13: Frequency response of a the second order system (5.23). The upper curve shows the gain ratio, M , and the lower curve shows the phase shift, θ . The parameters is Bode plot of the system with $\zeta = 0$ (dashed), 0.1, 0.2, 0.5, 0.7 and 1.0 (dashed-dot).

can convert this into the standard second order form by dividing through by m , giving

$$\ddot{q} + \frac{c}{m}\dot{q} + \frac{k}{m}q = \frac{1}{m}u.$$

Thus we see that the spring mass system has natural frequency and damping ratio given by

$$\omega_0 = \sqrt{\frac{k}{m}} \quad \zeta = \frac{c}{2\sqrt{km}}$$

(note that we have used the symbol k for the stiffness here; it should not be confused with the gain term in equation (5.22)). ∇

One of the other reasons why second order systems play such an important role in feedback systems is that even for more complicated systems the response is often dominated by the “dominant eigenvalues”. To define these more precisely, consider a system with eigenvalues λ_i , $i = 1, \dots, n$. We



define the damping factor for a complex eigenvalue λ to be

$$\zeta = \frac{-\operatorname{Re} \lambda}{|\lambda|}$$

We say that a complex conjugate pair of eigenvalues λ, λ^* is a dominant pair if it has the lowest damping factor compared with all other eigenvalues of the system.

Assuming that a system is stable, the dominant pair of eigenvalues tends to be the most important element of the response. To see this, assume that we have a system in Jordan form with a simple Jordan block corresponding to the dominant pair of eigenvalues:

$$\dot{z} = \begin{pmatrix} \lambda & & & \\ & \lambda^* & & \\ & & J_2 & \\ & & & \ddots \\ & & & & J_k \end{pmatrix} z + Bu$$

$$y = Cz.$$

(Note that the state z may be complex due to the Jordan transformation.) The response of the system will be a linear combination of the responses from each of the individual Jordan subsystems. As we see from Figure 5.12, for $\zeta < 1$ the subsystem with the slowest response is precisely the one with the smallest damping factor. Hence when we add the responses from each of the individual subsystems, it is the dominant pair of eigenvalues that will be dominant factor after the initial transients due to the other terms in the solution. While this simple analysis does not always hold (for example, if some non-dominant terms have large coefficients due to the particular form of the system), it is often the case that the dominant eigenvalues dominate the (step) response of the system. The following example illustrates the concept.

5.5 Linearization

As described in the beginning of the chapter, a common source of linear system models is through the *approximation* of a nonlinear system by a linear one. These approximations are aimed at studying the local behavior of a system, where the nonlinear effects are expected to be small. In this section we discuss how to locally approximate a system by its linearization and what

can be said about the approximation in terms of stability. We begin with an illustration of the basic concept using the speed control example from Chapter 2.

Example 5.10 (Cruise control). The dynamics for the cruise control system are derived in Section 3.1 and have the form

$$m \frac{dv}{dt} = \alpha_n u T(\alpha_n v) - mg C_r - \frac{1}{2} \rho C_v A v^2 - mg \sin \theta, \quad (5.27)$$

where the first term on the right hand side of the equation is the force generated by the engine and the remaining three terms are the rolling friction, aerodynamic drag and gravitational disturbance force. There is an equilibrium (v_e, u_e) when the force applied by the engine balances the disturbance forces.

To explore the behavior of the system near the equilibrium we will linearize the system. A Taylor series expansion of equation (5.27) around the equilibrium gives

$$\frac{d(v - v_e)}{dt} = a(v - v_e) - b_g(\theta - \theta_e) + b(u - u_e) \quad (5.28)$$

where

$$a = \frac{u_e \alpha_n^2 T'(\alpha_n v_e) - \rho C_v A v_e}{m} \quad b_g = g \cos \theta_e \quad b = \frac{\alpha_n T(\alpha_n v_e)}{m} \quad (5.29)$$

and terms of second and higher order have been neglected. For a car in fourth gear with $v_e = 25$ m/s, $\theta_e = 0$ and the numerical values for the car from Section 3.1, the equilibrium value for the throttle is $u_e = 0.1687$ and the model becomes

$$\frac{d(v - v_e)}{dt} = -0.0101(v - v_e) + 1.3203(u - u_e) - 9.8(\theta - \theta_e) \quad (5.30)$$

This linear model describes how small perturbations in the velocity about the nominal speed evolve in time.

Figure 5.14, which shows a simulation of a cruise controller with linear and nonlinear models, indicates that the differences between the linear and nonlinear models is not visible in the graph. ∇

Linear Approximation

To proceed more formally, consider a single input, single output nonlinear system

$$\begin{aligned} \frac{dx}{dt} &= f(x, u) & x \in \mathbb{R}^n, u \in \mathbb{R} \\ y &= h(x, u) & y \in \mathbb{R} \end{aligned} \quad (5.31)$$

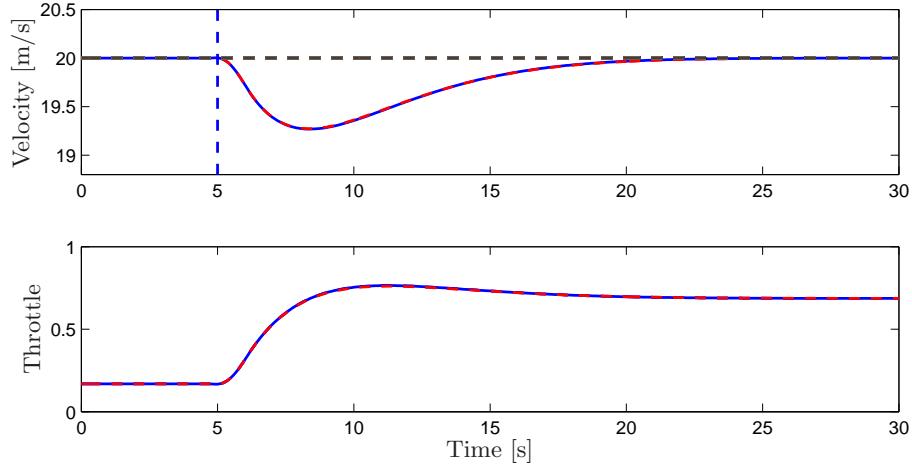


Figure 5.14: Simulated response of a vehicle with PI cruise control as it climbs a hill with a slope of 4° . The full lines is the simulation based on a nonlinear model and the dashed line shows the corresponding simulation using a linear model. The controller gains are $k_p = 0.5$ and $k_i = 0.1$.

with an equilibrium point at $x = x_e$, $u = u_e$. Without loss of generality, we assume that $x_e = 0$ and $u_e = 0$, although initially we will consider the general case to make the shift of coordinates explicit.

In order to study the *local* behavior of the system around the equilibrium point (x_e, u_e) , we suppose that $x - x_e$ and $u - u_e$ are both small, so that nonlinear perturbations around this equilibrium point can be ignored compared with the (lower order) linear terms. This is roughly the same type of argument that is used when we do small angle approximations, replacing $\sin \theta$ with θ and $\cos \theta$ with 1 for θ near zero.

In order to formalize this idea, we define a new set of state variables z , inputs v , and outputs w :

$$z = x - x_e \quad v = u - u_e \quad w = y - h(x_e, u_e).$$

These variables are all close to zero when we are near the equilibrium point, and so in these variables the nonlinear terms can be thought of as the higher order terms in a Taylor series expansion of the relevant vector fields (assuming for now that these exist).

Example 5.11. Consider a simple scalar system,

$$\dot{x} = 1 - x^3 + u.$$

The point $(x_e, u_e) = (1, 0)$ is an equilibrium point for this system and we can thus set

$$z = x - 1 \quad v = u.$$

We can now compute the equations in these new coordinates as

$$\begin{aligned}\dot{z} &= \frac{d}{dt}(x - 1) = \dot{x} \\ &= 1 - x^3 + u = 1 - (z + 1)^3 + v \\ &= 1 - z^3 - 3z^2 - 3z - 1 + v = -3z - 3z^2 - z^3 + v.\end{aligned}$$

If we now assume that x stays very close to the equilibrium point, then $z = x - x_e$ is small and $z \ll z^2 \ll z^3$. We can thus *approximate* our system by a *new* system

$$\dot{z} = -3z + v.$$

This set of equations should give behavior that is close to that of the original system as long as z remains small. ∇

More formally, we define the *Jacobian linearization* of the nonlinear system (5.31) as

$$\begin{aligned}\dot{z} &= Az + Bv \\ w &= Cz + Dv,\end{aligned}\tag{5.32}$$

where

$$\begin{aligned}A &= \left. \frac{\partial f(x, u)}{\partial x} \right|_{(x_e, u_e)} & B &= \left. \frac{\partial f(x, u)}{\partial u} \right|_{(x_e, u_e)} \\ C &= \left. \frac{\partial h(x, u)}{\partial x} \right|_{(x_e, u_e)} & D &= \left. \frac{\partial h(x, u)}{\partial u} \right|_{(x_e, u_e)}\end{aligned}\tag{5.33}$$

The system (5.32) approximates the original system (5.31) when we are near the equilibrium point that the system was linearized about.

It is important to note that we can only define the linearization of a system about an equilibrium point. To see this, consider a polynomial system

$$\dot{x} = a_0 + a_1x + a_2x^2 + a_3x^3 + u,$$

where $a_1 \neq 0$. There are a family of equilibrium points for this system given by $(x_e, u_e) = (x_e, -a_0 - a_1x_e - a_2x_e^2 - a_3x_e^3)$ and we can linearize around any of these. Suppose that we try to linearize around the origin of the system, $x = 0, u = 0$. If we drop the higher order terms in x , then we get

$$\dot{x} = a_0 + a_1x + u,$$

which is *not* the Jacobian linearization if $a_0 \neq 0$. The constant term must be kept and this is not present in (5.32). Furthermore, even if we kept the constant term in the approximate model, the system would quickly move away from this point (since it is “driven” by the constant term a_0) and hence the approximation could soon fail to hold.

Software for modeling and simulation frequently has facilities for performing linearization symbolically or numerically. The MATLAB command `trim` finds the equilibrium and `linmod` extracts linear state-space models from a SIMULINK system around an operating point.

Example 5.12 (Vehicle steering). Consider the vehicle steering system introduced in Section 2.8. The nonlinear equations of motion for the system are given by equations (2.21)–(2.23) and can be written as

$$\frac{d}{dt} \begin{pmatrix} x \\ y \\ \theta \end{pmatrix} = \begin{pmatrix} v_0 \frac{\cos(\alpha+\theta)}{\cos \alpha} \\ v_0 \frac{\sin(\alpha+\theta)}{\cos \alpha} \\ \frac{v_0}{b} \tan \delta \end{pmatrix},$$

where x , y and θ are the position and orientation of the center of mass of the vehicle, v_0 is the velocity of the rear wheel, δ is the angle of the front wheel and α is the angular deviation of the center of mass from the rear wheel along the instantaneous circle of curvature determined by the front wheel:

$$\alpha(\delta) = \arctan\left(\frac{a \tan \delta}{b}\right).$$

We are interested in the motion of the vehicle about a straight line path ($\theta = \theta_0$) with fixed velocity $v_0 \neq 0$. To find the relevant equilibrium point, we first set $\dot{\theta} = 0$ and we see that we must have $\delta = 0$, corresponding to the steering wheel being straight. This also yields $\alpha = 0$. Looking at the first two equations in the dynamics, we see that the motion in the xy direction is by definition *not* at equilibrium since $\dot{x}^2 + \dot{y}^2 = v_0^2 \neq 0$. Therefore we cannot formally linearize the full model.

Suppose instead that we are concerned with the lateral deviation of the vehicle from a straight line. For simplicity, we let $\theta_0 = 0$, which corresponds to driving along the x axis. We can then focus on the equations of motion in the y and θ directions, for which we have

$$\frac{d}{dt} \begin{pmatrix} y \\ \theta \end{pmatrix} = \begin{pmatrix} v_0 \frac{\sin(\alpha+\theta)}{\cos \alpha} \\ \frac{v_0}{b} \tan \delta \end{pmatrix}.$$

Abusing notation, we write $x = (y, \theta)$ and $u = \delta$ so that

$$f(x, u) = \begin{pmatrix} v_0 \frac{\sin(\alpha(u) + x_2)}{\cos \alpha(u)} \\ \frac{v_0}{b} \tan u \end{pmatrix}$$

where the equilibrium point of interest is now given by $x = (0, 0)$ and $u = 0$.

To compute the linearization the model around the equilibrium point, we make use of the formulas (5.33). A straightforward calculation yields

$$A = \left. \frac{\partial f(x, u)}{\partial x} \right|_{\substack{x=0 \\ u=0}} = \begin{pmatrix} 0 & v_0 \\ 0 & 0 \end{pmatrix} \delta \quad B = \left. \frac{\partial f(x, u)}{\partial u} \right|_{\substack{x=0 \\ u=0}} = \begin{pmatrix} v_0 \frac{a}{b} \\ \frac{v_0}{b} \end{pmatrix}$$

and the linearized system

$$\dot{z} = Az + Bv \tag{5.34}$$

thus provides an approximation to the original nonlinear dynamics.

A model can often be simplified further by introducing normalized dimension free variables. For this system, we can normalize lengths by the wheel base b and introduce a new time variable $\tau = v_0 t / b$. The time unit is thus the time it takes for the vehicle to travel one wheel base. We similarly normalize the lateral position and write $w_1 = y/b$, $w_2 = \theta$. The model (5.34) then becomes

$$\begin{aligned} \frac{dw}{d\tau} &= \begin{pmatrix} w_2 + \alpha v \\ v \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} w + \begin{pmatrix} \alpha \\ 1 \end{pmatrix} v \\ y &= \begin{pmatrix} 1 & 0 \end{pmatrix} w \end{aligned} \tag{5.35}$$

The normalized linear model for vehicle steering with non-slipping wheels is thus a linear system with only one parameter $\alpha = a/b$. ∇

Feedback Linearization

Another type of linearization is the use of feedback to convert the dynamics of a nonlinear system into a linear one. We illustrate the basic idea with an example.

Example 5.13 (Cruise control). Consider again the cruise control system from Example 5.10, whose dynamics is given in equation (5.27). If we choose u as a feedback law of the form

$$u = \frac{1}{\alpha_n T(\alpha_n v)} \left(u' + mgC_r + \frac{1}{2} \rho C_v A v^2 \right) \tag{5.36}$$

then the resulting dynamics become

$$m \frac{dv}{dt} = u' + d \quad (5.37)$$

where $d = mg \sin \theta$ is the disturbance force due the slope of the road. If we now define a feedback law for u' (such as a PID controller), we can use equation (5.36) to compute the final input that should be commanded.

Equation (5.37) is a linear differential equation. We have essentially “inverted out” the nonlinearity through the use of the feedback law (5.36). This requires that we have an accurate measurement of the vehicle velocity v as well as an accurate model of the torque characteristics of the engine, gear ratios, drag and friction characteristics and mass of the car. While such a model is not generally available (remembering that the parameter values can change), if we design a good feedback law for u' , then we can achieve robustness to these uncertainties. ∇

More generally, we say that a system of the form

$$\begin{aligned} \frac{dx}{dt} &= f(x, u) \\ y &= h(x) \end{aligned}$$

is *feedback linearizable* if we can find a control law $u = \alpha(x, v)$ such that the resulting closed loop system is input/output linear with input v and output u . To fully characterize such systems is beyond the scope of this text, but we note that in addition to changes in the input, we must also allow for (nonlinear) changes in the states that are used to describe the system, keeping only the input and output variables fixed. More details of this process can be found in the the textbooks by Isidori [Isi89] and Khalil [Kha92].



One case the comes up relatively frequently, and is hence worth special mention, is the set of mechanical systems of the form

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + N(q, \dot{q}) = B(q)u.$$

Here $q \in \mathbb{R}^n$ is the configuration of the mechanical system, $M(q) \in \mathbb{R}^{n \times n}$ is the configuration-dependent inertia matrix, $C(q, \dot{q})\dot{q} \in \mathbb{R}^n$ represents the Coriolis forces, $N(q, \dot{q}) \in \mathbb{R}^n$ are additional nonlinear forces (such as stiffness and friction) and $B(q) \in \mathbb{R}^{n \times p}$ is the input matrix. If $p = n$ then we have the same number of inputs and configuration variables and if we further

have that $B(q)$ is an invertible matrix for all configurations q , then we can choose

$$u = B^{-1}(q) (M(q)v - C(q, \dot{q})\dot{q} - N(q, \dot{q})). \quad (5.38)$$

The resulting dynamics become

$$M(q)\ddot{q} = M(q)v \quad \Rightarrow \quad \ddot{q} = v,$$

which is a linear system. We can now use the tools of linear systems theory to analyze and design control laws for the linearized system, remembering to apply equation (5.38) to obtain the actual input that will be applied to the system.

This type of control is common in robotics, where it goes by the name of *computed torque*, and aircraft flight control, where it is called *dynamic inversion*.

Local Stability of Nonlinear Systems



Having constructed a linearized model around an equilibrium point, we can now ask to what extent this model predicts the behavior of the original nonlinear system. The following theorem gives a partial answer for the case of stability.

Theorem 5.7. *Consider the system (5.31) and let $A \in \mathbb{R}^{n \times n}$ be defined as in equations (5.32) and (5.33). If the real part of the eigenvalues of A are strictly less than zero, then x_e is a locally asymptotically stable equilibrium point of (5.31).*

This theorem shows that *global* asymptotic stability of the linearization implies *local* asymptotic stability of the original nonlinear system. The estimates provided by the proof of the theorem can be used to give a (conservative) bound on the domain of attraction of the origin. Systematic techniques for estimating the bounds on the regions of attraction of equilibrium points of nonlinear systems is an important area of research and involves searching for the “best” Lyapunov functions.

The proof of this theorem is beyond the scope of this text, but can be found in [Kha92].

5.6 Further Reading

The idea to characterize dynamics by considering the responses to step inputs is due to Heaviside. The unit step is therefore also called the *Heaviside*

step function. The majority of the material in this chapter is very classical and can be found in most books on dynamics and control theory, including early works on control such as James, Nichols and Phillips [JNP47], and more recent textbooks such as Franklin, Powell and Emami-Naeini [FPEN05] and Ogata [Oga01]. The material on feedback linearization is typically presented in books on nonlinear control theory, such as Khalil [Kha92]. Tracer methods are described in [She62].

5.7 Exercises

1. Compute the full solution to the couple spring mass system in Example 5.6 by transforming the solution for the block diagonal system back into the original set of coordinates. Show that the system is asymptotically stable if m , b and k are all greater than zero.
2. Using the computation for the matrix exponential, show that equation (5.18) holds for the case of a 3×3 Jordan block. (Hint: decompose the matrix into the form $S + N$ where S is a diagonal matrix.)
3. Prove Proposition 5.6.
4. Show that the step response for an asymptotically stable linear system is given by equation (5.20).
5. Consider a first order system of the form

$$\begin{aligned}\dot{x} &= -\tau x + u \\ y &= x.\end{aligned}$$

We say that the parameter τ is the *time constant* for the system since the zero input system approaches the origin as $e^{-\tau t}$. For a first order system of this form, show that the rise time of the system is approximately 2τ , a 5% settling time corresponds to approximately 3τ and a 2% settling time corresponds to approximately 4τ .

-  6. Show that a signal $u(t)$ can be decomposed in terms of the impulse function $\delta(t)$ as

$$u(t) = \int_0^t \delta(t - \tau)u(\tau) d\tau$$

and use this decomposition plus the principle of superposition to show that the response of a linear system to an input $u(t)$ (assuming zero

initial condition) can be written as

$$y(t) = \int_0^t h(t-\tau)u(\tau) d\tau,$$

where $h(t)$ is the impulse response of the system.

7. Consider a linear discrete time system of the form

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k \\ y_k &= Cx_k + Du_k. \end{aligned}$$

- (a) Show that the general form of the output of a discrete time linear system is given by the discrete time convolution equation:

$$y_k = CA^k x_0 + \sum_{i=0}^k CA^i Bu_i + Du_k$$

- (b) Show that a discrete time linear system is asymptotically stable if and only if all eigenvalues of A have magnitude strictly less than 1.
(c) Let $u_k = A \sin(\omega k)$ represent an oscillatory input with frequency $\omega < \pi$ (to avoid “aliasing”). Show that the steady state component of the response has gain M and phase θ where

$$Me^{j\theta} = C(j\omega I - A)^{-1}B + D.$$

- (d) Show that if we have a nonlinear discrete time system

$$\begin{aligned} x_k &= f(x_k, u_k) & x_k \in \mathbb{R}^n, u \in \mathbb{R} \\ y_k &= h(x_k, u)k & y \in \mathbb{R} \end{aligned}$$

then we can linearize the system around an equilibrium point (x_e, u_e) by defining the matrices A , B , C and D as in equation (5.33).

8. Consider the consensus protocol introduced in Example 2.13. Show that if the connectivity graph of the sensor network is connected, then we can find a gain γ such that the agent states converge to the average value of the measure quantity.

Chapter 6

State Feedback

Intuitively, the state may be regarded as a kind of information storage or memory or accumulation of past causes. We must, of course, demand that the set of internal states Σ be sufficiently rich to carry all information about the past history of Σ to predict the effect of the past upon the future. We do not insist, however, that the state is the least such information although this is often a convenient assumption.

R. E. Kalman, P. L. Falb and M. A. Arbib, 1969 [KFA69].

This chapter describes how feedback of a system's state can be used shape the local behavior of a system. The concept of reachability is introduced and used to investigate how to "design" the dynamics of a system through assignment of its eigenvalues. In particular, it will be shown that under certain conditions it is possible to assign the system eigenvalues to arbitrary values by appropriate feedback of the system state.

6.1 Reachability

One of the fundamental properties of a control system is what set of points in the state space can be reached through the choice of a control input. It turns out that the property of "reachability" is also fundamental in understanding the extent to which feedback can be used to design the dynamics of a system.

Definition

We begin by disregarding the output measurements of the system and focusing on the evolution of the state, given by

$$\frac{dx}{dt} = Ax + Bu, \quad (6.1)$$

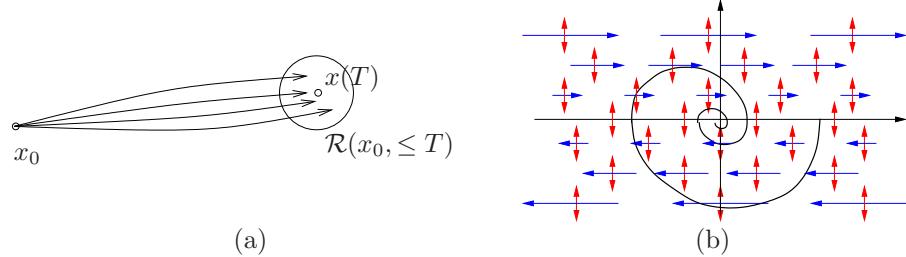


Figure 6.1: The reachable set for a control system: (a) the set $\mathcal{R}(x_0, \leq T)$ is the set of points reachable from x_0 in time less than T ; (b) phase portrait for the double integrator showing the natural dynamics (horizontal arrows), the control inputs (vertical arrows) and a sample path to the origin.

where $x \in \mathbb{R}^n$, $u \in \mathbb{R}$, A is an $n \times n$ matrix and B an $n \times 1$ matrix. A fundamental question is whether it is possible to find control signals so that any point in the state space can be reached through some choice of input. To study this, we define the reachable set $\mathcal{R}(x_0, \leq T)$ as the set of all points x_f such that there exists an input $u(t)$, $0 \leq t \leq T$ that steers the system from $x(0) = x_0$ to $x(T) = x_f$, as illustrated in Figure 6.1.

Definition 6.1 (Reachability). A linear system is *reachable* if for any $x_0, x_f \in \mathbb{R}^n$ there exists a $T > 0$ and $u: [0, T] \rightarrow \mathbb{R}$ such that the corresponding solution satisfies $x(0) = x_0$ and $x(T) = x_f$.

The set of points that we are most interested in reaching is the set of equilibrium points of the system (since we can remain at those points once we get there). The set of all possible equilibria for constant controls is given by

$$\mathcal{E} = \{x_e : Ax_e + bu_e = 0 \text{ for some } u_e \in \mathbb{R}\}.$$

This means that possible equilibria lie in a one (or possibly higher) dimensional subspace. If the matrix A is invertible this subspace is spanned by $A^{-1}B$.

In addition to reachability of equilibrium points, we can also ask whether it is possible to reach all points in the state space in a *transient* fashion. The following example provides some insight into the possibilities.

Example 6.1 (Double integrator). Consider a linear system consisting of a double integrator, whose dynamics are given by

$$\begin{aligned}\dot{x}_1 &= x_2 \\ \dot{x}_2 &= u.\end{aligned}$$

Figure 6.1b shows a phase portrait of the system. The open loop dynamics ($u = 0$) are shown as horizontal arrows pointed to the right for $x_2 > 0$ and to the left for $x_2 < 0$. The control input is represented by a double arrow in the vertical direction, corresponding to our ability to set the value of \dot{x}_2 . The set of equilibrium points \mathcal{E} corresponds to the x_1 axis, with $u_e = 0$.

Suppose first that we wish to reach the origin from an initial condition $(a, 0)$. We can directly move the state up and down in the phase plane, but we must rely on the natural dynamics to control the motion to the left and right. If $a > 0$, we can move the origin by first setting $u < 0$, which will cause x_2 to become negative. Once $x_2 < 0$, the value of x_1 will begin to decrease and we will move to the left. After a while, we can set u_2 to be positive, moving x_2 back toward zero and slowing the motion in the x_1 direction. If we bring $x_2 > 0$, we can move the system state in the opposite direction.

Figure 6.1b shows a sample trajectory bringing the system to the origin. Note that if we steer the system to an equilibrium point, it is possible to remain there indefinitely (since $\dot{x}_1 = 0$ when $x_2 = 0$), but if we go to any other point in the state space, we can only pass through the point in a transient fashion. ∇

To find general conditions under which a linear system is reachable, we will first give a heuristic argument based on formal calculations with impulse functions. We note that if we can reach all points in the state space through some choice of input, then we can also reach all equilibrium points. Hence reachability of the entire state space implies reachability of all equilibrium points.

Testing for Reachability

When the initial state is zero, the response of the state to a unit step in the input is given by

$$x(t) = \int_0^t e^{A(t-\tau)} B d\tau = A^{-1}(e^{At} - I)B \quad (6.2)$$

The derivative of a unit step function is the impulse function, $\delta(t)$, defined in Section 5.2. Since derivatives are linear operations, it follows (see Exercise 7) that the response of the system to an impulse function is thus the derivative of equation (6.2) (i.e., the impulse response),

$$\frac{dx}{dt} = e^{At} B.$$

Similarly we find that the response to the derivative of a impulse function is

$$\frac{d^2x}{dt^2} = Ae^{At}B.$$

Continuing this process and using the linearity of the system, the input

$$u(t) = \alpha_1\delta(t) + \alpha_2\dot{\delta}(t) + \alpha_3\ddot{\delta}(t) + \cdots + \alpha_n\delta^{(n-1)}(t)$$

gives the state

$$x(t) = \alpha_1e^{At}B + \alpha_2Ae^{At}B + \alpha_3A^2e^{At}B + \cdots + \alpha_nA^{n-1}e^{At}B.$$

Hence, right after the initial time $t = 0$, denoted $t = 0+$, we have

$$x(0+) = \alpha_1B + \alpha_2AB + \alpha_3A^2B + \cdots + \alpha_nA^{n-1}B.$$

The right hand is a linear combination of the columns of the matrix

$$W_r = \begin{pmatrix} B & AB & \cdots & A^{n-1}B \end{pmatrix}. \quad (6.3)$$

To reach an arbitrary point in the state space we thus require that there are n linear independent columns of the matrix W_r . The matrix is called the *reachability matrix*.

An input consisting of a sum of impulse functions and their derivatives is a very violent signal. To see that an arbitrary point can be reached with smoother signals we can also argue as follows. Assuming that the initial condition is zero, the state of a linear system is given by

$$x(t) = \int_0^t e^{A(t-\tau)}Bu(\tau)d\tau = \int_0^t e^{A\tau}Bu(t-\tau)d\tau.$$

It follows from the theory of matrix functions, specifically the Cayley-Hamilton theorem [Str88] that

$$e^{A\tau} = I\alpha_0(\tau) + A\alpha_1(\tau) + \cdots + A^{n-1}\alpha_{n-1}(\tau),$$

where $\alpha_i(\tau)$ are scalar functions, and we find that

$$\begin{aligned} x(t) = B \int_0^t \alpha_0(\tau)u(t-\tau)d\tau + AB \int_0^t \alpha_1(\tau)u(t-\tau)d\tau + \\ \cdots + A^{n-1}B \int_0^t \alpha_{n-1}(\tau)u(t-\tau)d\tau. \end{aligned}$$

Again we observe that the right hand side is a linear combination of the columns of the reachability matrix W_r given by equation (6.3). This basic approach leads to the following theorem.

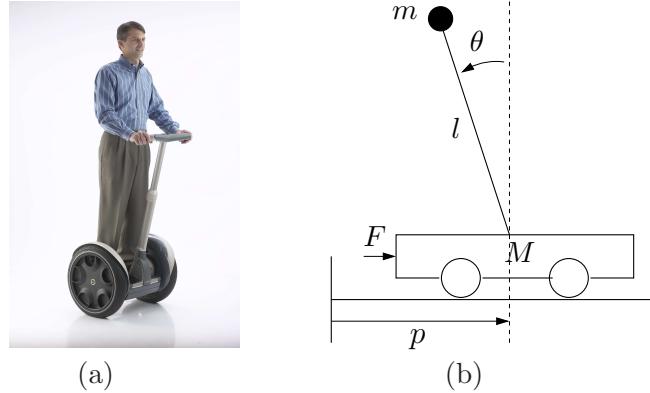


Figure 6.2: Balance system: (a) Segway human transportation system and (b) simplified diagram.

Theorem 6.1. *A linear system is reachable if and only the reachability matrix W_r is invertible.*

The formal proof of this theorem is beyond the scope of this text, but follows along the lines of the sketch above and can be found in most books on linear control theory, such as [CD91]. We illustrate the concept of reachability with the following example.

Example 6.2 (Reachability of balance systems). Consider the balance system introduced in Example 2.1 and shown in Figure 6.2. Recall that this system is a model for a class of examples in which the center of mass is balanced above a pivot point. One example is the Segway transportation system shown in the left hand figure, in which a natural question to ask is whether we can move from one stationary point to another by appropriate application of forces through the wheels.

The nonlinear equations of motion for the system are given in equation (2.7) and repeated here:

$$\begin{aligned} (M+m)\ddot{p} - ml \cos \theta \ddot{\theta} &= -c\dot{p} + ml \sin \theta \dot{\theta}^2 + F \\ (J+ml^2)\ddot{\theta} - ml \cos \theta \ddot{p} &= -\gamma \dot{\theta} + \theta mg l \sin \theta, \end{aligned} \quad (6.4)$$

For simplicity, we take $c = \gamma = 0$. Linearizing around the equilibrium point

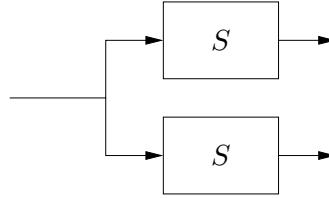


Figure 6.3: A non-reachable system.

$x_e = (p, 0, 0, 0)$, the dynamics matrix and the control matrix are

$$A = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & \frac{m^2 l^2 g}{M_t J_t - m^2 l^2} & 0 & 0 \\ 0 & \frac{M_t m g l}{M_t J_t - m^2 l^2} & 0 & 0 \end{pmatrix}, \quad B = \begin{pmatrix} 0 \\ 0 \\ \frac{J_t}{M_t J_t - m^2 l^2} \\ \frac{l m}{M_t J_t - m^2 l^2} \end{pmatrix},$$

The reachability matrix is

$$W_r = \begin{pmatrix} 0 & \frac{J_t}{M_t J_t - m^2 l^2} & 0 & \frac{g l^3 m^3}{(M_t J_t - m^2 l^2)^2} \\ 0 & \frac{l m}{M_t J_t - m^2 l^2} & 0 & \frac{g l^2 m^2 (m+M)}{(M_t J_t - m^2 l^2)^2} \\ \frac{J_t}{M_t J_t - m^2 l^2} & 0 & \frac{g l^3 m^3}{(M_t J_t - m^2 l^2)^2} & 0 \\ \frac{l m}{M_t J_t - m^2 l^2} & 0 & \frac{g^2 l^2 m^2 (m+M)}{(M_t J_t - m^2 l^2)^2} & 0 \end{pmatrix}. \quad (6.5)$$

This matrix has determinant

$$\det(W_r) = \frac{g^2 l^4 m^4}{(M_t J_t - m^2 l^2)^4} \neq 0$$

and we can conclude that the system is reachable. This implies that we can move the system from any initial state to any final state and, in particular, that we can always find an input to bring the system from an initial state to an equilibrium point. ∇

Systems That Are Not Reachable

It is useful of have an intuitive understanding of the mechanisms that make a system unreachable. An example of such a system is given in Figure 6.3. The system consists of two identical systems with the same input. Clearly, we can not separately cause the first and second system to do something

different since they have the same input. Hence we cannot reach arbitrary states and so the system is not reachable (Exercise 1).

More subtle mechanisms for non-reachability can also occur. For example, if there is a linear combination of states that always remains constant, then the system is not reachable. To see this, suppose that there exists a row vector H such that

$$0 = \frac{d}{dt} Hx = H(Ax + Bu) \quad \text{for all } u.$$

Then H is in the left null space of both A and B and it follows that

$$HW_r = H \left(BAB \cdots A^{n-1} B \right) = 0.$$

Hence the reachability matrix is not full rank. In this case, if we have an initial condition x_0 and we wish to reach a state x_f for which $Hx_0 \neq Hx_f$, then since $Hx(t)$ is constant, no input u can move from x_0 to x_f .

Reachable Canonical Form

As we have already seen in previous chapters, it is often convenient to change coordinates and write the dynamics of the system in the transformed coordinates $z = Tx$. One application of a change of coordinates is to convert a system into a canonical form in which it is easy to perform certain types of analysis. Once such canonical form is called reachable canonical form.

Definition 6.2 (Reachable canonical form). A linear state space system is in *reachable canonical form* if its dynamics are given by

$$\begin{aligned} \frac{dz}{dt} &= \begin{pmatrix} -a_1 & -a_2 & -a_3 & \dots & -a_n \\ 1 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & \dots & 0 \\ \vdots & & \ddots & \ddots & \vdots \\ 0 & & & 1 & 0 \end{pmatrix} z + \begin{pmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix} u & (6.6) \\ y &= \begin{pmatrix} b_1 & b_2 & b_3 & \dots & b_n \end{pmatrix} z. \end{aligned}$$

A block diagram for a system in reachable canonical form is shown in Figure 6.4. We see that the coefficients that appear in the A and B matrices show up directly in the block diagram. Furthermore, the output of the system is a simple linear combination of the outputs of the integration blocks.

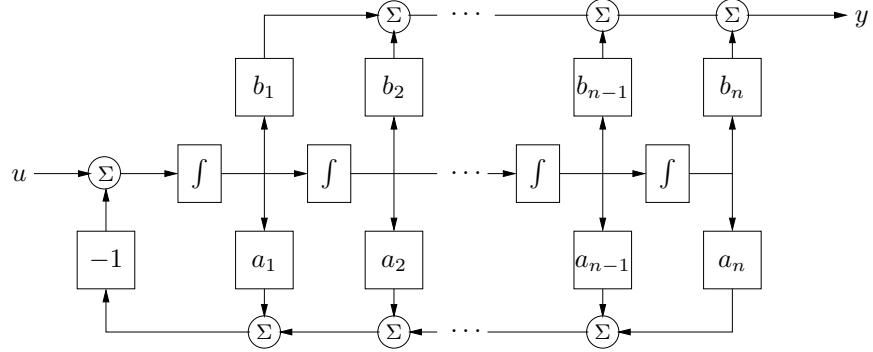


Figure 6.4: Block diagram for a system in reachable canonical form.

The characteristic polynomial for a system in reachable canonical form is given by

$$\lambda(s) = s^n + a_1 s^{n-1} + \cdots + a_{n-1} s + a_n. \quad (6.7)$$

The reachability matrix also has a relatively simple structure:

$$W_r = \begin{pmatrix} B & AB & \dots & A^{n-1}B \end{pmatrix} = \begin{pmatrix} 1 & -a_1 & a_1^2 - a_2 & \cdots & * \\ 0 & 1 & -a_1 & \cdots & * \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & 0 & 1 & * \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix},$$

where * indicates a possibly nonzero term. This matrix is clearly full rank since no column can be written as a linear combination of the others due to the triangular structure of the matrix.

We now consider the problem of changing coordinates such that the dynamics of a system can be written in reachable canonical form. Let A, B represent the dynamics of a given system and \tilde{A}, \tilde{B} be the dynamics in reachable canonical form. Suppose that we wish to transform the original system into reachable canonical form using a coordinate transformation $z = Tx$. As shown in the last chapter, the dynamics matrix and the control matrix for the transformed system are

$$\tilde{A} = TAT^{-1}$$

$$\tilde{B} = TB.$$

The reachability matrix for the transformed system then becomes

$$\tilde{W}_r = \begin{pmatrix} \tilde{B} & \tilde{A}\tilde{B} & \dots & \tilde{A}^{n-1}\tilde{B} \end{pmatrix}.$$

Transforming each element individually, we have

$$\begin{aligned}\tilde{A}\tilde{B} &= TAT^{-1}TB = TAB \\ \tilde{A}^2\tilde{B} &= (TAT^{-1})^2TB = TAT^{-1}TAT^{-1}TB = TA^2B \\ &\vdots \\ \tilde{A}^n\tilde{B} &= TA^nB.\end{aligned}$$

and hence the reachability matrix for the transformed system is

$$\tilde{W}_r = T \begin{pmatrix} B & AB & \cdots & A^{n-1}B \end{pmatrix} = TW_r. \quad (6.8)$$

Since W_r is invertible, we can thus solve for the transformation T that takes the system into reachable canonical form:

$$T = \tilde{W}_r W_r^{-1}.$$

The following example illustrates the approach.

Example 6.3. Consider a simple two dimensional system of the form

$$\dot{x} = \begin{pmatrix} \alpha & \omega \\ -\omega & \alpha \end{pmatrix} x + \begin{pmatrix} 0 \\ 1 \end{pmatrix} u.$$

We wish to find the transformation that converts the system into reachable canonical form:

$$\tilde{A} = \begin{pmatrix} -a_1 & -a_2 \\ 1 & 0 \end{pmatrix} \quad \tilde{B} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}.$$

The coefficients a_1 and a_2 can be determined by looking at the characteristic equation for the original system:

$$\lambda(s) = \det(sI - A) = s^2 - 2\alpha s + (\alpha^2 + \omega^2) \implies \begin{aligned} a_1 &= -2\alpha \\ a_2 &= \alpha^2 + \omega^2.\end{aligned}$$

The reachability matrix for each system is

$$W_r = \begin{pmatrix} 0 & \omega \\ 1 & \alpha \end{pmatrix} \quad \tilde{W}_r = \begin{pmatrix} 1 & -a_1 \\ 0 & 1 \end{pmatrix}.$$

The transformation T becomes

$$T = \tilde{W}_r W_r^{-1} \begin{pmatrix} -\frac{a_1+\alpha}{\omega} & 1 \\ \frac{1}{\omega} & 0 \end{pmatrix} = \begin{pmatrix} \frac{\alpha}{\omega} & 1 \\ \frac{1}{\omega} & 0 \end{pmatrix}$$

and hence the coordinates

$$\begin{pmatrix} z_1 \\ z_2 \end{pmatrix} = Tx = \begin{pmatrix} \frac{\alpha}{\omega}x_1 + x_2 \\ x_2 \end{pmatrix}$$

put the system in reachable canonical form. ∇

We summarize the results of this section in the following theorem.

Theorem 6.2. *Let (A, B) be the dynamics and control matrices for a reachable system. Then there exists a transformation $z = Tx$ such that in the transformed coordinates the dynamics and control matrices are in reachable canonical form (6.6) and the characteristic polynomial for A is given by*

$$\det(sI - A) = s^n + a_1s^{n-1} + \cdots + a_{n-1}s + a_n.$$

One important implication of this theorem is that for any reachable system, we can always assume without loss of generality that the coordinates are chosen such that the system is in reachable canonical form. This is particularly useful for proofs, as we shall see later in this chapter.

6.2 Stabilization by State Feedback

The state of a dynamical system is a collection of variables that permits prediction of the future development of a system. We now explore the idea of designing the dynamics a system through feedback of the state. We will assume that the system to be controlled is described by a linear state model and has a single input (for simplicity). The feedback control will be developed step by step using one single idea: the positioning of closed loop eigenvalues in desired locations.

Figure 6.5 shows a diagram of a typical control system using state feedback. The full system consists of the process dynamics, which we take to be linear, the controller elements, K and k_r , the reference input, r , and processes disturbances, d . The goal of the feedback controller is to regulate the output of the system, y , such that it tracks the reference input in the presence of disturbances and also uncertainty in the process dynamics.

An important element of the control design is the performance specification. The simplest performance specification is that of stability: in the absence of any disturbances, we would like the equilibrium point of the system to be asymptotically stable. More sophisticated performance specifications typically involve giving desired properties of the step or frequency

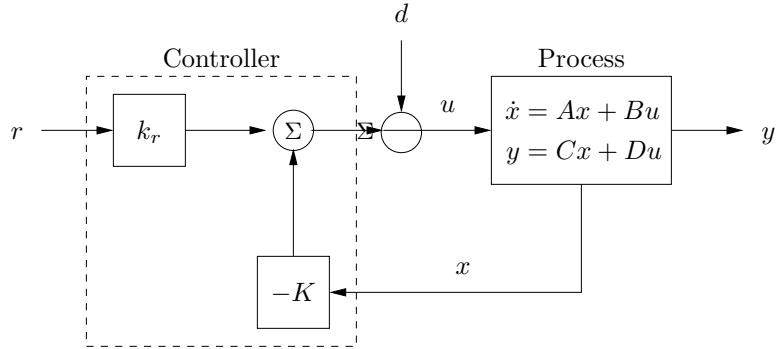


Figure 6.5: A feedback control system with state feedback.

response of the system, such as specifying the desired rise time, overshoot and settling time of the step response. Finally, we are often concerned with the disturbance rejection properties of the system: to what extent can we tolerate disturbance inputs d and still hold the output y near the desired value.

Consider a system described by the linear differential equation

$$\begin{aligned} \frac{dx}{dt} &= Ax + Bu \\ y &= Cx, \end{aligned} \tag{6.9}$$

where we have taken $D = 0$ for simplicity and ignored the disturbance signal d for now. Our goal is to drive the output y to a given reference value, r , and hold it there.

We begin by assuming that all components of the state vector are measured. Since the state at time t contains all information necessary to predict the future behavior of the system, the most general time invariant control law is a function of the state and the reference input:

$$u = \alpha(x, r).$$

If the feedback is restricted to be a linear, it can be written as

$$u = -Kx + k_r r \tag{6.10}$$

where r is the reference value, assumed for now to be a constant.

This control law corresponds to the structure shown in Figure 6.5. The negative sign is simply a convention to indicate that negative feedback is the

normal situation. The closed loop system obtained when the feedback (6.9) is applied to the system (6.10) is given by

$$\frac{dx}{dt} = (A - BK)x + Bk_rr \quad (6.11)$$

We attempt to determine the feedback gain K so that the closed loop system has the characteristic polynomial

$$p(s) = s^n + p_1s^{n-1} + \cdots + p_{n-1}s + p_n \quad (6.12)$$

This control problem is called the eigenvalue assignment problem or “pole placement” problem (we will define “poles” more formally in a later chapter).

Note that the k_r does not affect the stability of the system (which is determined by the eigenvalues of $A - BK$), but does affect the steady state solution. In particular, the equilibrium point and steady state output for the closed loop system are given by

$$x_e = -(A - BK)^{-1}Bk_rr \quad y_e = Cx_e,$$

hence k_r should be chosen such that $y_e = r$ (the desired output value). Since k_r is a scalar, we can easily solve to show

$$k_r = -1/(C(A - BK)^{-1}B). \quad (6.13)$$

Notice that k_r is exactly the inverse of the zero frequency gain of the closed loop system.

Using the gains K and k_r , we are thus able to design the dynamics of the closed loop system to satisfy our goal. To illustrate how to such construct a state feedback control law, we begin with a few examples that provide some basic intuition and insights.

Examples

Example 6.4 (Vehicle steering). In Example 5.12 we derived a normalized linear model for vehicle steering. The dynamics describing the lateral deviation where given by

$$A = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \quad B = \begin{pmatrix} \alpha \\ 1 \end{pmatrix}$$

$$C = \begin{pmatrix} 1 & 0 \end{pmatrix} \quad D = 0.$$

The reachability matrix for the system is thus

$$W_r = \begin{pmatrix} B & AB \end{pmatrix} = \begin{pmatrix} \alpha & 1 \\ 1 & 0 \end{pmatrix}.$$

The system is reachable since $\det W_r = -1 \neq 0$.

We now want to design a controller that stabilizes the dynamics and tracks a given reference value r of the lateral position of the vehicle. To do this we introduce the feedback

$$u = -Kx + k_rr = -k_1x_1 - k_2x_2 + k_rr,$$

and the closed loop system becomes

$$\begin{aligned} \frac{dx}{dt} &= (A - BK)x + Bk_rr = \begin{pmatrix} -\alpha k_1 & 1 - \alpha k_2 \\ -k_1 & -k_2 \end{pmatrix} x + \begin{pmatrix} \alpha k_r \\ k_r \end{pmatrix} r \\ y &= Cx + Du = \begin{pmatrix} 1 & 0 \end{pmatrix} x. \end{aligned} \quad (6.14)$$

The closed loop system has the characteristic polynomial

$$\det(sI - A + BK) = \det \begin{pmatrix} s + \alpha k_1 & \alpha k_2 - 1 \\ k_1 & s + k_2 \end{pmatrix} = s^2 + (\alpha k_1 + k_2)s + k_1.$$

Suppose that we would like to use feedback to design the dynamics of the system to have a characteristic polynomial

$$p(s) = s^2 + 2\zeta_c\omega_c s + \omega_c^2.$$

Comparing this with the characteristic polynomial of the closed loop system we see that the feedback gains should be chosen as

$$k_1 = \omega_c^2, \quad k_2 = 2\zeta_c\omega_c - \alpha\omega_c^2.$$

To have $x_1 = r$ in the steady state it must be required that the parameter k_r equal to $k_1 = \omega_c^2$. The control law can thus be written as

$$u = k_1(r - x_1) - k_2x_2 = \omega_c^2(r - x_1) - (2\zeta_c\omega_c - \alpha\omega_c^2)x_2.$$

∇

The example of the vehicle steering system illustrates how state feedback can be used to set the eigenvalues of the closed loop system to arbitrary values. The next example demonstrates that this is not always possible.

Example 6.5 (An unreachable system). Consider the system

$$\begin{aligned}\frac{dx}{dt} &= \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} x + \begin{pmatrix} 1 \\ 0 \end{pmatrix} u \\ y &= \begin{pmatrix} 1 & 0 \end{pmatrix} x\end{aligned}$$

with the control law

$$u = -k_1 x_1 - k_2 x_2 + k_r r.$$

The closed loop system is

$$\frac{dx}{dt} = \begin{pmatrix} -k_1 & 1 - k_2 \\ 0 & 0 \end{pmatrix} x + \begin{pmatrix} k_r \\ 0 \end{pmatrix} r.$$

This system has the characteristic polynomial

$$\det \begin{pmatrix} s + k_1 & -1 + k_2 \\ 0 & s \end{pmatrix} = s^2 + k_1 s = s(s + k_1),$$

which has zeros at $s = 0$ and $s = -k_1$. Since one closed loop eigenvalue is always equal to $s = 0$, independently of our choice of gains, it is not possible to obtain an arbitrary characteristic polynomial.

A visual inspection of the equations of motion shows that this system also has the property that it is not reachable. In particular, since $\dot{x}_2 = 0$, we can never steer x_2 between one value and another. Computation of the reachability matrix W_r verifies that the system is not reachable. ∇

The reachable canonical form has the property that the parameters of the system are the coefficients of the characteristic equation. It is therefore natural to consider systems on this form when solving the eigenvalue assignment problem. In the next example we investigate the case when the system is in reachable canonical form.

Example 6.6 (System in reachable canonical form). Consider a system in reachable canonical form, i.e,

$$\begin{aligned}\frac{dz}{dt} &= \tilde{A}z + \tilde{B}u = \begin{pmatrix} -a_1 & -a_2 & -a_3 & \dots & -a_n \\ 1 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & \dots & 0 \\ \vdots & & \ddots & \ddots & \vdots \\ 0 & & & 1 & 0 \end{pmatrix} z + \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \\ 0 \end{pmatrix} u \\ y &= \tilde{C}z = \begin{pmatrix} b_1 & b_2 & \dots & b_n \end{pmatrix} z.\end{aligned}\tag{6.15}$$

The open loop system has the characteristic polynomial

$$\det(sI - A) = s^n + a_1 s^{n-1} + \cdots + a_{n-1} s + a_n,$$

as we saw in Example 6.6.

Before making a formal analysis we will investigate the block diagram of the system shown in Figure 6.4. The characteristic polynomial is given by the parameters a_k in the figure. Notice that the parameter a_k can be changed by feedback from state x_k to the input u . It is thus straight forward to change the coefficients of the characteristic polynomial by state feedback.

Having developed some intuition we will now proceed formally. Introducing the control law

$$u = -\tilde{K}z + k_r r = -\tilde{k}_1 z_1 - \tilde{k}_2 z_2 - \cdots - \tilde{k}_n z_n + k_r r, \quad (6.16)$$

the closed loop system becomes

$$\begin{aligned} \frac{dz}{dt} &= \begin{pmatrix} -a_1 - \tilde{k}_1 & -a_2 - \tilde{k}_2 & -a_3 - \tilde{k}_3 & \dots & -a_n - \tilde{k}_n \\ 1 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & \dots & 0 \\ \vdots & & \ddots & \ddots & \vdots \\ 0 & & & 1 & 0 \end{pmatrix} z + \begin{pmatrix} k_r \\ 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix} r \\ y &= \begin{pmatrix} b_n & \dots & b_2 & b_1 \end{pmatrix} z. \end{aligned} \quad (6.17)$$

The feedback changes the elements of the first row of the A matrix, which corresponds to the parameters of the characteristic equation. The closed loop system thus has the characteristic polynomial

$$s^n + (a_l + \tilde{k}_1)s^{n-1} + (a_2 + \tilde{k}_2)s^{n-2} + \cdots + (a_{n-1} + \tilde{k}_{n-1})s + a_n + \tilde{k}_n.$$

Requiring this polynomial to be equal to the desired closed loop polynomial (6.12) we find that the controller gains should be chosen as

$$\begin{aligned} \tilde{k}_1 &= p_1 - a_1 \\ \tilde{k}_2 &= p_2 - a_2 \\ &\vdots \\ \tilde{k}_n &= p_n - a_n. \end{aligned}$$

This feedback simply replaces the parameters a_i in the system (6.17) by p_i . The feedback gain for a system in reachable canonical form is thus

$$\tilde{K} = \begin{pmatrix} p_1 - a_1 & p_2 - a_2 & \cdots & p_n - a_n \end{pmatrix}. \quad (6.18)$$

To have zero frequency gain equal to unity, the parameter k_r should be chosen as

$$k_r = \frac{a_n + \tilde{k}_n}{b_n} = \frac{p_n}{b_n}. \quad (6.19)$$

Notice that it is essential to know the precise values of parameters a_n and b_n in order to obtain the correct zero frequency gain. The zero frequency gain is thus obtained by precise calibration. This is very different from obtaining the correct steady state value by integral action, which we shall see in later sections. We thus find that it is easy to solve the eigenvalue assignment problem when the system has the structure given by equation (6.15). ∇

The General Case

We have seen through the examples how feedback can be used to design the dynamics of a system through assignment of its eigenvalues. To solve the problem in the general case, we simply change coordinates so that the system is in reachable canonical form. Consider the system (6.9). Change the coordinates by a linear transformation

$$z = Tx$$

so that the transformed system is in reachable canonical form (6.15). For such a system the feedback is given by equation (6.16), where the coefficients are given by equation (6.18). Transforming back to the original coordinates gives the feedback

$$u = -\tilde{K}z + k_r r = -\tilde{K}Tx + k_r r.$$

The results obtained can be summarized as follows.

Theorem 6.3 (Eigenvalue assignment by state feedback). *Consider the system given by equation (6.9),*

$$\begin{aligned} \frac{dx}{dt} &= Ax + Bu \\ y &= Cx, \end{aligned}$$

with one input and one output. Let $\lambda(s) = s^n + d_1 s^{n-1} + \cdots + a_{n-1} s + a_n$ be the characteristic polynomial of A . If the system is reachable then there exists a feedback

$$u = -Kx + k_r r$$

that gives a closed loop system with the characteristic polynomial

$$p(s) = s^n + p_1 s^{n-1} + \cdots + p_{n-1} s + p_n$$

and unity zero frequency gain between r and y . The feedback gain is given by

$$K = \tilde{K}T = \begin{pmatrix} p_1 - a_1 & p_2 - a_2 & \cdots & p_n - a_n \end{pmatrix} \tilde{W}_r W_r^{-1} \quad (6.20)$$

$$k_r = \frac{p_n}{a_n}, \quad (6.21)$$

where a_i are the coefficients of the characteristic polynomial of the matrix A and the matrices W_r and \tilde{W}_r are given by

$$W_r = \begin{pmatrix} B & AB & \cdots & A^{n-1}B \end{pmatrix} \quad \tilde{W}_r = \begin{pmatrix} 1 & a_1 & a_2 & \cdots & a_{n-1} \\ 0 & 1 & a_1 & \cdots & a_{n-2} \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 & a_1 \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix}^{-1}.$$

We have thus obtained a solution to the problem and the feedback has been described by a closed form solution.

For simple problems, the eigenvalue assignment problem can be solved by introducing the elements k_i of K as unknown variables. We then compute the characteristic polynomial

$$\lambda(s) = \det(sI - A + BK)$$

and equate coefficients of equal powers of s to the coefficients of the desired characteristic polynomial

$$p(s) = s^n + p_1 s^{n-1} + \cdots + p_{n-1} s + p_n.$$

This gives a system of linear equations to determine k_i . The equations can always be solved if the system is observable, exactly as we did in Example 6.4.

For systems of higher order it is more convenient to use equation (6.21), which can also be used for numeric computations. However, for large systems this is not numerically sound, because it involves computation of the characteristic polynomial of a matrix and computations of high powers of matrices. Both operations lead to loss of numerical accuracy. For this reason there are other methods that are better numerically. In MATLAB the state feedback can be computed by the procedure `place` or `acker`.

Example 6.7 (Predator prey). To illustrate how state feedback might be applied, consider the problem of regulating the population of an ecosystem by modulating the food supply. We use the predator prey model introduced in Section 3.7. The dynamics for the system are given by

$$\begin{aligned}\frac{dH}{dt} &= (r_h + u)H \left(1 - \frac{H}{K}\right) - \frac{aHL}{1 + aHT_h} \quad H \geq 0 \\ \frac{dL}{dt} &= r_l L \left(1 - \frac{L}{kH}\right) \quad L \geq 0\end{aligned}$$

We choose the following nominal parameters for the system, which correspond to the values used in previous simulations:

$$\begin{aligned}r_h &= 0.02 & K &= 500 & a &= 0.03 \\ r_l &= 0.01 & k &= 0.2 & T_h &= 5\end{aligned}$$

We take the parameter r_h , corresponding to the growth rate for hares, as the input to the system, which we might modulate by controlling a food source for the hares. This is reflected in our model by the term $(r_h + u)$ in the first equation.

To control this system, we first linearize the system around the equilibrium point of the system, (H_e, L_e) , which can be determined numerically to be $H \approx (6.5, 1.3)$. This yields a linear dynamical system

$$\frac{dd}{dt} \begin{pmatrix} z_1 \\ z_2 \end{pmatrix} = \begin{pmatrix} 0.001 & -0.01 \\ 0.002 & -0.01 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \end{pmatrix} + \begin{pmatrix} 6.4 \\ 0 \end{pmatrix} v$$

where $z_1 = L - L_e$, $z_2 = H - H_e$ and $v = u$. It is easy to check that the system is reachable around the equilibrium $(z, v) = (0, 0)$ and hence we can assign the eigenvalues of the system using state feedback.

Determining the eigenvalues of the closed loop system requires balancing the ability to modulate the input against the natural dynamics of the system. This can be done by the process of trial and error or by using some of the more systematic techniques discussed in the remainder of the text. For now, we simply choose the desired closed loop poles to be at $\lambda = \{-0.01, -0.02\}$. We can then solve for the feedback gains using the techniques described earlier, which results in

$$K = \begin{pmatrix} 0.005 & -0.15 \end{pmatrix}.$$

Finally, we choose the reference number of hares to be $r = 20$ and solve for the reference gain, k_r , using equation 6.13 to obtain $k_r = 0.003$.

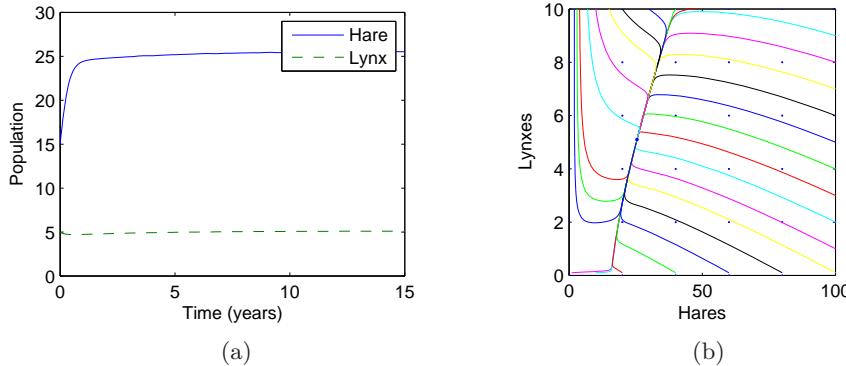


Figure 6.6: Simulation results for the controlled predatory prey system: (a) population of lynxes and hares as a function of time; (b) phase portrait for the controlled system.

Putting these steps together, our control law becomes

$$v = -Kz + k_r r.$$

In order to implement the control law, we must rewrite it using the original coordinates for the system, yielding

$$u = u_e + K(x - x_e) + k_r r = \begin{pmatrix} 0.005 & -0.15 \end{pmatrix} \begin{pmatrix} H - 6.5 \\ L - 1.3 \end{pmatrix} + 0.003 r.$$

This rule tells us how much we should modulate r_h as a function of the current number of lynxes and hares in the ecosystem. Figure 6.6a shows a simulation of the resulting closed loop system using the parameters defined above and starting an initial population of 15 hares and 5 lynxes. Note that the system quickly stabilizes the population of lynxes at the reference value ($r = 20$). A phase portrait of the system is given in Figure 6.6b, showing how other initial conditions converge to the stabilized equilibrium population. Notice that the dynamics are very different than the natural dynamics (shown in Figure 4.6 on page 120). ∇

6.3 State Feedback Design Issues

The location of the eigenvalues determines the behavior of the closed loop dynamics and hence where we place the eigenvalue is the main design decision to be made. As with all other feedback design problems, there are

tradeoffs between the magnitude of the control inputs, the robustness of the system to perturbations and the closed loop performance of the system, including step response, disturbance attenuation and noise injection. For simple systems, there are some basic guidelines that can be used and we briefly summarize them in this section.

We start by focusing on the case of second order systems, for which the closed loop dynamics have a characteristic polynomial of the form

$$\lambda(s) = s^2 + 2\zeta\omega_0 s + \omega_0^2. \quad (6.22)$$

Since we can solve for the step and frequency response of such a system analytically, we can compute the various metrics described in Sections 5.3 and 5.3 in closed form and write the formulas for these metrics in terms of ζ and ω_0 .

As an example, consider the step response for a control system with characteristic polynomial (6.22). This was derived in Section 5.4 and has the form

$$\begin{aligned} y(t) &= \frac{k}{\omega_0^2} \left(1 - e^{-\zeta\omega_0 t} \cos \omega_d t + \frac{\zeta}{\sqrt{1-\zeta^2}} e^{-\zeta\omega_0 t} \sin \omega_d t \right) & \zeta < 1 \\ y(t) &= \frac{k}{\omega_0^2} (1 - e^{\omega_0 t} - \omega_0 t) & \zeta = 1 \\ y(t) &= \frac{k}{\omega_0^2} \left(1 - e^{-\omega_0 t} - \frac{1}{2(1+\zeta)} e^{\omega_0(1-2\zeta)t} \right) & \zeta \geq 1. \end{aligned}$$

We focus on the case of $0 < \zeta < 1$ and leave the other cases as an exercise for the reader.

To compute the maximum overshoot, we rewrite the output as

$$y(t) = \frac{k}{\omega_0^2} \left(1 - \frac{1}{\sqrt{1-\zeta^2}} e^{-\zeta\omega_0 t} \sin(\omega_d t + \varphi) \right) \quad (6.23)$$

where $\varphi = \arccos \zeta$. The maximum overshoot will occur at the first time in which the derivative of y is zero, and hence we look for the time t_p at which

$$0 = \frac{k}{\omega_0^2} \left(\frac{\zeta\omega_0}{\sqrt{1-\zeta^2}} e^{-\zeta\omega_0 t} \sin(\omega_d t + \varphi) - \frac{\omega_d}{\sqrt{1-\zeta^2}} e^{-\zeta\omega_0 t} \cos(\omega_d t + \varphi) \right). \quad (6.24)$$

Eliminating the common factors, we are left with

$$\tan(\omega_d t_p + \varphi) = \frac{\sqrt{1-\zeta^2}}{\zeta}.$$

Table 6.1: Properties of the response to reference values of a second order system for $|\zeta| < 1$. The parameter $\varphi = \arccos \zeta$.

Property	Value	$\zeta = 0.5$	$\zeta = 1/\sqrt{2}$	$\zeta = 1$
Steady state error	$1/\omega_0^2$	$1/\omega_0^2$	$1/\omega_0^2$	$1/\omega_0^2$
Rise time	$T_r = 1/\omega_0 \cdot e^{\varphi/\tan\varphi}$	$1.8/\omega_0$	$2.2/\omega_0$	$2.7/\omega_0$
Overshoot	$M_p = e^{-\pi\zeta/\sqrt{1-\zeta^2}}$	16%	4%	0%
Settling time (2%)	$T_s \approx 4/\zeta\omega_0$	$8/\omega_0$	$5.7/\omega_0$	$4/\omega_0$

Since $\varphi = \arccos \zeta$, it follows that we must have $\omega_d t_p = \pi$ (for the first non-trivial extremum) and hence $t_p = \pi/\omega_d$. Substituting this back into equation (6.23), subtracting off the steady state value and normalizing, we have

$$M_p = e^{-\pi\zeta/\sqrt{1-\zeta^2}}.$$

Similar computations can be done for the other characteristics of a step response. Table 6.1 summarizes the calculations.

One way to visualize the effect of the closed loop eigenvalues on the dynamics is to use the eigenvalue plot in Figure 6.7. This chart shows representative step and frequency responses as a function of the location of the eigenvalues. The diagonal lines in the left half plane represent the damping ratio $\zeta = \sqrt{2} \approx 0.707$, a common value for many designs.

One important consideration that is missing from the analysis so far is the amount of control authority required to obtain the desired dynamics.

Example 6.8 (Drug administration). To illustrate the usage of these formulas, consider the two compartment model for drug administration, described in Section 3.6. The dynamics of the system is

$$\begin{aligned} \frac{dc}{dt} &= \begin{pmatrix} -k_0 - k_1 & k_1 \\ k_2 & -k_2 \end{pmatrix} c + \begin{pmatrix} b_0 \\ 0 \end{pmatrix} u \\ y &= \begin{pmatrix} 0 & 1 \end{pmatrix} x, \end{aligned}$$

where c_1 and c_2 are the concentrations of the drug in each compartment, $k_i, i = 0, \dots, 2$ and b are parameters of the system, u is the flow rate of the drug into compartment 1 and y is the concentration of the drug in

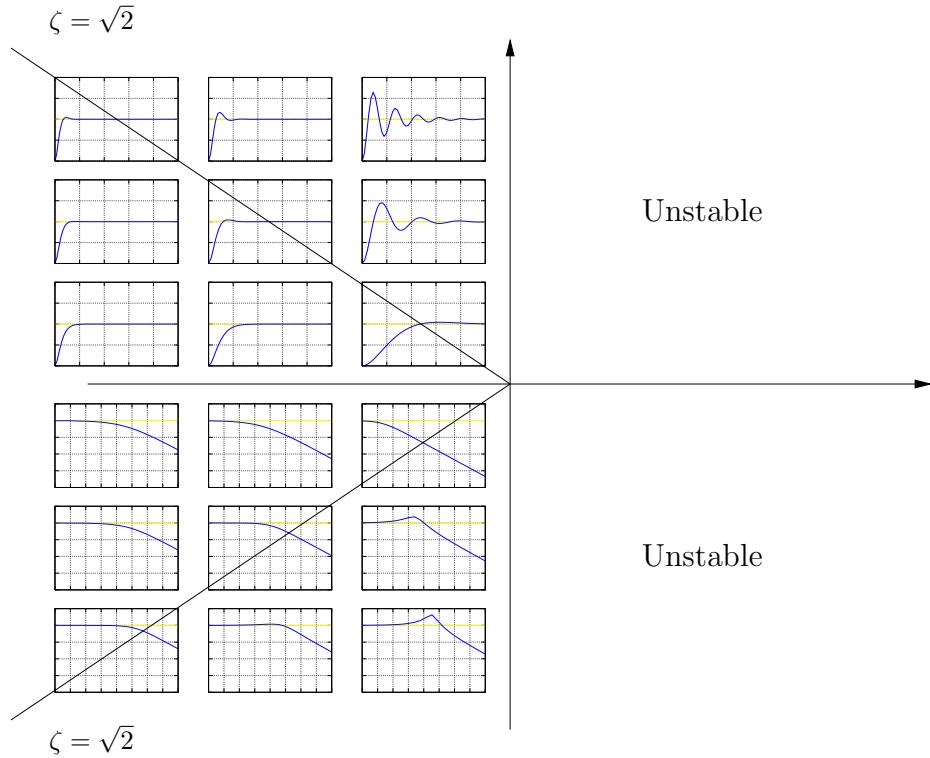


Figure 6.7: Representative step and frequency responses for second order systems. Step responses are shown in the upper half of the plot, with the location of the origin of the step response indicating the value of the eigenvalues. Frequency responses are shown in the lower half of the plot.

compartment 2. We assume that we can measure the concentrations of the drug in each compartment and we would like to design a feedback law to maintain the output at a given reference value r .

We choose $\zeta = 0.9$ to minimize the overshoot and choose the rise time to be $T_r = 10$ min. This gives a value for $\omega_0 = 0.22$ using the formulas in Table 6.1. We then compute the gain to place the eigenvalues at this location. The response of the controller is shown in Figure 6.8 and compared with an “open loop” strategy involving administering periodic doses of the drug. ∇

Our emphasis so far has only considered second order systems. For higher order systems, eigenvalue assignment is considerably more difficult, especially when trying to account for the many tradeoffs that are present in a feedback design. We illustrate some of the main ideas using the balance

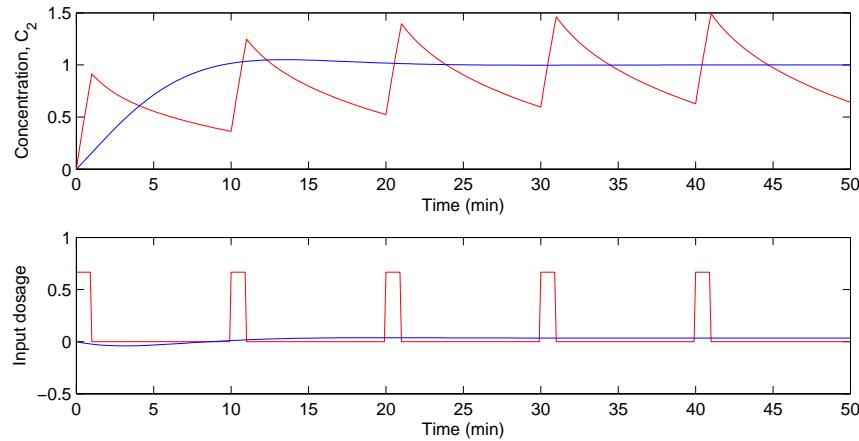


Figure 6.8: Comparison between drug administration using a sequence of doses versus continuously monitoring the concentrations and adjusting the dosage continuously.

system as an example.

To design state feedback controllers for more complicated systems, more sophisticated tools are needed. Optimal control techniques, such as the linear quadratic regular problem discussed below, are one approach that is available. One can also focus on the frequency response for performing the design, which is the subject of Chapters 8–12.

6.4 Integral Action

The controller based on state feedback achieves the correct steady state response to reference signals by careful calibration of the gain k_r . However, one of the primary uses of feedback is to allow good performance in the presence of uncertainty, and hence requiring that we have an *exact* model of the process is undesirable. An alternative to calibration is to make use of integral feedback, in which the controller uses an integrator to provide zero steady state error. The basic concept of integral feedback was already given in Section 1.5 and in Section 3.1; here we provide a more complete description and analysis.

The basic approach in integral feedback is to create a state within the controller that computes the integral of the error signal, which is then used as a feedback term. We do this by augmenting the description of the system

with a new state z :

$$\frac{d}{dt} \begin{pmatrix} x \\ z \end{pmatrix} = \begin{pmatrix} Ax + Bu \\ y - r \end{pmatrix} = \begin{pmatrix} Ax + Bu \\ Cx - r \end{pmatrix}$$

The state z is seen to be the integral of the error between the desired output, r , and the actual output, y . Note that if we find a compensator that stabilizes the system then necessarily we will have $\dot{z} = 0$ in steady state and hence $y = r$ in steady state.

Given the augmented system, we design a state space controller in the usual fashion, with a control law of the form

$$u = -Kx - k_i z + k_r r$$

where K is the usual state feedback term, k_i is the integral term and k_r is used to set the nominal input for the desired steady state. The resulting equilibrium point for the system is given as

$$x_e = -(A - BK)^{-1}B(k_r r - k_i z_e)$$

Note that the value of z_e is not specified, but rather will automatically settle to the value that makes $\dot{z} = y - r = 0$, which implies that at equilibrium the output will equal the reference value. This holds independently of the specific values of A , B and K , as long as the system is stable (which can be done through appropriate choice of K and k_i).

The final compensator is given by

$$\begin{aligned} u &= -Kx - k_i z + k_r r \\ \dot{z} &= y - r, \end{aligned}$$

where we have now included the dynamics of the integrator as part of the specification of the controller. This type of compensator is known as a *dynamic compensator* since it has its own internal dynamics. The following example illustrates the basic approach.

Example 6.9 (Cruise control). Consider the speed control example introduced in Section 3.1 and considered further in Example 5.10.

The linearized dynamics of the process around an equilibrium point v_e , u_e are given by

$$\begin{aligned} \dot{\tilde{v}} &= a\tilde{v} - b_g g\theta + b\tilde{u} \\ y &= v = \tilde{v} + v_e, \end{aligned}$$

where $\tilde{v} = v - v_e$, $\tilde{u} = u - u_e$, m is the mass of the car and θ is the angle of the road. The constant a depends on the throttle characteristic and is given in Example 5.10.

If we augment the system with an integrator, the process dynamics become

$$\begin{aligned}\dot{\tilde{v}} &= a\tilde{v} - g\theta + b\tilde{u} \\ \dot{z} &= r - y = (r - v_e) - \tilde{v},\end{aligned}$$

or, in state space form,

$$\frac{d}{dt} \begin{pmatrix} \tilde{v} \\ z \end{pmatrix} = \begin{pmatrix} a & 0 \\ -1 & 0 \end{pmatrix} \begin{pmatrix} \tilde{v} \\ z \end{pmatrix} + \begin{pmatrix} b \\ 0 \end{pmatrix} u + \begin{pmatrix} -g \\ 0 \end{pmatrix} \theta + \begin{pmatrix} 0 \\ r - v_e \end{pmatrix}.$$

Note that when the system is at equilibrium we have that $\dot{z} = 0$ which implies that the vehicle speed, $v = v_e + \tilde{v}$, should be equal to the desired reference speed, r . Our controller will be of the form

$$\begin{aligned}\dot{z} &= r - y \\ u &= -k_p \tilde{v} - k_i z + k_r r\end{aligned}$$

and the gains k_p , k_i and k_r will be chosen to stabilize the system and provide the correct input for the reference speed.

Assume that we wish to design the closed loop system to have characteristic polynomial

$$\lambda(s) = s^2 + a_1 s + a_2.$$

Setting the disturbance $\theta = 0$, the characteristic polynomial of the closed loop system is given by

$$\det(sI - (A - BK)) = s^2 + (bK - a)s - bk_i$$

and hence we set

$$K = \frac{a_1 + a}{b} \quad k_i = -\frac{a_2}{b}.$$

The resulting controller stabilizes the system and hence brings $\dot{z} = y - r$ to zero, resulting in perfect tracking. Notice that even if we have a small error in the values of the parameters defining the system, as long as the closed loop poles are still stable then the tracking error will approach zero. Thus the exact calibration required in our previous approach (using k_r) is not required. Indeed, we can even choose $k_r = 0$ and let the feedback controller do all of the work (Exercise 5).

Integral feedback can also be used to compensate for constant disturbances. Suppose that we choose $\theta \neq 0$, corresponding to climbing a (linearized) hill. The stability of the system is not affected by this external

disturbance and so we once again see that the car's velocity converges to the reference speed.

This ability to handle constant disturbances is a general property of controllers with integral feedback and is explored in more detail in Exercise 6.

∇

6.5 Linear Quadratic Regulators

In addition to selecting the closed loop eigenvalue locations to accomplish a certain objective, another way that the gains for a state feedback controller can be chosen is by attempting to optimize a cost function.

The infinite horizon, linear quadratic regulator (LQR) problem is one of the most common optimal control problems. Given a multi-input linear system

$$\dot{x} = Ax + Bu \quad x \in \mathbb{R}^n, u \in \mathbb{R}^m,$$

we attempt to minimize the quadratic cost function

$$\tilde{J} = \int_0^\infty (x^T Q_x x + u^T Q_u u) dt$$

where $Q_x \geq 0$ and $Q_u > 0$ are symmetric, positive (semi-) definite matrices of the appropriate dimension. This cost function represents a tradeoff between the distance of the state from the origin and the cost of the control input. By choosing the matrices Q_x and Q_u , described in more detail below, we can balance the rate of convergence of the solutions with the cost of the control.

The solution to the LQR problem is given by a linear control law of the form

$$u = -Q_u^{-1}B^T Px$$

where $P \in \mathbb{R}^{n \times n}$ is a positive definite, symmetric matrix that satisfies the equation

$$PA + A^T P - PBQ_u^{-1}B^T P + Q_x = 0. \quad (6.25)$$

Equation (6.25) is called the *algebraic Riccati equation* and can be solved numerically (for example, using the `lqr` command in MATLAB).

One of the key questions in LQR design is how to choose the weights Q_x and Q_u . In order to guarantee that a solution exists, we must have $Q_x \geq 0$ and $Q_u > 0$. In addition, there are certain “observability” conditions on Q_x that limit its choice. We assume here $Q_x > 0$ to insure that solutions to the algebraic Riccati equation always exists.

To choose specific values for the cost function weights Q_x and Q_u , we must use our knowledge of the system we are trying to control. A particularly simple choice of weights is to use diagonal weights

$$Q_x = \begin{pmatrix} q_1 & 0 & \cdots \\ 0 & \ddots & \\ 0 & \cdots & q_n \end{pmatrix} \quad Q_u = \rho \begin{pmatrix} r_1 & 0 & \cdots \\ 0 & \ddots & \\ \cdots & 0 & r_n \end{pmatrix}.$$

For this choice of Q_x and Q_u , the individual diagonal elements describe how much each state and input (squared) should contribute to the overall cost. Hence, we can take states that should remain very small and attach higher weight values to them. Similarly, we can penalize an input versus the states and other inputs through choice of the corresponding input weight.

6.6 Further Reading

The importance of state models and state feedback was discussed in the seminal paper by Kalman [Kal60] where the state feedback gain was obtained by solving an optimization problem that minimized a quadratic loss function. The notions of reachability and observability (next chapter) are also due to Kalman [Kal61b]; see also [Gil63, KHN63]. We note that in most textbooks the term “controllability” is used instead of “reachability”, but we prefer the latter term because it is more descriptive of the fundamental property of being able to reach arbitrary states.

Most undergraduate textbooks on control will contain material on state space systems, including, for example, Franklin, Powell and Emami-Naeini [FPEN05] and Ogata [Oga01]. Friedland’s textbook [Fri04] covers the material in the previous, current and next chapter in considerable detail, including the topic of optimal control.

6.7 Exercises

1. Consider the system shown in Figure 6.3. Write the dynamics of the two systems as

$$\begin{aligned} \frac{dx}{dt} &= Ax + Bu \\ \frac{dz}{dt} &= Az + Bu. \end{aligned}$$

Observe that if x and z have the same initial condition, they will always have the same state, regardless of the input that is applied. Show that this violates the definition of reachability and further show that the reachability matrix W_r is not full rank.

2. Show that the characteristic polynomial for a system in reachable canonical form is given by equation (6.7).
3. Consider a system on reachable canonical form. Show that the inverse of the reachability matrix is given by

$$\tilde{W}_r^{-1} = \begin{pmatrix} 1 & a_1 & a_2 & \cdots & a_n \\ 0 & 1 & a_1 & \cdots & a_{n-1} \\ \vdots & & & & \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix} \quad (6.26)$$

4. Extend the argument in Section 6.1 to show that if a system is reachable from an initial state of zero, it is reachable from a non-zero initial state.
5. Build a simulation for the speed controller designed in Example 6.9 and show that with $k_r = 0$, the system still achieves zero steady state error.
6. Show that integral feedback can be used to compensate for a constant disturbance by giving zero steady state error even when $d \neq 0$.
7. Show that if $y(t)$ is the output of a linear system corresponding to input $u(t)$, then the output corresponding to an input $\dot{u}(t)$ is given by $\dot{y}(t)$. (Hint: use the definition of the derivative: $\dot{y}(t) = \lim_{\epsilon \rightarrow 0} (y(t + \epsilon) - y(t))/\epsilon$.)

Chapter 7

Output Feedback

There are none.

Abstract for “Guaranteed Margins for LQG Regulators”, John Doyle, 1978 [Doy78].

In the last chapter we considered the use of state feedback to modify the dynamics of a system through feedback. In many applications, it is not practical to measure all of the states directly and we can measure only a small number of outputs (corresponding to the sensors that are available). In this chapter we show how to use output feedback to modify the dynamics of the system, through the use of observers (also called “state estimators”). We introduce the concept of observability and show that if a system is observable, it is possible to recover the state from measurements of the inputs and outputs to the system.

7.1 Observability

In Section 6.2 of the previous chapter it was shown that it is possible to find a feedback that gives desired closed loop eigenvalues provided that the system is reachable and that all states are measured. For many situations, it is highly unrealistic to assume that all states are measured. In this section we will investigate how the state can be estimated by using a mathematical model and a few measurements. It will be shown that the computation of the states can be done by a dynamical system called an *observer*.

Consider a system described by

$$\begin{aligned}\frac{dx}{dt} &= Ax + Bu \\ y &= Cx + Du,\end{aligned}\tag{7.1}$$

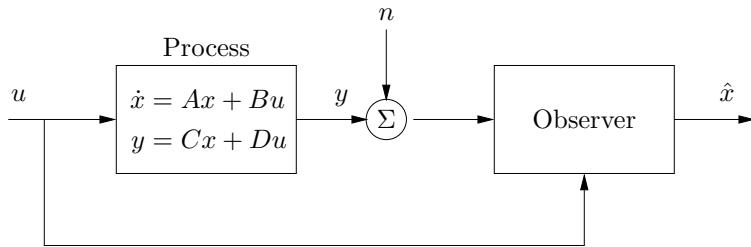


Figure 7.1: Block diagram for an observer.

where $x \in \mathbb{R}^n$ is the state, $u \in \mathbb{R}$ the input, and $y \in \mathbb{R}$ the measured output. We wish to estimate the state of the system from its inputs and outputs, as illustrated in Figure 7.1. We assume that there is only one measured signal, i.e. that the signal y is a scalar and that C is a (row) vector. This signal may be corrupted by noise, n , although we shall start by considering the noise-free case. We write \hat{x} for the state estimate given by the observer.

Definition 7.1 (Observability). A linear system is *observable* if for any $T > 0$ it is possible to determine the state of the system $x(T)$ through measurements of $y(t)$ and $u(t)$ on the interval $[0, T]$.

The problem of observability is one that has many important applications, even outside of feedback systems. If a system is observable, then there are no “hidden” dynamics inside it; we can understand everything that is going on through observation (over time) of the inputs and outputs. As we shall see, the problem of observability is of significant practical interest because it will tell if a set of sensors are sufficient for controlling a system. Sensors combined with a mathematical model can also be viewed as a “virtual sensor” that gives information about variables that are not measured directly. The definition above holds for nonlinear systems as well, and the results discussed here have extensions to the nonlinear case.

When discussing reachability in the last chapter we neglected the output and focused on the state. Similarly, it is convenient here to initially neglect the input and focus on the system

$$\begin{aligned} \frac{dx}{dt} &= Ax \\ y &= Cx. \end{aligned} \tag{7.2}$$

We wish to understand when it is possible to determine the state from observations of the output.

The output itself gives the projection of the state on vectors that are rows of the matrix C . The observability problem can immediately be solved if the matrix C is invertible. If the matrix is not invertible we can take derivatives of the output to obtain

$$\frac{dy}{dt} = C \frac{dx}{dt} = CAx.$$

From the derivative of the output we thus get the projection of the state on vectors which are rows of the matrix CA . Proceeding in this way we get

$$\begin{pmatrix} y \\ \dot{y} \\ \ddot{y} \\ \vdots \\ y^{(n-1)} \end{pmatrix} = \begin{pmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{n-1} \end{pmatrix} x. \quad (7.3)$$

We thus find that the state can be determined if the matrix

$$W_o = \begin{pmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{n-1} \end{pmatrix} \quad (7.4)$$

has n independent rows. It turns out that we need not consider any derivatives higher than $n - 1$ (this is an application of the Cayley-Hamilton theorem [Str88]).

The calculation can easily be extended to systems with inputs. The state is then given by a linear combination of inputs and outputs and their higher derivatives. We leave this as an exercise for the reader.

In practice, differentiation can give very large errors when there is measurement noise and therefore the method sketched above is not particularly practical. We will address this issue in more detail in the next section, but for now we have the following basic result:

Theorem 7.1. *A linear system of the form (7.1) is observable if and only if the observability matrix W_o is full rank.*

Proof. The sufficiency of the observability rank condition follows from the analysis above. To prove necessity, suppose that the system is observable

but W_o is not full rank. Let $v \in \mathbb{R}^n$, $v \neq 0$ be a vector in the null space of W_o , so that $W_o v = 0$. If we let $x(0) = v$ be the initial condition for the system and choose $u = 0$, then the output is given by $y(t) = Ce^{At}v$. Since e^{At} can be written as a power series in A and since A^n and higher powers can be rewritten in terms of lower powers of A (by the Cayley-Hamilton theorem), it follows that the output will be identically zero (the reader should fill in the missing steps if this is not clear). However, if both the input and output of the system are 0, then a valid estimate of the state is $\hat{x} = 0$ for all time, which is clearly incorrect since $x(0) = v \neq 0$. Hence by contradiction we must have that W_o is full rank if the system is observable. \square

Example 7.1 (Bicycle dynamics). To demonstrate the concept of observability, we consider the bicycle system, introduced in Section 3.2. Consider the linearized model for the dynamics in equation (3.5), which has the form

$$J \frac{d^2\varphi}{dt^2} - \frac{Dv_0}{b} \frac{d\delta}{dt} = mgh\varphi + \frac{mv_0^2 h}{b} \delta,$$

where φ is the tilt of the bicycle and δ is the steering angle. Taking the torque on the handle bars as an input and the lateral deviation as the output, we can write the dynamics in state space form as (Exercise 3.3)

$$\begin{aligned} \frac{d}{dt} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} &= \begin{pmatrix} 0 & mgh/J \\ 1 & 0 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \end{pmatrix} u \\ y &= \begin{pmatrix} Dv_0 & mv_0^2 h \\ bJ & bJ \end{pmatrix} x. \end{aligned}$$

The observability of this system determines whether it is possible to determine the entire system state (tilt angle and tilt rate) from observations of the input (steering angle) and output (vehicle position).

The observability matrix is

$$W_0 = \begin{pmatrix} \frac{Dv_0}{bJ} & \frac{mv_0^2 h}{bJ} \\ \frac{mv_0^2 h}{bJ} & \frac{mgh}{J} \cdot \frac{Dv_0}{bJ} \end{pmatrix}$$

and its determinant is

$$\det W_o = \left(\frac{Dv_0}{bJ} \right)^2 \frac{mgh}{J} - \left(\frac{mv_0^2 h}{bJ} \right)^2.$$

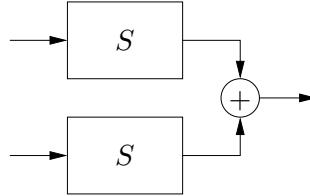


Figure 7.2: A non-observable system.

Under most choices of parameters, the determinant will be nonzero and hence the system is observable. However, if the parameters of the system are chosen such that

$$\frac{mv_0h}{D} = \sqrt{\frac{mgh}{J}}$$

then we see that W_o becomes singular and the system is not observable. This case is explored in more detail in the exercises. ∇

Example 7.2 (Unobservable systems). It is useful to have an understanding of the mechanisms that make a system unobservable. Such a system is shown in Figure 7.2. The system is composed of two identical systems whose outputs are added. It seems intuitively clear that it is not possible to deduce the states from the output since we cannot deduce the individual output contributions from the sum. This can also be seen formally (Exercise 1). ∇

As in the case of reachability, certain canonical forms will be useful in studying observability. We define the observable canonical form to be the dual of the reachable canonical form.

Definition 7.2 (Observable canonical form). A linear state space system is in *observable canonical form* if its dynamics are given by

$$\begin{aligned} \frac{dz}{dt} &= \begin{pmatrix} -a_1 & 1 & 0 & \cdots & 0 \\ -a_2 & 0 & 1 & & 0 \\ \vdots & & & \ddots & \\ -a_{n-1} & 0 & 0 & & 1 \\ -a_n & 0 & 0 & \cdots & 0 \end{pmatrix} z + \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_{n-1} \\ b_n \end{pmatrix} u \\ y &= \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \end{pmatrix} z + Du. \end{aligned}$$

Figure 7.3 shows a block diagram for a system in observable canonical form. As in the case of reachable canonical form, we see that the coeffi-

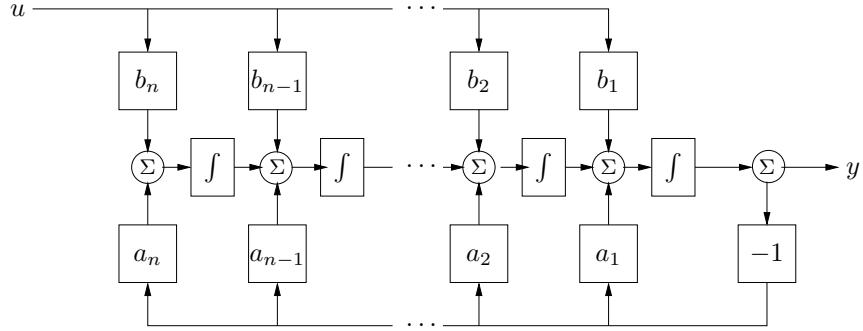


Figure 7.3: Block diagram of a system on observable canonical form.

ients in the system description appear directly in the block diagram. The characteristic equation for a system in observable canonical form is given by

$$\lambda(s) = s^n + a_1 s^{n-1} + \cdots + a_{n-1} s + a_n. \quad (7.5)$$

It is possible to reason about the observability of a system in observable canonical form by studying the block diagram. If the input u and the output are available the state x_1 can clearly be computed. Differentiating x_1 we also obtain the input to the integrator that generates x_1 and we can now obtain $x_2 = \dot{x}_1 + a_1 x_1 - b_1 u$. Proceeding in this way we can clearly compute all states. The computation will however require that the signals are differentiated.

We can now proceed with a formal analysis. The observability matrix for a system in observable canonical form is given by

$$W_o = \begin{pmatrix} 1 & 0 & 0 & \dots & 0 \\ -a_1 & 1 & 0 & \dots & 0 \\ -a_1^2 - a_1 a_2 & -a_1 & 1 & \dots & 0 \\ \vdots & & \ddots & & \vdots \\ * & & \dots & & 1 \end{pmatrix},$$

where $*$ represents an entry whose exact value is not important. The rows of this matrix are linearly independent (since it is lower triangular) and hence W_o is full rank. A straightforward but tedious calculation shows that the

inverse of the observability matrix has a simple form, given by

$$W_o^{-1} = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ a_1 & 1 & 0 & \cdots & 0 \\ a_2 & a_1 & 1 & \cdots & 0 \\ \vdots & & & \ddots & \\ a_{n-1} & a_{n-2} & a_{n-3} & \cdots & 1 \end{pmatrix}.$$

As in the case of reachability, it turns out that if a system is observable then there always exists a transformation T that converts the system into reachable canonical form (Exercise 3). This is very useful for proofs, since it lets us assume that a system is in reachable canonical form without any loss of generality.

7.2 State Estimation

Having defined the concept of observability, we now return to the question of how to construct an observer for a system. We will look for observers that can be represented as a linear dynamical system that takes the inputs and outputs of the system we are observing and produces an estimate of the system's state. That is, we wish to construct a dynamical system of the form

$$\frac{d\hat{x}}{dt} = F\hat{x} + Gu + Hy,$$

where u and y are the input and output of the original system and $\hat{x} \in \mathbb{R}^n$ is an estimate of the state with the property that $\hat{x}(t) \rightarrow x(t)$ as $t \rightarrow \infty$.

The Basic Observer

For a system governed by equation (7.1), we can attempt to determine the state simply by simulating the equations with the correct input. An estimate of the state is then given by

$$\frac{d\hat{x}}{dt} = A\hat{x} + Bu. \quad (7.6)$$

To find the properties of this estimate, introduce the estimation error

$$\tilde{x} = x - \hat{x}.$$

It follows from equations (7.1) and (7.6) that

$$\frac{d\tilde{x}}{dt} = A\tilde{x}.$$

If matrix A has all its eigenvalues in the left half plane, the error \tilde{x} will thus go to zero and hence equation (7.6) is a dynamical system whose output converges to the state of the system (7.1).

The observer given by equation (7.6) uses only the process input u ; the measured signal does not appear in the equation. We must also require that the system is stable and essentially our estimator converges because the state of both the observer and the estimator are going zero. This is not very useful in a control design context since we want to have our estimate converge quickly to a nonzero state, so that we can make use of it in our controller. We will therefore attempt to modify the observer so that the output is used and its convergence properties can be designed to be fast relative to the system's dynamics. This version will also work for unstable systems.

Consider the observer

$$\frac{d\hat{x}}{dt} = A\hat{x} + Bu + L(y - C\hat{x}). \quad (7.7)$$

This can be considered as a generalization of equation (7.6). Feedback from the measured output is provided by adding the term $L(y - C\hat{x})$, which is proportional to the difference between the observed output and the output that is predicted by the observer. To investigate the observer (7.7), form the error $\tilde{x} = x - \hat{x}$. It follows from equations (7.1) and (7.7) that

$$\frac{d\tilde{x}}{dt} = (A - LC)\tilde{x}.$$

If the matrix L can be chosen in such a way that the matrix $A - LC$ has eigenvalues with negative real parts, the error \tilde{x} will go to zero. The convergence rate is determined by an appropriate selection of the eigenvalues.

The problem of determining the matrix L such that $A - LC$ has prescribed eigenvalues is very similar to the eigenvalue assignment problem that was solved in the previous chapter. In fact, since the eigenvalues of the matrix and its transpose are the same, it is equivalent to search for L^T such that $A^T - C^T L^T$ has the desired eigenvalues. This is precisely the eigenvalue assignment problem that we solved in the previous chapter, with $\tilde{A} = A^T$, $\tilde{B} = C^T$ and $\tilde{K} = L^T$. Thus, using the results of Theorem 6.3, we can have the following theorem on observer design:

Theorem 7.2 (Observer design by eigenvalue assignment). *Consider the system given by*

$$\begin{aligned} \frac{dx}{dt} &= Ax + Bu \\ y &= Cx \end{aligned} \quad (7.8)$$

with one input and one output. Let $\lambda(s) = s^n + a_1s^{n-1} + \cdots + a_{n-1}s + a_n$ be the characteristic polynomial for A . If the system is observable then the dynamical system

$$\frac{d\hat{x}}{dt} = A\hat{x} + Bu + L(y - C\hat{x}) \quad (7.9)$$

is an observer for the system, with L chosen as

$$L = W_o^{-1}\tilde{W}_o \begin{pmatrix} p_1 - a_1 \\ p_2 - a_2 \\ \vdots \\ p_n - a_n \end{pmatrix}, \quad (7.10)$$

and the matrices W_o and \tilde{W}_o given by

$$W_o = \begin{pmatrix} C \\ CA \\ \vdots \\ CA^{n-1} \end{pmatrix} \quad \tilde{W}_o = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ a_1 & 1 & 0 & \cdots & 0 \\ a_2 & a_1 & 1 & \cdots & 0 \\ \vdots & & & & \\ a_{n-1} & a_{n-2} & a_{n-3} & \cdots & 1 \end{pmatrix}^{-1}.$$

The resulting observer error $\tilde{x} = x - \hat{x}$ is governed by a differential equation having the characteristic polynomial

$$p(s) = s^n + p_1s^{n-1} + \cdots + p_n.$$

The dynamical system (7.9) is called an observer for (the states of) the system (7.8) because it will generate an approximation of the states of the system from its inputs and outputs. This particular form of an observer is a much more useful form than the one given by pure differentiation in equation (7.3).

Interpretation of the Observer

The observer is a dynamical system whose inputs are the process input u and process output y . The rate of change of the estimate is composed of two terms. One term, $A\hat{x} + Bu$, is the rate of change computed from the model with \hat{x} substituted for x . The other term, $L(y - \hat{y})$, is proportional to the difference $e = y - \hat{y}$ between measured output y and its estimate $\hat{y} = C\hat{x}$. The estimator gain L is a matrix that tells how the error e is weighted and distributed among the states. The observer thus combines measurements

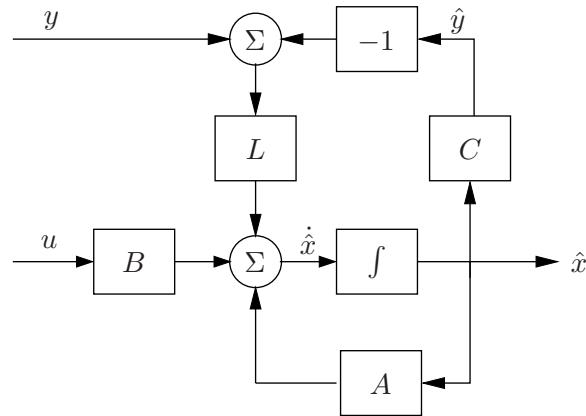


Figure 7.4: Block diagram of the observer. Notice that the observer contains a copy of the process.

with a dynamical model of the system. A block diagram of the observer is shown in Figure 7.4.

Notice the similarity between the problems of finding a state feedback and finding the observer. The key is that both of these problems are equivalent to the same algebraic problem. In eigenvalue assignment it is attempted to find K so that $A - BK$ has given eigenvalues. For the observer design it is instead attempted to find L so that $A - LC$ has given eigenvalues. The following equivalence can be established between the problems:

$$\begin{aligned} A &\leftrightarrow A^T & K &\leftrightarrow L^T \\ B &\leftrightarrow C^T & W_r &\leftrightarrow W_o^T \end{aligned}$$

The observer design problem is often called the *dual* of the state feedback design problem. The similarity between design of state feedback and observers also means that the same computer code can be used for both problems.

Computing the Observer Gain

The observer gain can be computed in several different ways. For simple problems it is convenient to introduce the elements of L as unknown parameters, determine the characteristic polynomial of the observer and identify it with the desired characteristic polynomial. Another alternative is to use the fact that the observer gain can be obtained by inspection if the system is in observable canonical form. The observer gain is then obtained by transformation to the canonical form. There are also reliable numerical algorithms,

which are identical to the algorithms for computing the state feedback. The procedures are illustrated by example.

Example 7.3 (Vehicle steering). Consider the normalized, linear model for vehicle steering in Example 5.12. The dynamics relating steering angle u to lateral path deviation y is given by the state space model

$$\begin{aligned}\frac{dx}{dt} &= \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} x + \begin{pmatrix} \alpha \\ 1 \end{pmatrix} u \\ y &= \begin{pmatrix} 1 & 0 \end{pmatrix} x.\end{aligned}\tag{7.11}$$

Recall that the state x_1 represents the lateral path deviation and that x_2 represents turning rate. We will now derive an observer that uses the system model to determine turning rate from the measured path deviation.

The observability matrix is

$$W_o = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix},$$

i.e., the identity matrix. The system is thus observable and the eigenvalue assignment problem can be solved. We have

$$A - LC = \begin{pmatrix} -l_1 & 1 \\ -l_2 & 0 \end{pmatrix},$$

which has the characteristic polynomial

$$\det(sI - A + LC) = \det \begin{pmatrix} s + l_1 & -1 \\ l_2 & s \end{pmatrix} = s^2 + l_1 s + l_2.$$

Assuming that it is desired to have an observer with the characteristic polynomial

$$s^2 + p_1 s + p_2 = s^2 + 2\zeta_o \omega_o s + \omega_o^2,$$

the observer gains should be chosen as

$$\begin{aligned}l_1 &= p_1 = 2\zeta_o \omega_o \\ l_2 &= p_2 = \omega_o^2.\end{aligned}$$

The observer is then

$$\frac{d\hat{x}}{dt} = A\hat{x} + Bu + L(y - Cx) = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \hat{x} + \begin{pmatrix} 0 \\ 1 \end{pmatrix} u + \begin{pmatrix} l_1 \\ l_2 \end{pmatrix} (y - \hat{x}_1).$$

∇

For larger systems, the `place` or `acker` commands can be used in MATLAB. Note that these functions are the same as the ones used for eigenvalue assignment with state feedback; for estimator design, one simply uses the transpose of the dynamics matrix and the output matrix.

7.3 Control using Estimated State

In this section we will consider the same system as in the previous sections, i.e., the state space system described by

$$\begin{aligned}\frac{dx}{dt} &= Ax + Bu \\ y &= Cx.\end{aligned}\tag{7.12}$$

We wish to design a feedback controller for the system where only the output is measured. As before, we will assume that u and y are scalars. We also assume that the system is reachable and observable. In Chapter 6 we found a feedback of the form

$$u = Kx + k_rr$$

for the case that all states could be measured and in Section 7.2 we have developed an observer that can generate estimates of the state \hat{x} based on inputs and outputs. In this section we will combine the ideas of these sections to find a feedback that gives desired closed loop eigenvalues for systems where only outputs are available for feedback.

If all states are not measurable, it seems reasonable to try the feedback

$$u = -K\hat{x} + k_rr\tag{7.13}$$

where \hat{x} is the output of an observer of the state, i.e.

$$\frac{d\hat{x}}{dt} = A\hat{x} + Bu + L(y - C\hat{x}).\tag{7.14}$$

Since the system (7.12) and the observer (7.14) both are of state dimension n , the closed loop system has state dimension $2n$. The states of the combined system are x and \hat{x} . The evolution of the states is described by equations (7.12), (7.13) and (7.14). To analyze the closed loop system, the state variable \hat{x} is replaced by

$$\tilde{x} = x - \hat{x}.\tag{7.15}$$

Subtraction of equation (7.14) from equation (7.12) gives

$$\frac{d\tilde{x}}{dt} = Ax - A\hat{x} - L(y - C\hat{x}) = A\tilde{x} - LC\tilde{x} = (A - LC)\tilde{x}.$$

Returning to the process dynamics, introducing u from equation (7.13) into equation (7.12) and using equation (7.15) to eliminate \hat{x} gives

$$\begin{aligned}\frac{dx}{dt} &= Ax + Bu = Ax - BK\hat{x} + Bk_rr = Ax - BK(x - \tilde{x}) + Bk_rr \\ &= (A - BK)x + BK\tilde{x} + Bk_rr.\end{aligned}$$

The closed loop system is thus governed by

$$\frac{d}{dt} \begin{pmatrix} x \\ \tilde{x} \end{pmatrix} = \begin{pmatrix} A - BK & BK \\ 0 & A - LC \end{pmatrix} \begin{pmatrix} x \\ \tilde{x} \end{pmatrix} + \begin{pmatrix} Bk_r \\ 0 \end{pmatrix} r. \quad (7.16)$$

Notice that the state \tilde{x} , representing the observer error, is not affected by the command signal r . This is desirable since we do not want the reference signal to generate observer errors.

Since the dynamics matrix is block diagonal, we find that the characteristic polynomial of the closed loop system is

$$\lambda(s) = \det(sI - A + BK) \det(sI - A + LC).$$

This polynomial is a product of two terms: the characteristic polynomial of the closed loop system obtained with state feedback and the characteristic polynomial of the observer error. The feedback (7.13) that was motivated heuristically thus provides a very neat solution to the eigenvalue assignment problem. The result is summarized as follows.

Theorem 7.3 (Eigenvalue assignment by output feedback). *Consider the system*

$$\begin{aligned}\frac{dx}{dt} &= Ax + Bu \\ y &= Cx.\end{aligned}$$

The controller described by

$$\begin{aligned}u &= -K\hat{x} + k_rr \\ \frac{d\hat{x}}{dt} &= A\hat{x} + Bu + L(y - C\hat{x})\end{aligned}$$

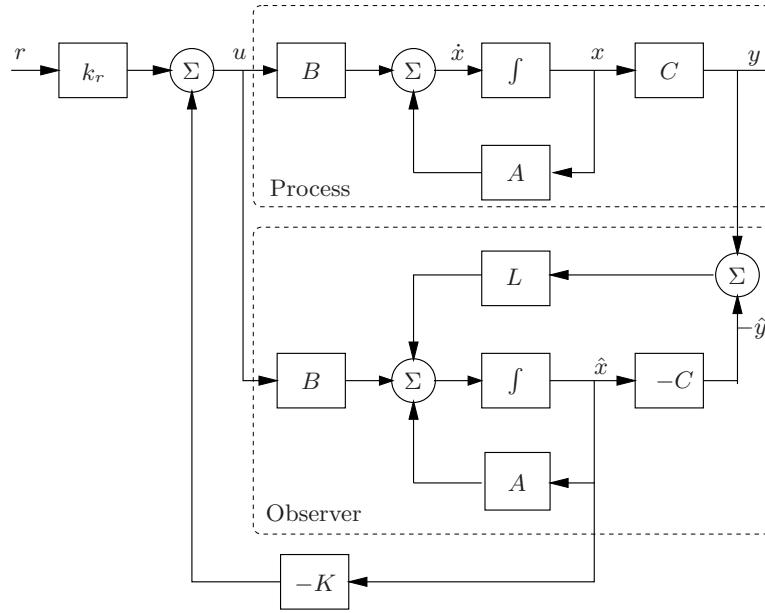


Figure 7.5: Block diagram of a control system that combines state feedback with an observer.

gives a closed loop system with the characteristic polynomial

$$\lambda(s) = \det(sI - A + BK) \det(sI - A + LC).$$

This polynomial can be assigned arbitrary roots if the system is reachable and observable.

The controller has a strong intuitive appeal: it can be thought of as composed of two parts, one state feedback and one observer. The feedback gain K can be computed as if all state variables can be measured. This property is called the *separation principle* and it allows us to independently solve for the state space controller and the state space estimator.

A block diagram of the controller is shown in Figure 7.5. Notice that the controller contains a dynamical model of the plant. This is called the *internal model principle*: the controller contains a model of the process being controlled. Indeed, the dynamics of the controller is due to the observer and can thus be viewed as a dynamical system with input y and output u :

$$\begin{aligned} \frac{d\hat{x}}{dt} &= (A - BK - LC)\hat{x} + Ly \\ u &= -K\hat{x} + k_r r. \end{aligned} \tag{7.17}$$

Example 7.4 (Vehicle steering). Consider again the normalized, linear model for vehicle steering in Example 5.12. The dynamics relating steering angle u to lateral path deviation y is given by the state space model (7.11). Combining the state feedback derived in Example 6.4 with the observer determined in Example 7.3 we find that the controller is given by

$$\begin{aligned}\frac{d\hat{x}}{dt} &= A\hat{x} + Bu + L(y - Cx) = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \hat{x} + \begin{pmatrix} 0 \\ 1 \end{pmatrix} u + \begin{pmatrix} l_1 \\ l_2 \end{pmatrix} (y - \hat{x}_1) \\ u &= -K\hat{x} + k_r r = k_1(r - x_1) - k_2 x_2\end{aligned}$$

The controller is thus a dynamical system of second order. Elimination of the variable u gives

$$\begin{aligned}\frac{d\hat{x}}{dt} &= (A - BK - LC)\hat{x} + Ly + Bk_r r \\ &= \begin{pmatrix} -l_1 - \alpha k_1 & 1 - \alpha k_2 \\ -k_1 - l_2 & -k_2 \end{pmatrix} \hat{x} + \begin{pmatrix} l_1 \\ l_2 \end{pmatrix} y + \begin{pmatrix} \alpha \\ 1 \end{pmatrix} k_1 r \\ u &= -K\hat{x} + k_r r = -\begin{pmatrix} k_1 & k_2 \end{pmatrix} \hat{x} + k_1 r.\end{aligned}$$

The controller is a dynamical system of second order, with two inputs y and r and one output u . ∇

7.4 Kalman Filtering



One of the principal uses of observers in practice is to estimate the state of a system in the presence of *noisy* measurements. We have not yet treated noise in our analysis and a full treatment of stochastic dynamical systems is beyond the scope of this text. In this section, we present a brief introduction to the use of stochastic systems analysis for constructing observers. We work primarily in discrete time to avoid some of the complications associated with continuous time random processes and to keep the mathematical prerequisites to a minimum. This section assumes basic knowledge of random variables and stochastic processes.

Consider a discrete time, linear system with dynamics

$$\begin{aligned}x_{k+1} &= Ax_k + Bu_k + Fv_k \\ y_k &= Cx_k + w_k,\end{aligned}\tag{7.18}$$

where v_k and w_k are Gaussian, white noise processes satisfying

$$\begin{aligned} E\{v_k\} &= 0 & E\{w_k\} &= 0 \\ E\{v_k v_j^T\} &= \begin{cases} 0 & k \neq j \\ R_v & k = j \end{cases} & E\{w_k w_j^T\} &= \begin{cases} 0 & k \neq j \\ R_w & k = j \end{cases} \\ E\{v_k w_j^T\} &= 0. \end{aligned} \quad (7.19)$$

We assume that the initial condition is also modeled as a Gaussian random variable with

$$E\{x_0\} = x_0 \quad E\{x_0 x_0^T\} = P_0. \quad (7.20)$$

We wish to find an estimate \hat{x}_k that minimizes the mean square error $E\{(x_k - \hat{x}_k)(x_k - \hat{x}_k)^T\}$ given the measurements $\{y(\delta) : 0 \leq \tau \leq t\}$. We consider an observer in the same basic form as derived previously:

$$\hat{x}_{k+1} = A\hat{x}_k + Bu_k + L_k(y_k - C\hat{x}_k). \quad (7.21)$$

The following theorem summarizes the main result.

Theorem 7.4. *Consider a random process x_k with dynamics (7.18) and noise processes and initial conditions described by equations (7.19) and (7.20). The observer gain L that minimizes the mean square error is given by*

$$L_k = A^T P_k C^T (R_w + CP_k C^T)^{-1},$$

where

$$\begin{aligned} P_{k+1} &= (A - LC)P_k(A - LC)^T + R_v + LR_w L^T \\ P_0 &= E\{X(0)X^T(0)\}. \end{aligned} \quad (7.22)$$

Before we prove this result, we reflect on its form and function. First, note that the Kalman filter has the form of a *recursive* filter: given $P_k = E\{E_k E_k^T\}$ at time k , can compute how the estimate and covariance *change*. Thus we do not need to keep track of old values of the output. Furthermore, the Kalman filter gives the estimate \hat{x}_k and the covariance $P_{E,k}$, so we can see how reliable the estimate is. It can also be shown that the Kalman filter extracts the maximum possible information about output data. If we form the residual between the measured output and the estimated output,

$$e_k = y_k - C\hat{x}_k,$$

we can show that for the Kalman filter the correlation matrix is

$$R_e(j, k) = W\delta_{jk}.$$

In other words, the error is a white noise process, so there is no remaining dynamic information content in the error.

In the special case when the noise is stationary (Q, R constant) and if P_k converges, then the observer gain is constant:

$$K = A^T P C^T (R_w + C P C^T),$$

where

$$P = A P A^T + R_v - A P C^T (R_w + C P C^T)^{-1} C P A^T.$$

We see that the optimal gain depends on both the process noise and the measurement noise, but in a nontrivial way. Like the use of LQR to choose state feedback gains, the Kalman filter permits a systematic derivation of the observer gains given a description of the noise processes. The solution for the constant gain case is solved by the `d1qe` command in MATLAB.

Proof (of theorem). We wish to minimize the mean square of the error, $E\{(x_k - \hat{x}_k)(x_k - \hat{x}_k)^T\}$. We will define this quantity as P_k and then show that it satisfies the recursion given in equation (7.22). By definition,

$$\begin{aligned} P_{k+1} &= E\{x_{k+1}x_{k+1}^T\} \\ &= (A - LC)P_k(A - LC)^T + R_v + LR_wL^T \\ &= AP_kA^T - AP_kC^TL^T - LCA^T + L(R_w + CP_kC^T)L^T \end{aligned}$$

Letting $R_\epsilon = (R_w + CP_kC^T)$, we have

$$\begin{aligned} P_{k+1} &= AP_kA^T - AP_kC^TL^T - LCA^T + LR_\epsilon L^T \\ &= AP_kA^T + (L - AP_kC^TR_\epsilon^{-1})R_\epsilon(L - AP_kC^TR_\epsilon^{-1})^T \\ &\quad - AP_kC^TR_\epsilon^{-1}CP_k^TA^T + R_w. \end{aligned}$$

In order to minimize this expression, we choose $L = AP_kC^TR_\epsilon^{-1}$ and the theorem is proven. \square

The Kalman filter can also be applied to continuous time stochastic processes. The mathematical derivation of this result requires more sophisticated tools, but the final form of the estimator is relatively straightforward.

Consider a continuous stochastic system

$$\begin{aligned} \dot{x} &= Ax + Bu + Fv & E\{v(s)v^T(t)\} &= Q(t)\delta(t-s) \\ y &= Cx + w & E\{w(s)w^T(t)\} &= R(t)\delta(t-s) \end{aligned}$$

Assume that the disturbance v and noise w are zero-mean and Gaussian (but not necessarily stationary):

$$\begin{aligned}\text{pdf}(v) &= \frac{1}{\sqrt[n]{2\pi} \sqrt{\det Q}} e^{-\frac{1}{2} v^T Q^{-1} v} \\ \text{pdf}(w) &= \dots \quad (\text{using R})\end{aligned}$$

We wish to find the estimate $\hat{x}(t)$ that minimizes the mean square error $E\{(x(t) - \hat{x}(t))(x(t) - \hat{x}(t))^T\}$ given $\{y(\tau) : 0 \leq \tau \leq t\}$.

Theorem 7.5 (Kalman-Bucy, 1961). *The optimal estimator has the form of a linear observer*

$$\dot{\hat{x}} = A\hat{x} + Bu + L(y - C\hat{x})$$

where $L(t) = P(t)C^T R^{-1}$ and $P(t) = E\{(x(t) - \hat{x}(t))(x(t) - \hat{x}(t))^T\}$ and satisfies

$$\dot{P} = AP + PA^T - PC^T R^{-1}(t)CP + FQ(t)F^T$$

$$P(0) = E\{x(0)x^T(0)\}$$

7.5 State Space Control Systems

In this section we consider a collection of additional topics on the design and analysis of control systems using state space tools.

Computer Implementation

The controllers obtained so far have been described by ordinary differential equations. They can be implemented directly using analog components, whether electronic circuits, hydraulic valves or other physical devices. Since in modern engineering applications most controllers are implemented using computers we will briefly discuss how this can be done.

A computer controlled system typically operates periodically: every cycle, signals from the sensors are sampled and converted to digital form by the A/D converter, the control signal is computed, and the resulting output is converted to analog form for the actuators (as shown in Figure 1.3 on page 5). To illustrate the main principles of how to implement feedback in this environment, we consider the controller described by equations (7.13) and (7.14), i.e.,

$$\begin{aligned}u &= -K\hat{x} + k_r r \\ \frac{d\hat{x}}{dt} &= A\hat{x} + Bu + K(y - C\hat{x}).\end{aligned}$$

The first equation consists only of additions and multiplications and can thus be implemented directly on a computer. The second equation has to be approximated. A simple way is to approximate the derivative by a difference

$$\frac{dx}{dt} \approx \frac{\hat{x}(t_{k+1}) - \hat{x}(t_k)}{h} = A\hat{x}(t_k) + Bu(t_k) + K(y(t_k) - C\hat{x}(t_k))$$

where t_k are the sampling instants and $h = t_{k+1} - t_k$ is the sampling period. Rewriting the equation to isolate $x(t_{k+1})$, we get

$$\hat{x}(t_{k+1}) = \hat{x}(t_k) + h(A\hat{x}(t_k) + Bu(t_k) + K(y(t_k) - C\hat{x}(t_k))). \quad (7.23)$$

The calculation of the estimated state at time t_{k+1} only requires addition and multiplication and can easily be done by a computer. A section of pseudo code for the program that performs this calculation is

```
% Control algorithm - main loop
r = adin(ch1) % read setpoint from ch1
y = adin(ch2) % get process output from ch2
u = C*xhat + Kr*r % compute control variable
daout(ch1, u) % set analog output on ch1
xhat = xhat + h*(A*x+B*u+L*(y-C*x)) % update state estimate
```

The program runs periodically at a fixed rate h . Notice that the number of computations between reading the analog input and setting the analog output has been minimized. The state is updated after the analog output has been set. The program has an array of states, $xhat$, that represents the state estimate. The choice of sampling period requires some care.

There are several practical issues that also must be dealt with. For example it is necessary to filter a signal before it is sampled so that the filtered signal has little frequency content above $f_s/2$ where f_s is the sampling frequency. If controllers with integral action are used, it is also necessary to provide protection so that the integral does not become too large when the actuator saturates. This issue, called *integrator windup*, is studied in more detail in Chapter 10. Care must also be taken so that parameter changes do not cause disturbances.

A General Controller Structure



We now consider a general control structure that pulls together the various results the the previous and current chapters. This structure is one that appears in may places in control theory and is the heart of most modern control systems.

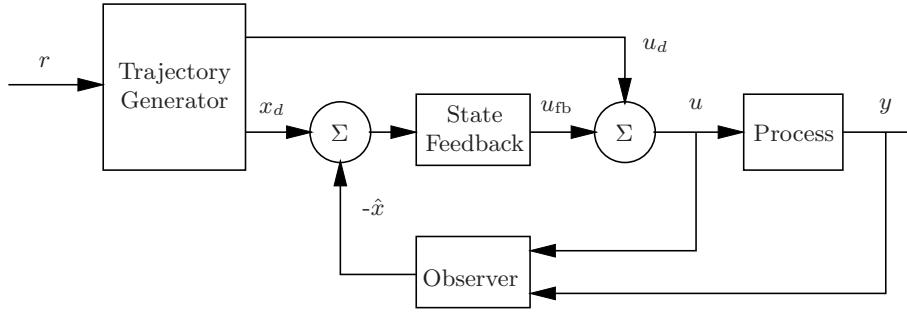


Figure 7.6: Block diagram of a controller based on a structure with two degrees of freedom. The controller consists of a command signal generator, state feedback and an observer.

We begin by generalizing the way we handle the reference input. So far reference signals have been introduced simply by adding them to the state feedback through a gain k_r . A more sophisticated way of doing this is shown by the block diagram in Figure 7.6, where the controller consists of three parts: an observer that computes estimates of the states based on a model and measured process inputs and outputs, a state feedback and a trajectory generator that generates the desired behavior of all states x_d and a feedforward signal u_d . The signal u_d is such that it generates the desired behavior of the states when applied to the system, under the ideal conditions of no disturbances and no modeling errors. The controller is said to have *two degrees of freedom* because the response to command signals and disturbances are decoupled. Disturbance responses are governed by the observer and the state feedback and the response to command signals is governed by the trajectory generator (feedforward).

We start with the full nonlinear dynamics of the process

$$\begin{aligned}\dot{x} &= f(x, u) \\ y &= h(x, u).\end{aligned}\tag{7.24}$$

Assume that the trajectory generator is able to generate a desired trajectory (x_d, u_d) that satisfies the dynamics (7.24) and satisfies $r = h(x_d, u_d)$. To design the controller, we construct the error system. We will assume for simplicity that $f(x, u) = f(x) + g(x)u$ (i.e., the system is nonlinear in the state, but linear in the input; this is often the case in applications). Let

$e = x - x_d$, $v = u - u_d$ and compute the dynamics for the error:

$$\begin{aligned}\dot{e} &= \dot{x} - \dot{x}_d = f(x) + g(x)u - f(x_d) + g(x_d)u_d \\ &= f(e + x_d) - f(x_d) + g(e + x_d)(v + u_d) - g(x_d)u_d \\ &= F(e, v, x_d(t), u_d(t))\end{aligned}$$

In general, this system is time varying.

For trajectory tracking, we can assume that e is small (if our controller is doing a good job) and so we can linearize around $e = 0$:

$$\dot{e} \approx A(t)e + B(t)v$$

where

$$A(t) = \frac{\partial F}{\partial e} \Big|_{(x_d(t), u_d(t))} \quad B(t) = \frac{\partial F}{\partial v} \Big|_{(x_d(t), u_d(t))}.$$

It is often the case that $A(t)$ and $B(t)$ depend only on x_d , in which case it is convenient to write $A(t) = A(x_d)$ and $B(t) = B(x_d)$.

Assume now that x_d and u_d are either constant or slowly varying (with respect to the performance criterion). This allows us to consider just the (constant) linear system given by $(A(x_d), B(x_d))$. If we design a state feedback controller $K(x_d)$ for each x_d , then we can regulate the system using the feedback

$$v = K(x_d)e.$$

Substituting back the definitions of e and v , our controller becomes

$$u = K(x_d)(x - x_d) + u_d$$

This form of controller is called a *gain scheduled* linear controller with *feed-forward* u_d .

Finally, we consider the observer. We can use the full nonlinear dynamics for the prediction portion of the observer and the linearized system for the correction term:

$$\dot{\hat{x}} = f(\hat{x}, u) + L(\hat{x})(y - h(\hat{x}, u))$$

where $L(\hat{x})$ is the observer gain obtained by linearizing the system around the currently estimate state. This form of the observer is known as an *extended Kalman filter* and has proven to be a very effective means of estimating the state of a nonlinear system.

To get some insight into the overall behavior of the system, we consider what happens when the command signal is changed. To fix the ideas let us assume that the system is in equilibrium with the observer state \hat{x} equal to

the process state x . When the command signal is changed a feedforward signal $u_d(t)$ is generated. This signal has the property that the process output gives the desired state $x_d(t)$ when the feedforward signal is applied to the system. The process state changes in response to the feedforward signal. The observer tracks the state perfectly because the initial state was correct. The estimated state \hat{x} will thus be equal to the desired state x_d and the feedback signal $L(x_d - \hat{x})$ is zero. If there are some disturbances or some modeling errors the feedback signal will be different from zero and attempt to correct the situation.

The controller given in Figure 7.6 is a very general structure. There are many ways to generate the feedforward signal and there are also many different ways to compute the feedback gain K and the observer gain L . Note that once again the internal model principle applies: the controller contains a model of the system to be controlled.



The Kalman Decomposition

In this chapter and the previous one, we have seen that two fundamental properties of a linear input/output system are reachability and observability. It turns out that these two properties can be used to classify the dynamics of a system. The key result is Kalman's decomposition theorem, which says that a linear system can be divided into four subsystems: \mathcal{S}_{ro} which is reachable and observable, $\mathcal{S}_{r\bar{o}}$ which is reachable but not observable, $\mathcal{S}_{\bar{r}o}$ which is not reachable but is observable, and $\mathcal{S}_{\bar{r}\bar{o}}$ which is neither reachable nor observable.

We will first consider this in the special case of systems where the matrix A has distinct eigenvalues. In this case we can find a set of coordinates such that the A matrix is diagonal and, with some additional reordering of the states, the system can be written as

$$\begin{aligned} \frac{dz}{dt} &= \begin{pmatrix} \Lambda_{ro} & 0 & 0 & 0 \\ 0 & \Lambda_{r\bar{o}} & 0 & 0 \\ 0 & 0 & \Lambda_{\bar{r}o} & 0 \\ 0 & 0 & 0 & \Lambda_{\bar{r}\bar{o}} \end{pmatrix} z + \begin{pmatrix} \beta_{ro} \\ \beta_{r\bar{o}} \\ 0 \\ 0 \end{pmatrix} u \\ y &= \begin{pmatrix} \gamma_{ro} & 0 & \gamma_{\bar{r}o} & 0 \end{pmatrix} z + Du. \end{aligned}$$

All states z_k such that $\beta_k \neq 0$ are controllable and all states such that $\gamma_k \neq 0$ are observable. The frequency response of the system is given by

$$G(s) = \gamma_{ro}(sI - A_{ro})^{-1}\beta_{ro} + D$$

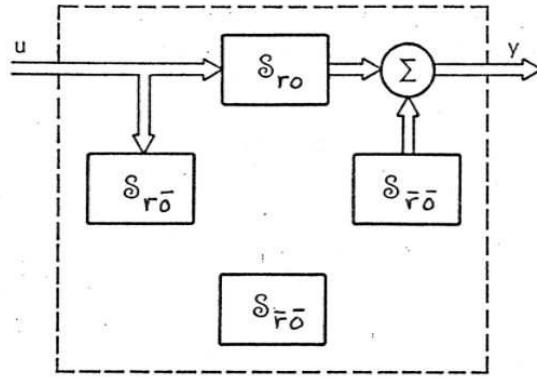


Figure 7.7: Kalman's decomposition of a linear system with distinct eigenvalues.

and it is uniquely given by the subsystem that is reachable and observable. Thus from the input/output point of view, it is only the reachable and observable dynamics that matter. A block diagram of the system illustrating this property is given in Figure 7.7.

The general case of the Kalman decomposition is more complicated and requires some additional linear algebra. Introduce the reachable subspace \mathcal{X}_r which is the linear subspace spanned by the columns of the reachability matrix W_r . The state space is the direct sum of \mathcal{X}_r and another linear subspace $\mathcal{X}_{\bar{r}}$. Notice that \mathcal{X}_r is unique but that $\mathcal{X}_{\bar{r}}$ can be chosen in many different ways. Choosing coordinates with $x_r \in \mathcal{X}_r$ and $x_{\bar{r}} \in \mathcal{X}_{\bar{r}}$ the system equations can be written as

$$\frac{d}{dt} \begin{pmatrix} x_r \\ x_{\bar{r}} \end{pmatrix} = \begin{pmatrix} A_{11} & A_{12} \\ 0 & A_{22} \end{pmatrix} \begin{pmatrix} x_r \\ x_{\bar{r}} \end{pmatrix} + \begin{pmatrix} B_1 \\ 0 \end{pmatrix} u, \quad (7.25)$$

where the states x_r are reachable and $x_{\bar{r}}$ are non-reachable.

Introduce the unique subspace $\mathcal{X}_{\bar{o}}$ of non-observable states. This is the right null space of the observability matrix W_o . The state space is the direct sum of $\mathcal{X}_{\bar{o}}$ and the non-unique subspace \mathcal{X}_o . Choosing a coordinate system with $x_o \in \mathcal{X}_o$ and $x_{\bar{o}} \in \mathcal{X}_{\bar{o}}$ the system equations can be written as

$$\begin{aligned} \frac{d}{dt} \begin{pmatrix} x_o \\ x_{\bar{o}} \end{pmatrix} &= \begin{pmatrix} A_{11} & 0 \\ A_{21} & A_{22} \end{pmatrix} \begin{pmatrix} x_o \\ x_{\bar{o}} \end{pmatrix} \\ y &= \begin{pmatrix} C_1 & 0 \end{pmatrix} \begin{pmatrix} x_o \\ x_{\bar{o}} \end{pmatrix}, \end{aligned} \quad (7.26)$$

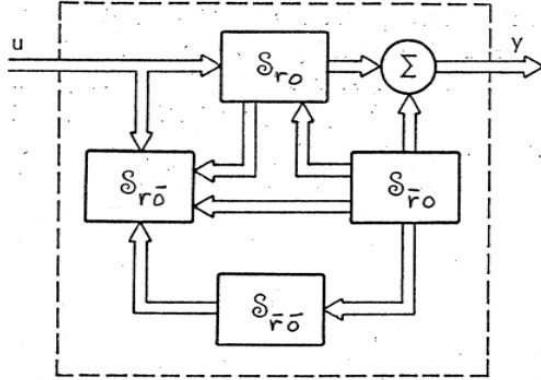


Figure 7.8: Kalman's decomposition of a linear system with general eigenvalues.

where the states x_o are observable and $x_{\bar{o}}$ are not observable.

The intersection of two linear subspaces is also a linear subspace. Introduce $\mathcal{X}_{r\bar{o}}$ as the intersection of \mathcal{X}_r and $\mathcal{X}_{\bar{o}}$ and the complementary linear subspace \mathcal{X}_{ro} , which together with $\mathcal{X}_{r\bar{o}}$ spans \mathcal{X}_r . Finally, we introduce the linear subspace $\mathcal{X}_{\bar{r}o}$ which together with $\mathcal{X}_{r\bar{o}}$, $\mathcal{X}_{r\bar{o}}$ and $\mathcal{X}_{\bar{r}\bar{o}}$ spans the full state space. Notice that the decomposition is not unique because only the subspace $\mathcal{X}_{r\bar{o}}$ is unique.

Combining the representations (7.25) and (7.26) we find that a linear system can be transformed to the form

$$\begin{aligned} \frac{dx}{dt} &= \begin{pmatrix} A_{11} & 0 & A_{13} & 0 \\ A_{21} & A_{22} & A_{23} & A_{24} \\ 0 & 0 & A_{33} & 0 \\ 0 & 0 & A_{43} & A_{44} \end{pmatrix} x + \begin{pmatrix} B_1 \\ B_2 \\ 0 \\ 0 \end{pmatrix} u \\ y &= \begin{pmatrix} C_1 & 0 & C_2 & 0 \end{pmatrix} x, \end{aligned} \quad (7.27)$$

where the state vector has been partitioned as

$$x = \begin{pmatrix} x_{ro} \\ x_{r\bar{o}} \\ x_{\bar{r}o} \\ x_{\bar{r}\bar{o}} \end{pmatrix}$$

A block diagram of the system is shown in Figure 7.8. By tracing the arrows in the diagram we find that the input influences the systems S_{ro} and

$\mathcal{S}_{\bar{r}o}$ and that the output is influenced by \mathcal{S}_{ro} and $\mathcal{S}_{\bar{r}o}$. The system $\mathcal{S}_{\bar{r}o}$ is neither connected to the input nor the output. The frequency response of the system is thus

$$G(s) = C_1(sI - A_{11})^{-1}B_1, \quad (7.28)$$

which is the dynamics of the reachable and observable subsystem \mathcal{S}_{ro} .

7.6 Further Reading

The notion of observability is due to Kalman [Kal61b] and, combined with the dual notion of reachability, it was a major stepping stone toward establishing state space control theory beginning in the 1960s. For linear systems the output is a projection of the state and it may seem unnecessary to estimate the full state since a projection is already available. Luenberger [Lue71] constructed an reduced order observer that only reconstructs the state that is not measured directly.

The main result of this chapter is the general controller structure in Figure 7.6. This controller structure emerged as a result of solving optimization problems. The observer first appeared as the Kalman filter which was also the solution to an optimization problem [Kal61a, KB61]. It was then shown that the solution to an optimization with output feedback could be obtained by combining a state feedback with a Kalman filter [JT61, GF71]. Later it was found that the controller with the same structure also emerged as solutions of other simpler deterministic control problems like the ones discussed in this chapter [?, ?]. Much later it was shown that solutions to robust control problems also had a similar structure but with different ways of computing observer and state feedback gains [DGKF89]. The material is now an essential part of the tools in control.

A more detailed presentation of stochastic control theory is given in [Åst70].

7.7 Exercises

1. Show that the system depicted in Figure 7.2 is not observable.
2. Consider a system under a coordinate transformation $z = Tx$, where $T \in \mathbb{R}^{n \times n}$ is an invertible matrix. Show that the observability matrix for the transformed system is given by $\tilde{W}_o = W_o T^{-1}$ and hence observability is independent of the choice of coordinates.

3. Show that if a system is observable, then there exists a change of coordinates $z = Tx$ that puts the transformed system into reachable canonical form.

Chapter 8

Transfer Functions

The typical regulator system can frequently be described, in essentials, by differential equations of no more than perhaps the second, third or fourth order. . . In contrast, the order of the set of differential equations describing the typical negative feedback amplifier used in telephony is likely to be very much greater. As a matter of idle curiosity, I once counted to find out what the order of the set of equations in an amplifier I had just designed would have been, if I had worked with the differential equations directly. It turned out to be 55.

Henrik Bode, 1960 [Bod60].

This chapter introduces the concept of the *transfer function*, which is a compact description of the input/output relation for a linear system. Combining transfer functions with block diagrams gives a powerful method for dealing with complex linear systems. The relationship between transfer functions and other system descriptions of dynamics is also discussed.

8.1 Frequency Domain Analysis

Figure 8.1 shows a block diagram for a typical control system, consisting of a process to be controlled and a (dynamic) compensator, connected in a feedback loop. We saw in the previous two chapters how to analyze and design such systems using state space descriptions of the blocks. As was mentioned in Chapter 2, an alternative approach is to focus on the input/output characteristics of the system. Since it is the inputs and outputs that are used to connect the systems, one could expect that this point of view would allow an understanding of the overall behavior of the system. Transfer functions are the main tool in implementing this point of view for linear systems.

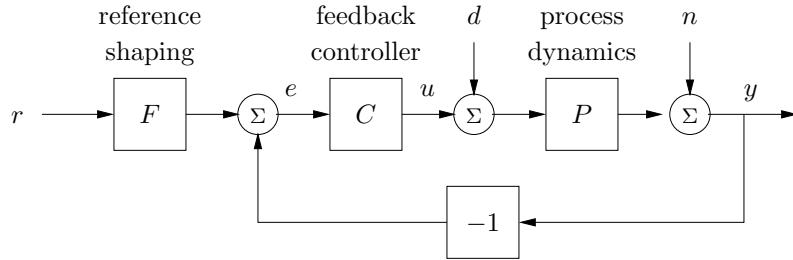


Figure 8.1: A block diagram for a feedback control system.

The basic idea of the transfer function comes from looking at the frequency response of a system. Suppose that we have an input signal that is periodic. Then we can always decompose this signal into the sum of a set of sines and cosines,

$$u(t) = \sum_{k=1}^{\infty} a_k \sin(k\omega t) + b_k \cos(k\omega t),$$

where ω is the fundamental frequency of the periodic input. Each of the terms in this input generates a corresponding sinusoidal output (in steady state), with possibly shifted magnitude and phase. The magnitude gain and phase at each frequency is determined by the frequency response, given in equation (5.21):

$$G(s) = C(sI - A)^{-1}B + D, \quad (8.1)$$

where we set $s = j(k\omega)$ for each $k = 1, \dots, \infty$. If we know the steady state frequency response $G(s)$, we can thus compute the response to any (periodic) signal using superposition.

The transfer function generalizes this notion to allow a broader class of input signals besides periodic ones. As we shall see in the next section, the transfer function represents the response of the system to an “exponential input,” $u = e^{st}$. It turns out that the form of the transfer function is precisely the same as equation (8.1). This should not be surprising since we derived equation (8.1) by writing sinusoids as sums of complex exponentials. Formally, the transfer function corresponds to the Laplace transform of the steady state response of a system, although one does not have to understand the details of Laplace transforms in order to make use of transfer functions.

The power of transfer functions is that they allow a particularly convenient form for manipulating and analyzing complex feedback systems. As we shall see, there are many graphical representations of transfer functions that

capture interesting properties of dynamics. Transfer functions also make it possible to express the changes in a system because of modeling error, which is essential when discussing sensitivity to process variations of the sort discussed in Chapter 12. In particular, using transfer functions it is possible to analyze what happens when dynamic models are approximated by static models or when high order models are approximated by low order models. One consequence is that we can introduce concepts that express the degree of stability of a system.

The main limitation of transfer functions is that they can only be used for linear systems. While many of the concepts for state space modeling and analysis extend to nonlinear systems, there is no such analog for transfer functions and there are only limited extensions of many of the ideas to nonlinear systems. Hence for the remainder of the text we shall limit ourselves to linear models. However, it should be pointed out that despite this limitation, transfer functions still remain a valuable tool for designing controllers for nonlinear systems, chiefly through constructing their linear approximations around an equilibrium point of interest.

8.2 Derivation of the Transfer Function

As we have seen in previous chapters, the input/output dynamics of a linear system has two components: the initial condition response and the forced response. In addition, we can speak of the transient properties of the system and its steady state response to an input. The transfer function focuses on the steady state response due to a given input, and provides a mapping between inputs and their corresponding outputs. In this section, we will derive the transfer function in terms of the “exponential response” of a linear system.

Transmission of Exponential Signals

To formally compute the transfer function of a system, we will make use of a special type of signal, called an *exponential signal*, of the form e^{st} where $s = \sigma + j\omega$ is a complex number. Exponential signals play an important role in linear systems. They appear in the solution of differential equations and in the impulse response of linear systems, and many signals can be represented as exponentials or sums of exponentials. For example, a constant signal is simply $e^{\alpha t}$ with $\alpha = 0$. Damped sine and cosine signals can be represented by

$$e^{(\sigma+j\omega)t} = e^{\sigma t} e^{j\omega t} = e^{\sigma t} (\cos \omega t + i \sin \omega t),$$

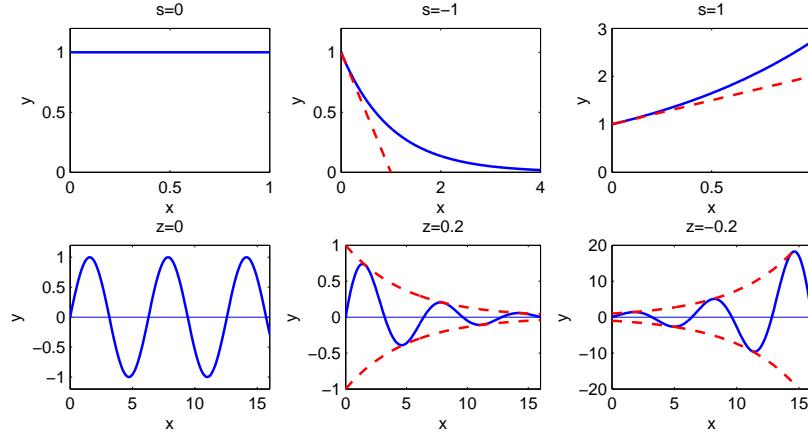


Figure 8.2: Examples of exponential signals.

where $\sigma < 0$ determines the decay rate. Many other signals can be represented by linear combinations of exponentials. Figure 8.2 give examples of signals that can be represented by complex exponentials. As in the case of sinusoidal signals, we will allow complex valued signals in the derivation that follows, although in practice we always add together combinations of signals that result in real-valued functions.

To investigate how a linear system responds to the exponential input $u(t) = e^{st}$ we consider the state space system

$$\begin{aligned}\dot{x} &= Ax + Bu \\ y &= Cx + Du.\end{aligned}\tag{8.2}$$

Let the input signal be $u(t) = e^{st}$ and assume that $s \neq \lambda_i(A)$, $i = 1, \dots, n$, where $\lambda_i(A)$ is the i th eigenvalue of A . The state is then given by

$$x(t) = e^{At}x(0) + \int_0^t e^{A(t-\tau)}Be^{s\tau} d\tau = e^{At}x(0) + e^{At} \int_0^t e^{(sI-A)\tau}B d\tau.$$

If $s \neq \lambda(A)$ the integral can be evaluated and we get

$$\begin{aligned}x(t) &= e^{At}x(0) + e^{At}(sI - A)^{-1}e^{(sI-A)\tau} \Big|_{\tau=0}^t B \\ &= e^{At}x(0) + e^{At}(sI - A)^{-1}(e^{(sI-A)t} - I)B \\ &= e^{At}(x(0) - (sI - A)^{-1}B) + (sI - A)^{-1}Be^{st}.\end{aligned}$$

The output of equation (8.2) is thus

$$\begin{aligned} y(t) &= Cx(t) + Du(t) \\ &= Ce^{At} \left(x(0) - (sI - A)^{-1}B \right) + \left(C(sI - A)^{-1}B + D \right) e^{st}, \end{aligned} \quad (8.3)$$

a linear combination of the exponential functions e^{st} and e^{At} . The first term in equation (8.3) is the transient response of the system. Recall that e^{AT} can be written in terms of the eigenvalues of A (using the Jordan form) and hence the transient response is a linear combinations of terms of the form $e^{\lambda_i t}$, where λ_i are eigenvalues of A . If the system is stable then $e^{AT} \rightarrow 0$ as $t \rightarrow \infty$ and this term dies away.

The second term of the output (8.3) is proportional to the input $u(t) = e^{st}$. This term is called the *pure exponential response*. If the initial state is chosen as

$$x(0) = (sI - A)^{-1}B,$$

then the output only consists of the pure exponential response and both the state and the output are proportional to the input:

$$\begin{aligned} x(t) &= (sI - A)^{-1}Be^{st} = (sI - A)^{-1}Bu(t) \\ y(t) &= (C(sI - A)^{-1}B + D)e^{st} = (C(sI - A)^{-1}B + D)u(t). \end{aligned}$$

The map from the input to output,

$$G_{yu}(s) = C(sI - A)^{-1}B + D, \quad (8.4)$$

is the *transfer function* of the system (8.2); the function

$$G_{xu}(s) = (sI - A)^{-1}B$$

is the transfer function from input to state. Note that this latter transfer function is actually a *vector* of n transfer functions (one for each state). Using transfer functions the response of the system (8.2) to an exponential input is thus

$$y(t) = Ce^{At} \left(x(0) - (sI - A)^{-1}B \right) + G_{yu}(s)e^{st}. \quad (8.5)$$

An important point in the derivation of the transfer function is the fact that we have restricted s so that $s \neq \lambda_i(A)$, $i = 1, \dots, n$, where $\lambda_i(A)$. At those values of s , we see that the response of the system is singular (since $sI - A$ will fail to be invertible). These correspond to “modes” of

the system and are particularly problematic when $\operatorname{Re} s \geq 0$, since this can result in bounded inputs creating unbounded outputs. This situation can only happen when the system has eigenvalues with either positive or zero real part, and hence it relates to the stability of the system. In particular, if a linear system is asymptotically stable, then bounded inputs will always produce bounded outputs.

Coordinate Changes

The matrices A , B and C in equation (8.2) depend on the choice of coordinate system for the states. Since the transfer function relates input to outputs, it should be invariant to coordinate changes in the state space. To show this, consider the model (8.2) and introduce new coordinates z by the transformation $z = Tx$, where T is a nonsingular matrix. The system is then described by

$$\begin{aligned}\dot{z} &= T(Ax + Bu) = TAT^{-1}z + TBu = \tilde{A}z + \tilde{B}u \\ y &= Cx + DU = CT^{-1}z + Du = \tilde{C}z + Du\end{aligned}$$

This system has the same form as equation (8.2) but the matrices A , B and C are different:

$$\tilde{A} = TAT^{-1} \quad \tilde{B} = TB \quad \tilde{C} = CT^{-1} \quad \tilde{D} = D. \quad (8.6)$$

Computing the transfer function of the transformed model we get

$$\begin{aligned}\tilde{G}(s) &= \tilde{C}(sI - \tilde{A})^{-1}\tilde{B} + D \\ &= CT^{-1}T(sI - A)^{-1}T^{-1}TB + D \\ &= CT^{-1}(sI - TAT^{-1})^{-1}TB + D \\ &= C(T^{-1}(sI - TAT^{-1})T)^{-1}B + D \\ &= C(sI - A)^{-1}B + D = G(s),\end{aligned}$$

which is identical to the transfer function (8.4) computed from the system description (8.2). The transfer function is thus invariant to changes of the coordinates in the state space.



Another property of the transfer function is that it corresponds to the portion of the state space dynamics that are both reachable and observable. In particular, if we make use of the Kalman decomposition (Section 7.5), then the transfer function only depends on the dynamics on the reachable and observable subspace, \mathcal{S}_{ro} (Exercise 2).

Transfer Functions for Linear Differential Equations

Consider a linear input/output system described by the differential equation

$$\frac{d^n y}{dt^n} + a_1 \frac{d^{n-1} y}{dt^{n-1}} + \cdots + a_n y = b_0 \frac{d^m u}{dt^m} + b_1 \frac{d^{m-1} u}{dt^{m-1}} + \cdots + b_m u, \quad (8.7)$$

where u is the input and y is the output. This type of description arises in many applications, as described briefly in Section 2.2. Note that here we have generalized our previous system description to allow both the input and its derivatives to appear.

To determine the transfer function of the system (8.7), let the input be $u(t) = e^{st}$. Since the system is linear, there is an output of the system that is also an exponential function $y(t) = y_0 e^{st}$. Inserting the signals in equation (8.7) we find

$$(s^n + a_1 s^{n-1} + \cdots + a_n) y_0 e^{st} = (b_0 s^m + b_1 s^{m-1} + \cdots + b_m) e^{-st}$$

and the response of the system can be completely described by two polynomials

$$\begin{aligned} a(s) &= s^n + a_1 s^{n-1} + \cdots + a_{n-1} s + a_n \\ b(s) &= b_0 s^m + b_1 s^{m-1} + \cdots + b_{m-1} s + b_m. \end{aligned} \quad (8.8)$$

The polynomial $a(s)$ is the characteristic polynomial of the ordinary differential equation. If $a(s) \neq 0$ it follows that

$$y(t) = y_0 e^{st} = \frac{b(s)}{a(s)} e^{st} = G(s)u(t). \quad (8.9)$$

The transfer function of the system (8.7) is thus the rational function

$$G(s) = \frac{b(s)}{a(s)}, \quad (8.10)$$

where the polynomials $a(s)$ and $b(s)$ are given by equation (8.8). Notice that the transfer function for the system (8.7) can be obtained by inspection, since the coefficients of $a(s)$ and $b(s)$ are precisely the coefficients of the derivatives of u and y .

Equations (8.7)–(8.10) can be used to compute the transfer functions of many simple ODEs. The following table gives some of the more common forms:

Type	ODE	Transfer Function
Integrator	$\dot{y} = u$	$\frac{1}{s}$
Differentiator	$y = \dot{u}$	s
First order system	$\dot{y} + ay = u$	$\frac{1}{s+a}$
Double Integrator	$\ddot{y} = u$	$\frac{1}{s^2}$
Damped oscillator	$\ddot{y} + 2\zeta\omega_n\dot{y} + \omega_n^2 = u$	$\frac{1}{s^2 + 2\zeta\omega_n s + \omega_n^2}$
PID controller	$y = k_p u + k_d \dot{u} + k_i \int u$	$k_p + k_d s + \frac{k_i}{s}$
Time delay	$y(t) = u(t - \tau)$	$e^{-\tau s}$

The first five of these follow directly from the analysis above. For the PID controller, we let the input be $u(t) = e^{st}$ and search for a solution $y(t) = e^{st}$. It follows that

$$y(t) = k_p e^{st} + k_d s e^{st} + \frac{k_i}{s} e^{st},$$

giving the indicated transfer function.

Time delays appear in many systems: typical examples are delays in nerve propagation, communication and mass transport. A system with a time delay has the input/output relation

$$y(t) = u(t - T). \quad (8.11)$$

As before the input be $u(t) = e^{st}$. Assuming that there is an output of the form $y(t) = y_0 e^{st}$ and inserting into equation (8.11) we get

$$y(t) = y_0 e^{st} = e^{s(t-T)} = e^{-sT} e^{st} = e^{-sT} u(t).$$

The transfer function of a time delay is thus $G(s) = e^{-sT}$ which is not a rational function, but is analytic except at infinity.

Example 8.1 (Operational amplifiers). To further illustrate the use of exponential signals, we consider the operational amplifier circuit introduced in Section 3.3 and reproduced in Figure 8.3. The model introduced in Section 3.3 is a simplification because the linear behavior of the amplifier was modeled as a constant gain. In reality there is significant dynamics in the

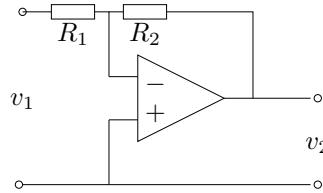


Figure 8.3: Schematic diagram of a stable amplifier based on negative feedback around an operational amplifier.

amplifier and the static model $v_{\text{out}} = -kv$ (equation (3.10)), should therefore be replaced by a dynamic model. In the linear range the amplifier, we can model the op amp as having a steady state frequency response

$$\frac{v_{\text{out}}}{v} = -\frac{k}{1+sT} =: G(s). \quad (8.12)$$

This response corresponds to a first order system with time constant T ; typical parameter values are $k = 10^6$ and $T = 1$.

Since all of the elements of the circuit are modeled as being linear, if we drive the input v_1 with an exponential signal e^{st} then in steady state all signals will be exponentials of the same form. This allows us to manipulate the equations describing the system in an algebraic fashion. Hence we can write

$$\frac{v_1 - v}{R_1} = \frac{v - v_2}{R_2} \quad \text{and} \quad v_2 = G(s)v, \quad (8.13)$$

using the fact that the current into the amplifier is very small, as we did in Section 3.3. We can now “solve” for v_1 in terms of v by eliminating v_2 in the first equation:

$$v_1 = R_1 \left(\frac{v}{R_1} + \frac{v}{R_2} - \frac{v_2}{R_2} \right) = R_1 \left(\frac{1}{R_1} + \frac{1}{R_2} - \frac{G(s)}{R_2} \right) v.$$

Rewriting v in terms of v_1 and substituting into the second formula (8.13), we obtain

$$\frac{v_2}{v_1} = \frac{R_2 G(s)}{R_1 + R_2 - R_1 G(s)} = \frac{R_2 k}{(R_1 + R_2)(1 + sT) + kR_1}.$$

This model for the frequency response shows that when s is large in magnitude (very fast signals) the frequency response of the circuit drops off. Note also that if we take T to be very small (corresponding to an op amp with a very fast response time), our circuit performs well up to higher

frequencies. In the limit that $T = 0$, we recover the responds that we derived in Section 3.3.

Note that in solving this example, we bypassed explicitly writing the signals as $v = v_0 e^{st}$ and instead worked directly with v , assuming it was an exponential. This shortcut is very handy in solving problems of this sort.

∇



Although we have focused thus far on ordinary differential equations, transfer functions can also be used for other types of linear systems. We illustrate this via an example of a transfer function for a partial differential equation.

Example 8.2 (Transfer function for heat propagation). Consider the one dimensional heat propagation in a semi-infinite metal rod. Assume that the input is the temperature at one end and that the output is the temperature at a point on the rod. Let θ be the temperature at time t and position x . With proper choice of length scales and units, heat propagation is described by the partial differential equation

$$\frac{\partial \theta}{\partial t} = \frac{\partial^2 \theta}{\partial^2 x}, \quad (8.14)$$

and the point of interest can be assumed to have $x = 1$. The boundary condition for the partial differential equation is

$$\theta(0, t) = u(t).$$

To determine the transfer function we choose the input as $u(t) = e^{st}$. Assume that there is a solution to the partial differential equation of the form $\theta(x, t) = \psi(x)e^{st}$, and insert this into equation (8.14) to obtain

$$s\psi(x) = \frac{d^2\psi}{dx^2},$$

with boundary condition $\psi(0) = e^{st}$. This ordinary differential equation (with independent variable x) has the solution

$$\psi(x) = Ae^{x\sqrt{s}} + Be^{-x\sqrt{s}}.$$

Matching the boundary conditions gives $A = 0$ and $B = e^{st}$, so the solution is

$$y(t) = \theta(1, t) = \psi(1)e^{st} = e^{-\sqrt{s}}e^{st} = e^{-\sqrt{s}}u(t).$$

The system thus has the transfer function $G(s) = e^{-\sqrt{s}}$. As in the case of a time delay, the transfer function is not a simple ratio of polynomials, but it is an analytic function.

∇

Transfer Function Properties

The transfer function has many useful physical interpretations and the features of a transfer function are often associated with important system properties.

The *zero frequency gain* of a system is given by the magnitude of the transfer function at $s = 0$. It represents the ratio of the steady state value of the output with respect to a step input (which can be represented as $u = e^{st}$ with $s = 0$). For a state space system, we computed the zero frequency gain in equation (5.20):

$$G(0) = D - CA^{-1}B.$$

For a system written as a linear ODE, as in equation (8.7), if we assume that the input and output of the system are constants y_0 and u_0 , then we find that $a_n y_0 = b_m u_0$. Hence the zero frequency gain is

$$G(0) = \frac{y_0}{u_0} = \frac{b_m}{a_n}. \quad (8.15)$$

Next consider a linear system with the rational transfer function

$$G(s) = \frac{b(s)}{a(s)}.$$

The roots of the polynomial $a(s)$ are called *poles* of the system and the roots of $b(s)$ are called the *zeros* of the system. If p is a pole it follows that $y(t) = e^{pt}$ is a solution of equation (8.7) with $u = 0$ (the homogeneous solution). The function e^{pt} is called a *mode* of the system. The unforced motion of the system after an arbitrary excitation is a weighted sum of the modes. Since the pure exponential output corresponding to the input $u(t) = e^{st}$ with $a(s) \neq 0$ is $G(s)e^{st}$ it follows that the pure exponential output is zero if $b(s) = 0$. Zeros of the transfer function thus block the transmission of the corresponding exponential signals.

For a state space system with transfer function $G(s) = C(sI - A)^{-1}B + D$, the poles of the transfer function are the eigenvalues of the matrix A in the state space model. One easy way to see this is to notice that the value of $G(s)$ is unbounded when s is an eigenvalue of a system since this is precisely the set of points where the characteristic polynomial $\lambda(s) = \det(sI - A) = 0$ (and hence $sI - A$ is non-invertible). It follows that the poles of a state space system depend only on the matrix A , which represents the intrinsic dynamics of the system.

To find the zeros of a state space system, we observe that the zeros are complex numbers s such that the input $u(t) = e^{st}$ gives zero output. Inserting the pure exponential response $x(t) = x_0 e^{st}$ and $y(t) = 0$ in equation (8.2) gives

$$\begin{aligned} se^{st}x_0 &= Ax_0e^{st} + Bu_0e^{st} \\ 0 &= Ce^{st}x_0 + De^{st}u_0, \end{aligned}$$

which can be written as

$$\begin{pmatrix} sI - A & B \\ C & D \end{pmatrix} \begin{pmatrix} x_0 \\ u_0 \end{pmatrix} = 0.$$

This equation has a solution with nonzero x_0, u_0 only if the matrix on the left does not have full rank. The zeros are thus the values s such that

$$\det \begin{pmatrix} sI - A & B \\ C & D \end{pmatrix} = 0. \quad (8.16)$$

Since the zeros depend on A, B, C and D , they therefore depend on how the inputs and outputs are coupled to the states. Notice in particular that if the matrix B has full rank then the matrix has n linearly independent rows for all values of s . Similarly there are n linearly independent columns if the matrix C has full rank. This implies that systems where the matrices B or C are of full rank do not have zeros. In particular it means that a system has no zeros if it is fully actuated (each state can be controlled independently) or if the full state is measured.

A convenient way to view the poles and zeros of a transfer function is through a *pole zero diagram*, as shown in Figure 8.4. In this diagram, each pole is marked with a cross and each zero with a circle. If there are multiple poles or zeros at a fixed location, these are often indicated with overlapping crosses or circles (or other annotations). Poles in the left half plane correspond to stable models of the system and poles in the right half plane correspond to unstable modes. Notice that the gain must also be given to have a complete description of the transfer function.

8.3 Block Diagrams and Transfer Functions

The combination of block diagrams and transfer functions is a powerful way to represent control systems. Transfer functions relating different signals in the system can be derived by purely algebraic manipulations of the transfer

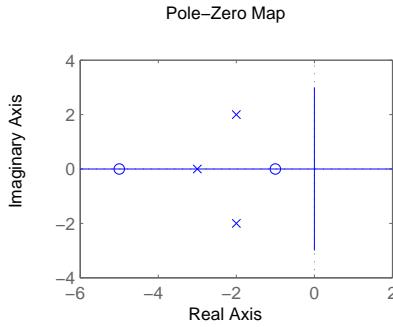


Figure 8.4: A pole zero diagram for a transfer function with zeros at -5 and -1 , and poles at -3 and $-2 \pm 2j$. The circles represent the locations of the zeros and the crosses the locations of the poles.

functions of the blocks using *block diagram algebra*. To show how this can be done, we will begin with simple combinations of systems.

Consider a system which is a cascade combination of systems with the transfer functions $G_1(s)$ and $G_2(s)$, as shown in Figure 8.5a. Let the input of the system be $u = e^{st}$. The pure exponential output of the first block is the exponential signal G_1u , which is also the input to the second system. The pure exponential output of the second system is

$$y = G_2(G_1u) = (G_2G_1)u.$$

The transfer function of the system is thus $G = G_2G_1$, i.e. the product of the transfer functions. The order of the individual transfer functions is due to the fact that we place the input signal on the right hand side of this

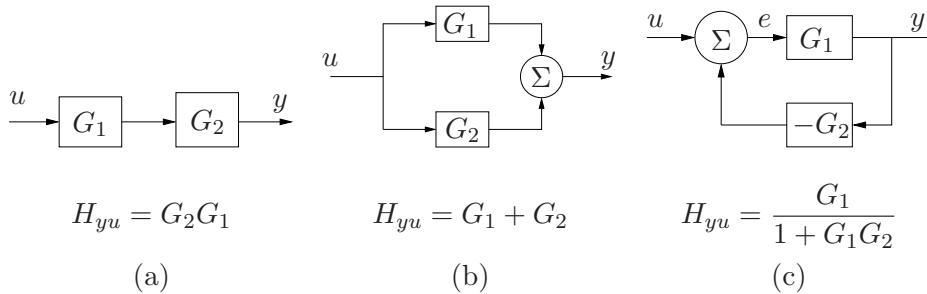


Figure 8.5: Interconnections of linear systems: (a) series, (b) parallel and (c) feed-back connections.

expression, hence we first multiply by G_1 and then by G_2 . Unfortunately, this has the opposite ordering from the diagrams that we use, where we typically have the signal flow from left to right, so one needs to be careful. The ordering is important if either G_1 or G_2 is a vector-valued transfer function, as we shall see in some examples.

Consider next a parallel connection of systems with the transfer functions G_1 and G_2 , as shown in Figure 8.5b. Letting $u = e^{st}$ be the input to the system, the pure exponential output of the first system is then $y_1 = G_1 u$ and the output of the second system is $y_2 = G_2 u$. The pure exponential output of the parallel connection is thus

$$y = G_1 u + G_2 u = (G_1 + G_2)u$$

and the transfer function for a parallel connection $G = G_1 + G_2$.

Finally, consider a feedback connection of systems with the transfer functions G_1 and G_2 , as shown in Figure 8.5c. Let $u = e^{st}$ be the input to the system, y the pure exponential output, and e be the pure exponential part of the intermediate signal given by the sum of u and the output of the second block. Writing the relations for the different blocks and the summation unit we find

$$y = G_1 e \quad e = u - G_2 y.$$

Elimination of e gives

$$y = G_1(u - G_2 y),$$

hence

$$(1 + G_1 G_2)y = G_1 u,$$

which implies

$$y = \frac{G_1}{1 + G_1 G_2} u.$$

The transfer function of the feedback connection is thus

$$G = \frac{G_1}{1 + G_1 G_2}.$$

These three basic interconnections can be used as the basis for computing transfer functions for more complicated systems, as shown in the following examples.

Example 8.3 (Control system transfer functions). Consider the system in Figure 8.6, which was given already at the beginning of the chapter. The system has three blocks representing a process P , a feedback controller C and

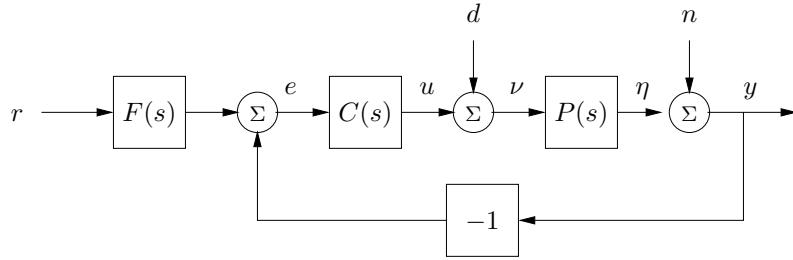


Figure 8.6: Block diagram of a feedback system.

a feedforward controller F . There are three external signals, the reference r , the load disturbance d and the measurement noise n . A typical problem is to find out how the error e is related to the signals r , d and n .

To derive the transfer function we simply assume that all signals are exponential functions, drop the arguments of signals and transfer functions and trace the signals around the loop. We begin with the signal in which we are interested, in this case the error e , given by

$$e = Fr - y.$$

The signal y is the sum of n and η , where η is the output of the process and u is the output of the controller:

$$y = n + \eta \quad \eta = P(d + u) \quad u = Ce.$$

Combining these equations gives

$$\begin{aligned} e &= Fr - y = Fr - (n + \eta) = Fr - (n + P(d + u)) \\ &= Fr - (n + P(d + Ce)) \end{aligned}$$

and hence

$$e = Fr - (n + P(d + Ce)) = Fr - n - Pd - PCe.$$

Finally, solving this equation for e gives

$$e = \frac{F}{1 + PC}r - \frac{1}{1 + PC}n - \frac{P}{1 + PC}d = G_{er}r + G_{en}n + G_{ed}d \quad (8.17)$$

and the error is thus the sum of three terms, depending on the reference r , the measurement noise n and the load disturbance d . The functions

$$G_{er} = \frac{F}{1 + PC} \quad G_{en} = \frac{-1}{1 + PC} \quad G_{ed} = \frac{-P}{1 + PC} \quad (8.18)$$

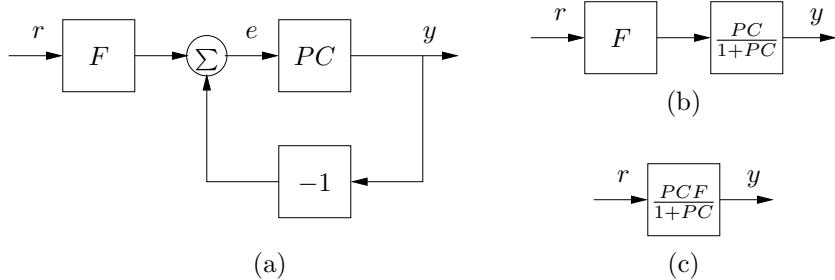


Figure 8.7: Example of block diagram algebra.

are the transfer functions from reference r , noise n and disturbance d to the error e .

We can also derive transfer functions by manipulating the block diagrams directly, as illustrated in Figure 8.7. Suppose we wish to compute the transfer function between the reference r and the output y . We begin by combining the process and controller blocks in Figure 8.6 to obtain the diagram in Figure 8.7a. We can now eliminate the feedback look (Figure 8.7b) and then use the series interconnection rule to obtain

$$G_{yr} = \frac{PCF}{1 + PC}. \quad (8.19)$$

Similar manipulations can be used to obtain other transfer functions. ∇

The example illustrates an effective way to manipulate the equations to obtain the relations between inputs and outputs in a feedback system. The general idea is to start with the signal of interest and to trace signals around the feedback loop until coming back to the signal we started with. With a some practice, equations (8.17) and (8.18) can be written directly by inspection of the block diagram. Notice that all terms in equation (8.17) and (8.18) have the same denominators. There may, however, be factors that cancel due to the form of the numerator.

Example 8.4 (Vehicle steering). Consider the linearized model for vehicle steering introduced in Example 2.8. In Examples 6.4 and 7.3 we designed a state feedback compensator and state estimator. A block diagram for the resulting control system is given in Figure 8.8. Note that we have split the estimator into two components, $G_{\hat{x}u}(s)$ and $G_{\hat{x}y}(s)$, corresponding to its inputs u and y . The controller can be described as the sum of two (open loop) transfer functions

$$u = G_{uy}(s)y + G_{ur}(s)r.$$

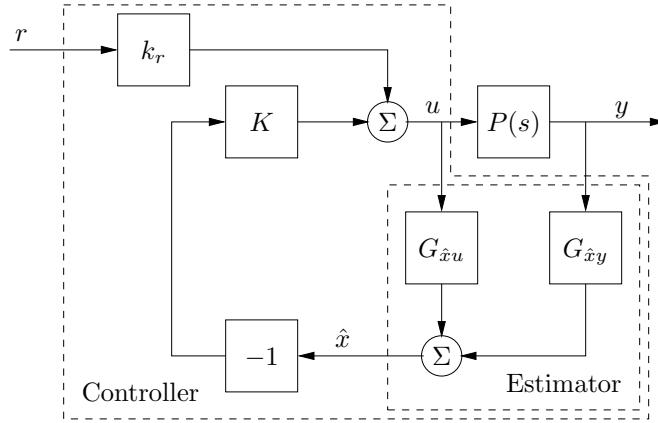


Figure 8.8: Block diagram for the steering control system.

The first transfer function, $G_{uy}(s)$, describes the feedback term and the second, $G_{ur}(s)$, describes the feedforward term. We call these “open loop” transfer functions because they represent the relationships between the signals without considering the dynamics of the process (e.g., removing $P(s)$ from the system description). To derive these functions, we compute the transfer functions for each block and then use block diagram algebra.

We begin with the estimator, which takes u and y as its inputs and produces an estimate \hat{x} . The dynamics for this process was derived in Example 7.3 and is given by

$$\begin{aligned} \frac{d\hat{x}}{dt} &= (A - LC)\hat{x} + Ly + Bu \\ \hat{x} &= \underbrace{(sI - (A - LC))^{-1}Bu}_{G_{\hat{x}u}} + \underbrace{(sI - (A - LC))^{-1}Ly}_{G_{\hat{x}y}}. \end{aligned}$$

Using the expressions for A , B , C and L from Example 7.3, we obtain

$$G_{\hat{x}u} = \begin{pmatrix} \alpha s + 1 \\ \frac{s^2 + l_1 s + l_2}{s + l_1 - \alpha l_2} \end{pmatrix} \quad G_{\hat{x}y} = \begin{pmatrix} \frac{l_1 s + l_2}{s^2 + l_1 s + l_2} \\ \frac{l_2 s}{s^2 + l_1 s + l_2} \end{pmatrix}.$$

We can now proceed to compute the transfer function for the overall control system. Using block diagram algebra, we have

$$G_{uy} = \frac{-KG_{\hat{x}y}}{1 + KG_{\hat{x}u}} = -\frac{s(k_1 l_1 + k_2 l_2) + k_1 l_2}{s^2 + s(\alpha k_1 + k_2 + l_1) + k_1 + l_2 + k_2 l_1 - \alpha k_2 l_2}$$

and

$$G_{ur} = \frac{k_r}{1 + KG_{\hat{x}u}} = k_1 \frac{s^2 + l_1 s + l_2}{s^2 + s(\alpha k_1 + k_2 + l_1) + k_1 + l_2 + k_2 l_1 - \alpha k_2 l_2}.$$

Finally, we compute the full closed loop dynamics. We begin by deriving the transfer function for the process, $P(s)$. We can compute this directly from the state space description of the dynamics, which was given in Example 6.4. Using that description, we have

$$P = G_{yu} = C(sI - A)^{-1}B + D = \begin{pmatrix} 1 & 0 \end{pmatrix} \begin{pmatrix} s & -1 \\ 0 & s \end{pmatrix}^{-1} \begin{pmatrix} \alpha \\ 1 \end{pmatrix} = \frac{\alpha s + 1}{s^2}.$$

The transfer function for the full closed loop system between the input r and the output y is then given by

$$G_{yr} = \frac{k_r P(s)}{1 - P(s)G_{yu}(s)} = \frac{k_1(\alpha s + 1)}{s^2 + (k_1\alpha + k_2)s + k_1}.$$

Note that the observer gains do not appear in this equation. This is because we are considering steady state analysis and, in steady state, the estimated state exactly tracks the state of the system if we assume perfect models. We will return to this example in Chapter 12 to study the robustness of this particular approach. ∇

The combination of block diagrams and transfer functions is a powerful tool because it is possible both to obtain an overview of a system and find details of the behavior of the system.

Pole/Zero Cancellations

Because transfer functions are often polynomials in s , it can sometimes happen that the numerator and denominator have a common factor, which can be canceled. Sometimes these cancellations are simply algebraic simplifications, but in other situations these cancellations can mask potential fragilities in the model. In particular, if a pole/zero cancellation occurs due to terms in separate blocks that just happen to coincide, the cancellation may not occur if one of the systems is slightly perturbed. In some situations this can result in severe differences between the expected behavior and the actual behavior, as illustrated in this section.

To illustrate when we can have pole/zero cancellations, consider the block diagram shown in Figure 8.6 with $F = 1$ (no feedforward compensation) and C and P given by

$$C = \frac{n_c(s)}{d_c(s)} \quad P = \frac{n_p(s)}{d_p(s)}.$$

The transfer function from r to e is then given by

$$G_{er} = \frac{1}{1 + PC} = \frac{d_c(s)d_p(s)}{d_c(s)d_p(s) + n_c(s)n_p(s)}.$$

If there are common factors in the numerator and denominator polynomials, then these terms can be factored out and eliminated from both the numerator and denominator. For example, if the controller has a zero at $s = a$ and the process has a pole at $s = a$, then we will have

$$G_{er} = \frac{(s+a)d'_c(s)d_p(s)}{(s+a)d_c(s)d'_p(s) + (s+a)n'_c(s)n_p(s)} = \frac{d'_c(s)d_p(s)}{d_c(s)d'_p(s) + n'_c(s)n_p(s)},$$

where $n'_c(s)$ and $d'_p(s)$ represent the relevant polynomials with the term $s+a$ factored out.

Suppose instead that we compute the transfer function from d to e , which represents the effect of a disturbance on the error between the reference and the output. This transfer function is given by

$$G_{ed} = \frac{d'_c(s)n_p(s)}{(s+a)d_c(s)d'_p(s) + (s+a)n'_c(s)n_p(s)}.$$

Notice that if $a < 0$ then the pole is in the right half plane and the transfer function G_{ed} is *unstable*. Hence, even though the transfer function from r to e appears to be OK (assuming a perfect pole/zero cancellation), the transfer function from d to e can exhibit unbounded behavior. This unwanted behavior is typical of an *unstable pole/zero cancellation*.

It turns out that the cancellation of a pole with a zero can also be understood in terms of the state space representation of the systems. Reachability or observability is lost when there are cancellations of poles and zeros (Exercise 11). A consequence is that the transfer function only represents the dynamics in the reachable and observable subspace of a system (see Section 7.5).

8.4 The Bode Plot

The frequency response of a linear system can be computed from its transfer function by setting $s = j\omega$, corresponding to a complex exponential

$$u(t) = e^{j\omega t} = \cos(\omega t) + j \sin(\omega t).$$

The resulting output has the form

$$y(t) = M e^{j\omega t + \varphi} = M \cos(\omega t + \varphi) + j M \sin(\omega t + \varphi)$$

where M and φ are the gain and phase of G :

$$M = |G(j\omega)| \quad \varphi = \angle G(j\omega) = \arctan \frac{\text{Im } G(j\omega)}{\text{Re } G(j\omega)}.$$

The phase of G is also called the *argument* of G , a term that comes from the theory of complex variables.

It follows from linearity that the response to a single sinusoid (\sin or \cos) is amplified by M and phase shifted by φ . Note that $\varphi \in [0, 2\pi)$, so the arctangent must be taken respecting the signs of the numerator and denominator. It will often be convenient to represent the phase in degrees rather than radians. We will use the notation $\angle G(j\omega)$ for the phase in degrees and $\arg G(j\omega)$ for the phase in radians. In addition, while we always take $\arg G(j\omega)$ to be in the range $[0, 2\pi)$, we will take $\angle G(j\omega)$ to be continuous, so that it can take on values outside of the range of 0 to 360° .

The frequency response $G(j\omega)$ can thus be represented by two curves: the gain curve and the phase curve. The gain curve gives gain $|G(j\omega)|$ as a function of frequency ω and the phase curve gives phase $\angle G(j\omega)$ as a function of frequency ω . One particularly useful way of drawing these curves is to use a log/log scale for the magnitude plot and a log/linear scale for the phase plot. This type of plot is called a *Bode plot* and is shown in Figure 8.9.

Part of the popularity of Bode plots is that they are easy to sketch and to interpret. Consider a transfer function which is a ratio of polynomial terms $G(s) = (b_1(s)b_2(s))/(a_1(s)a_2(s))$. We have

$$\log |G(s)| = \log |b_1(s)| + \log |b_2(s)| - \log |a_1(s)| - \log |a_2(s)|$$

and hence we can compute the gain curve by simply adding and subtracting gains corresponding to terms in the numerator and denominator. Similarly

$$\angle G(s) = \angle b_1(s) + \angle b_2(s) - \angle a_1(s) - \angle a_2(s)$$

and so the phase curve can be determined in an analogous fashion. Since a polynomial is a product of terms of the type

$$k, \quad s, \quad s+a, \quad s^2 + 2\zeta as + a^2,$$

it suffices to be able to sketch Bode diagrams for these terms. The Bode plot of a complex system is then obtained by adding the gains and phases of the terms.

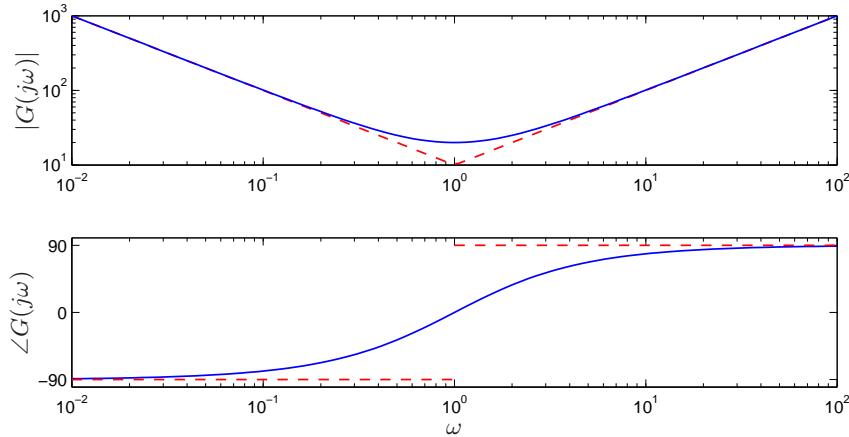


Figure 8.9: Bode plot of the transfer function $C(s) = 20 + 10/s + 10s$ of an ideal PID controller. The top plot is the gain curve and bottom plot is the phase curve. The dashed lines show straight line approximations of the gain curve and the corresponding phase curve.

The simplest term in a transfer function is a power of s , s^k , where $k > 0$ if the term appears in the numerator and $k < 0$ if the term is in the denominator. The magnitude and phase of the term are given by

$$\log |G(j\omega)| = k \log \omega, \quad \angle G(j\omega) = 90k.$$

The gain curve is thus a straight line with slope k and the phase curve is a constant at $90^\circ \times k$. The case when $k = 1$ corresponds to a differentiator and has slope 1 with phase 90° . The case when $k = -1$ corresponds to an integrator and has slope 1 with phase 90° . Bode plots of the various powers of k are shown in Figure 8.10.

Consider next the transfer function of a first order system, given by

$$G(s) = \frac{a}{s + a}.$$

We have

$$\log G(s) = \log a - \log s + a$$

and hence

$$\log |G(j\omega)| = \log a - \frac{1}{2} \log (\omega^2 + a^2), \quad \angle G(j\omega) = -\frac{180}{\pi} \arctan \omega/a.$$

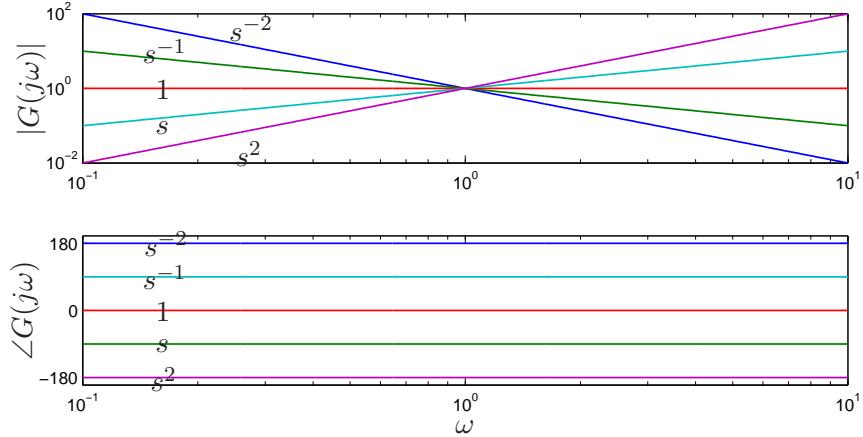


Figure 8.10: Bode plot of the transfer functions $G(s) = s^k$ for $k = -2, -1, 0, 1, 2$.

The Bode plot is shown in Figure 8.11a, with the magnitude normalized by the zero frequency gain. Both the gain curve and the phase curve can be approximated by the following straight lines

$$\log |G(j\omega)| \approx \begin{cases} \log a & \text{if } \omega < a \\ -\log \omega & \text{if } \omega > a \end{cases}$$

$$\angle G(j\omega) \approx \begin{cases} 0 & \text{if } \omega < a/10 \\ -45 - 45(\log \omega - \log a) & a/10 < \omega < 10a \\ -180 & \text{if } \omega > 10a. \end{cases}$$

Notice that a first order system behaves like a constant for low frequencies and like an integrator for high frequencies. Compare with the Bode plot in Figure 8.10.

Finally, consider the transfer function for a second order system

$$G(s) = \frac{\omega_0^2}{s^2 + 2a\zeta s + \omega_0^2}.$$

We have

$$\log |G(j\omega)| = 2 \log |\omega_0| - \log |(-\omega^2 + 2j\omega_0\zeta\omega + \omega_0^2)|$$

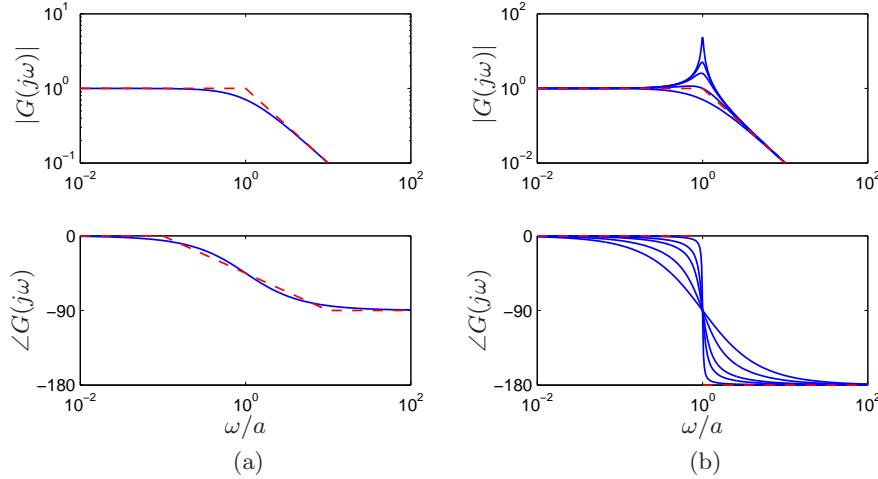


Figure 8.11: Bode plots of the systems $G(s) = a/(s+a)$ (left) and $G(s) = \omega_0^2/(s^2 + 2\zeta\omega_0s + \omega_0^2)$ (right). The full lines show the Bode plot and the dashed lines show the straight line approximations to the gain curves and the corresponding phase curves. The plot for second order system has $\zeta = 0.02, 0.1, 0.2, 0.5$ and 1.0 .

and hence

$$\begin{aligned} \log |G(j\omega)| &= 2 \log \omega_0 - \frac{1}{2} \log (\omega^4 + 2\omega_0^2\omega^2(2\zeta^2 - 1) + \omega_0^4) \\ \angle G(j\omega) &= -\frac{180}{\pi} \arctan \frac{2\zeta\omega_0\omega}{\omega_0^2 - \omega^2} \end{aligned}$$

The gain curve has an asymptote with zero slope for $\omega \ll \omega_0$. For large values of ω the gain curve has an asymptote with slope -2 . The largest gain $Q = \max_\omega |G(j\omega)| \approx 1/(2\zeta)$, called the *Q value*, is obtained for $\omega \approx \omega_0$. The phase is zero for low frequencies and approaches 180° for large frequencies. The curves can be approximated with the following piece-wise linear expressions

$$\log |G(j\omega)| \approx \begin{cases} 0 & \text{if } \omega \ll \omega_0, \\ -2 \log \omega & \text{if } \omega \gg \omega_0 \end{cases} \quad \angle G(j\omega) \approx \begin{cases} 0 & \text{if } \omega \ll \omega_0, \\ -180 & \text{if } \omega \gg \omega_0 \end{cases}.$$

The Bode plot is shown in Figure 8.11b. Note that the asymptotic approximation is poor near $\omega = a$ and the Bode plot depends strongly on ζ near this frequency.

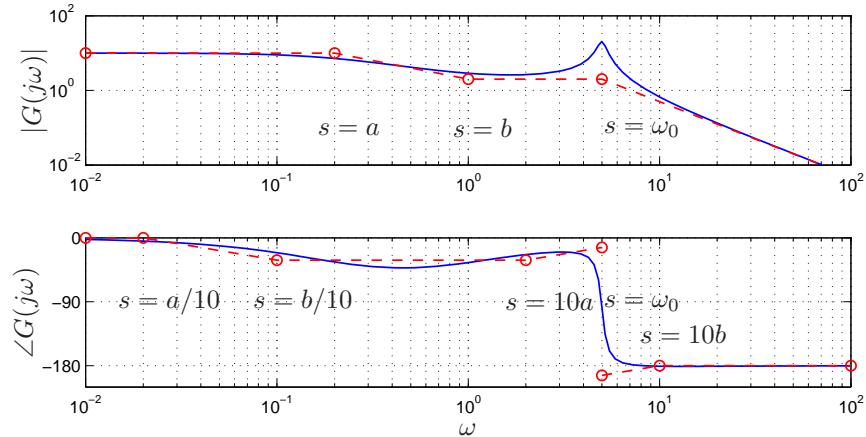


Figure 8.12: Sample Bode plot with asymptotes that give approximate curve.

Given the Bode plots of the basic functions, we can now sketch the frequency response for a more general system. The following example illustrates the basic idea.

Example 8.5. Consider the transfer function given by

$$G(s) = \frac{k(s + b)}{(s + a)(s^2 + 2\zeta\omega_0 s + \omega_0^2)} \quad a \ll b \ll \omega_0.$$

The Bode plot for this transfer function is shown in Figure 8.12, with the complete transfer function shown in blue (solid) and a sketch of the Bode plot shown in red (dashed).

We begin with the magnitude curve. At low frequency, the magnitude is given by

$$G(0) = \frac{kb}{a\omega^2}.$$

When we hit the pole at $s = a$, the magnitude begins to decrease with slope -1 until it hits the zero at $s = b$. At that point, we increase the slope by 1 , leaving the asymptote with net slope 0 . This slope is used until we reach the second order pole at $s = \omega_c$, at which point the asymptote changes to slope -2 . We see that the magnitude curve is fairly accurate except in the region of the peak of the second order pole (since for this case ζ is reasonably small).

The phase curve is more complicated, since the effect of the phase stretches out much further. The effect of the pole begins at $s = a/10$,

at which point we change from phase 0 to a slope of $-45^\circ/\text{decade}$. The zero begins to affect the phase at $s = b/10$, giving us a flat section in the phase. At $s = 10a$ the phase contributions from the pole end and we are left with a slope of $+45^\circ/\text{decade}$ (from the zero). At the location of the second order pole, $s \approx j\omega_c$, we get a jump in phase of -180° . Finally, at $s = 10b$ the phase contributions of the zero end and we are left with phase -180 degrees. We see that the straight line approximation for the phase is not as accurate as it was for the gain curve, but it does capture the basic features of the phase changes as a function of frequency. ∇

The Bode plot gives a quick overview of a system. Many properties can be read from the plot and because logarithmic scales are used the plot gives the properties over a wide range of frequencies. Since any signal can be decomposed into a sum of sinusoids it is possible to visualize the behavior of a system for different frequency ranges. Furthermore when the gain curves are close to the asymptotes, the system can be approximated by integrators or differentiators. Consider for example the Bode plot in Figure 8.9. For low frequencies the gain curve of the Bode plot has the slope -1 which means that the system acts like an integrator. For high frequencies the gain curve has slope $+1$ which means that the system acts like a differentiator.

8.5 Transfer Functions from Experiments

The transfer function of a system provides a summary of the input/output response and is very useful for analysis and design. However, modeling from first principles can be difficult and time consuming. Fortunately, we can often build an input/output model for a given application by directly measuring the frequency response and fitting a transfer function to it. To do so, we perturb the input to the system using a sinusoidal signal at a fixed frequency. When steady state is reached, the amplitude ratio and the phase lag gives the frequency response for the excitation frequency. The complete frequency response is obtained by sweeping over a range of frequencies.

By using correlation techniques it is possible to determine the frequency response very accurately and an analytic transfer function can be obtained from the frequency response by curve fitting. The success of this approach has led to instruments and software that automate this process, called *spectrum analyzers*. We illustrate the basic concept through two examples.

Example 8.6 (Atomic force microscope). To illustrate the utility of spectrum analysis, we consider the dynamics of the atomic force microscope,

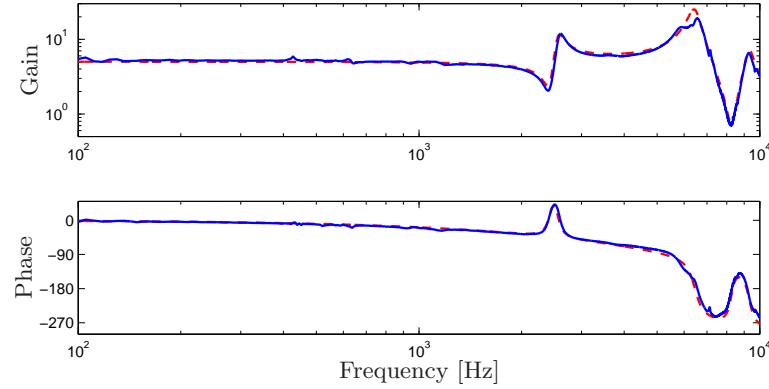


Figure 8.13: Frequency response of a piezoelectric drive for an atomic force microscope. The input is the voltage to the drive amplifier and the output is the output of the amplifier that measures beam deflection.

introduced in Section 3.5. Experimental determination of the frequency response is particularly attractive for this system because its dynamics are very fast and hence experiments can be done quickly. A typical example is given in Figure 8.13, which shows an experimentally determined frequency response (solid line). In this case the frequency response was obtained in less than a second. The transfer function

$$G(s) = \frac{k\omega_2^2\omega_3^2\omega_5^2(s^2 + 2\zeta_1\omega_1 s + \omega_1^2)(s^2 + 2\zeta_4\omega_4 s + \omega_4^2)e^{-sT}}{\omega_1^2\omega_4^2(s^2 + 2\zeta_2\omega_2 s + \omega_2^2)(s^2 + 2\zeta_3\omega_3 s + \omega_3^2)(s^2 + 2\zeta_5\omega_5 s + \omega_5^2)}$$

with $\omega_1 = 2420$, $\zeta_1 = 0.03$, $\omega_2 = 2550$, $\zeta_2 = 0.03$, $\omega_3 = 6450$, $\zeta_3 = 0.042$, $\omega_4 = 8250$, $\zeta_4 = 0.025$, $\omega_5 = 9300$, $\zeta_5 = 0.032$, $T = 10^{-4}$, and $k = 5$. was fit to the data (dashed line). The frequencies associated with the zeros are located where the gain curve has minima and the frequencies associated with the poles are located where the gain curve has local maxima. The relative damping are adjusted to give a good fit to maxima and minima. When a good fit to the gain curve is obtained the time delay is adjusted to give a good fit to the phase curve. ∇

Experimental determination of frequency response is less attractive for systems with slow dynamics because the experiment takes a long time.

Example 8.7 (Pupillary light reflex dynamics). The human eye is an organ that is easily accessible for experiments. It has a control system that adjusts

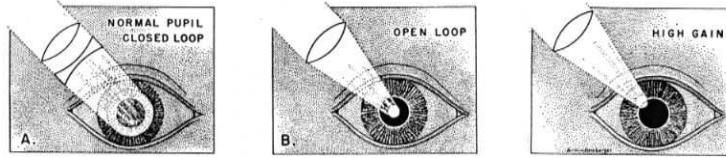


Figure 8.14: Light stimulation of the eye. In A the light beam is so large that it always covers the whole pupil, giving the closed loop dynamics. In B the light is focused into a beam which is so narrow that it is not influenced by the pupil opening, giving the open loop dynamics. In C the light beam is focused on the edge of the pupil opening, which has the effect of increasing the gain of the system since small changes in the pupil opening have a large effect on the amount of light entering the eye. From [Sta59].

the pupil opening to regulate the light intensity at the retina. This control system was explored extensively by Stark in the late 1960s [Sta68]. To determine the dynamics, light intensity on the eye was varied sinusoidally and the pupil opening was measured. A fundamental difficulty is that the closed loop system is insensitive to internal system parameters, so analysis of a closed loop system thus gives little information about the internal properties of the system. Stark used a clever experimental technique that allowed him to investigate both open and closed loop dynamics. He excited the system by varying the intensity of a light beam focused on the eye and he measured pupil area; see Figure 8.14. By using a wide light beam that covers the whole pupil the measurement gives the closed loop dynamics. The open loop dynamics were obtained by using a narrow beam, which is small enough that it is not influenced by the pupil opening. The result of one experiment for determining open loop dynamics is given in Figure 8.15. Fitting a transfer function to the gain curves gives a good fit for $G(s) = \frac{0.17}{(1 + 0.08s)^3}$. This curve gives a poor fit to the phase curve as shown by the dashed curve in Figure 8.15. The fit to the phase curve is improved by adding a time delay, which leaves the gain curve unchanged while substantially modifying the phase curve. The final fit gives the model

$$G(s) = \frac{0.17}{(1 + 0.08s)^3} e^{-0.2s}.$$

The Bode plot of this is shown with dashed curves in Figure 8.15. ∇

Notice that for both the AFM drive and the pupillary dynamics it is not easy to derive appropriate models from first principles. In practice, it is

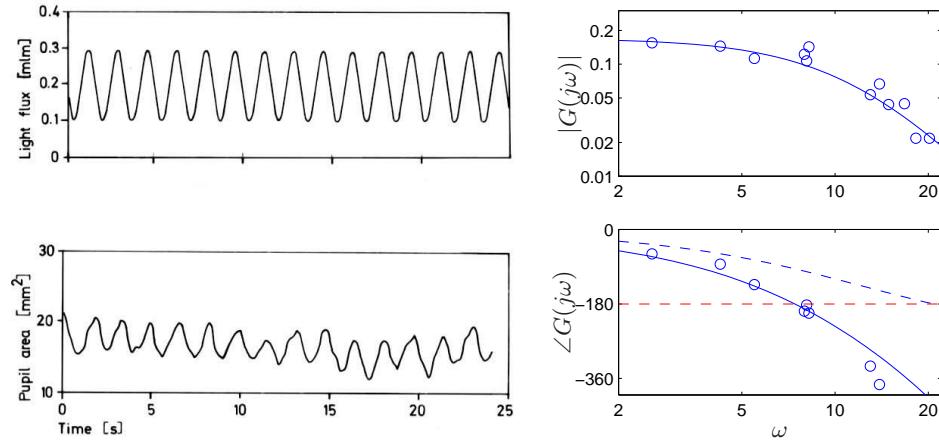


Figure 8.15: Sample curves from open loop frequency response of the eye (left) and Bode plot for the open loop dynamics (right). Redrawn from the data of [Sta59]. The dashed curve in the Bode plot is the minimum phase curve corresponding to the gain curve.

often fruitful to use a combination of analytical modeling and experimental identification of parameters.

8.6 Laplace Transforms

Transfer functions are typically introduced using Laplace transforms and in this section we derive the transfer function using this formalism. We assume basic familiarity with Laplace transforms; students who are not familiar with them can safely skip this section.

Traditionally, Laplace transforms were also used to compute responses of linear system to different stimuli. Today we can easily generate the responses using computers. Only a few elementary properties are needed for basic control applications. There is, however, a beautiful theory for Laplace transforms that makes it possible to use many powerful tools of the theory of functions of a complex variable to get deep insights into the behavior of systems.

Definitions and Properties

Consider a time function $f : \mathbb{R}^+ \rightarrow \mathbb{R}$ which is integrable and grows no faster than $e^{s_0 t}$ for some finite $s_0 \in \mathbb{R}$ and large t . The Laplace transform maps f

to a function $F = \mathcal{L}f : \mathbb{C} \rightarrow \mathbb{C}$ of a complex variable. It is defined by

$$F(s) = \int_0^\infty e^{-st} f(t) dt, \quad \operatorname{Re} s > s_0. \quad (8.20)$$

The transform has some properties that makes it very well suited to deal with linear systems.

First we observe that the transform is linear because

$$\begin{aligned} \mathcal{L}(af + bg) &= \int_0^\infty e^{-st} (af(t) + bg(t)) dt \\ &= a \int_0^\infty e^{-st} f(t) dt + b \int_0^\infty e^{-st} g(t) dt = a\mathcal{L}f + b\mathcal{L}g. \end{aligned} \quad (8.21)$$

Next we will calculate the Laplace transform of the derivative of a function. We have

$$\mathcal{L}\frac{df}{dt} = \int_0^\infty e^{-st} f'(t) dt = e^{-st} f(t) \Big|_0^\infty + s \int_0^\infty e^{-st} f(t) dt = -f(0) + s\mathcal{L}f,$$

where the second equality is obtained by integration by parts. We thus obtain the following important formula for the transform of a derivative

$$\mathcal{L}\frac{df}{dt} = s\mathcal{L}f - f(0) = sF(s) - f(0). \quad (8.22)$$

This formula is particularly simple if the initial conditions are zero because it follows that differentiation of a function corresponds to multiplication of the transform with s .

Since differentiation corresponds to multiplication with s we can expect that integration corresponds to division by s . This is true, as can be seen by calculating the Laplace transform of an integral. We have

$$\begin{aligned} \mathcal{L} \int_0^t f(\tau) d\tau &= \int_0^\infty \left(e^{-st} \int_0^t f(\tau) d\tau \right) dt \\ &= -\frac{e^{-st}}{s} \int_0^t e^{-s\tau} f(\tau) d\tau \Big|_0^\infty + \int_0^\infty \frac{e^{-s\tau}}{s} f(\tau) d\tau = \frac{1}{s} \int_0^\infty e^{-s\tau} f(\tau) d\tau, \end{aligned}$$

hence

$$\mathcal{L} \int_0^t f(\tau) d\tau = \frac{1}{s} \mathcal{L}f = \frac{1}{s} F(s). \quad (8.23)$$

Integration of a time function thus corresponds to dividing the Laplace transform by s .

The Laplace Transform of a Convolution

Consider a linear time-invariant system with zero initial state. The relation between the input u and the output y is given by the convolution integral

$$y(t) = \int_0^\infty h(t-\tau)u(\tau) d\tau,$$

where $h(t)$ is the impulse response for the system. We will now consider the Laplace transform of such an expression. We have

$$\begin{aligned} Y(s) &= \int_0^\infty e^{-st}y(t) dt = \int_0^\infty e^{-st} \int_0^\infty h(t-\tau)u(\tau) d\tau dt \\ &= \int_0^\infty \int_0^t e^{-s(t-\tau)}e^{-s\tau}h(t-\tau)u(\tau) d\tau dt \\ &= \int_0^\infty e^{-s\tau}u(\tau) d\tau \int_0^\infty e^{-st}h(t) dt = H(s)U(s) \end{aligned}$$

The result can be written as $Y(s) = H(s)U(s)$ where H , U and Y are the Laplace transforms of h , u and y . The system theoretic interpretation is that the Laplace transform of the output of a linear system is a product of two terms, the Laplace transform of the input $U(s)$ and the Laplace transform of the impulse response of the system $H(s)$. A mathematical interpretation is that the Laplace transform of a convolution is the product of the transforms of the functions that are convolved. The fact that the formula $Y(s) = H(s)U(s)$ is much simpler than a convolution is one reason why Laplace transforms have become popular in control.

The Transfer Function

The properties (8.21) and (8.22) makes the Laplace transform ideally suited for dealing with linear differential equations. The relations are particularly simple if all initial conditions are zero.

Consider for example a linear state space system described by

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx + Du. \end{aligned}$$

Taking Laplace transforms under the assumption that all initial values are zero gives

$$\begin{aligned} sX(s) &= AX(s) + BU(s) \\ Y(s) &= CX(s) + DU(s). \end{aligned}$$

Elimination of $X(s)$ gives

$$Y(s) = \left(C(sI - A)^{-1}B + D \right) U(s). \quad (8.24)$$

The transfer function is thus $G(s) = C(sI - A)^{-1}B + D$ (compare with equation (8.4)).

The formula (8.24) has a strong intuitive interpretation because it tells that the Laplace transform of the output is the product of the transfer function of the system and the transform of the input. In the transform domain the action of a linear system on the input is simply a multiplication with the transfer function. The transfer function is a natural generalization of the concept of gain of a system.

8.7 Further Reading

Heaviside, who introduced the idea to characterize dynamics by the response to a unit step function, also introduced a formal operator calculus for analyzing linear systems. This was a significant advance because it gave the possibility to analyze linear systems algebraically. Unfortunately it was difficult to formalize Heaviside's calculus properly. This was not done until the mathematician Laurent Schwartz developed the *distribution theory* in the late 1940s. Schwartz was given the Fields Medal in 1950. The idea of characterizing a linear system by its steady state response to sinusoids was introduced by Fourier in his investigation of heat conduction in solids [Fou07]. Much later it was used by Steinmetz when he introduced the $j\omega$ method to develop a theory for alternating currents.

The concept of transfer functions was an important part of classical control theory; see [JNP47]. It was introduced via the Laplace transform by Gardner Barnes [GB42], who also used it to calculate response of linear systems. The Laplace transform was very important in the early phase of control because it made it possible to find transients via tables. The Laplace transform is of less importance today when responses to linear systems can easily be generated using computers. For a mathematically inclined audience it is still a very convenient to introduce the transfer function via the Laplace transform, which is an important part of applied mathematics. For an audience with less background in mathematics it may be preferable to introduce the transfer function via the particular solution generated by the input e^{st} as was done in Section 8.2.

There are many excellent books on the use of Laplace transforms and transfer functions for modeling and analysis of linear input/output systems.

Traditional texts on control, such as [FPEN05] and [DB04], are representative examples.

8.8 Exercises

1. Let $G(s)$ be the transfer function for a linear system. Show that if we apply an input $u(t) = A \sin(\omega t)$ then the steady state output is given by $y(t) = |G(j\omega)|A \sin(\omega t + \arg G(j\omega))$.
2. Show that the transfer function of a system only depends on the dynamics in the reachable and observable subspace of the Kalman decomposition.
3. The linearized model of the pendulum in the upright position is characterized by the matrices

$$A = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}, \quad B = \begin{pmatrix} 0 \\ 1 \end{pmatrix}, \quad C = \begin{pmatrix} 1 & 0 \end{pmatrix}, \quad D = 0.$$

Determine the transfer function of the system.

4. Compute the frequency response of a PI controller using an op amp with frequency response given by equation (8.12).
5. Consider the speed control system given in Example 6.9. Compute the transfer function between the throttle position u , angle of the road θ and the speed of the vehicle v assuming a nominal speed v_e with corresponding throttle position u_e .
6. Consider the differential equation

$$\frac{d^n y}{dt^n} + a_1 \frac{d^{n-1} y}{dt^{n-1}} + a_2 \frac{d^{n-2} y}{dt^{n-2}} + \cdots + a_n y = 0$$

Let λ be a root of the polynomial

$$s^n + a_1 s^{n-1} + \cdots + a_n = 0.$$

Show that the differential equation has the solution $y(t) = e^{\lambda t}$.

7. Consider the system

$$\frac{d^n y}{dt^n} + a_1 \frac{d^{n-1} y}{dt^{n-1}} + \cdots + a_n y = b_1 \frac{d^{n-1} u}{dt^{n-1}} + b_2 \frac{d^{n-2} u}{dt^{n-2}} + \cdots + b_n u,$$

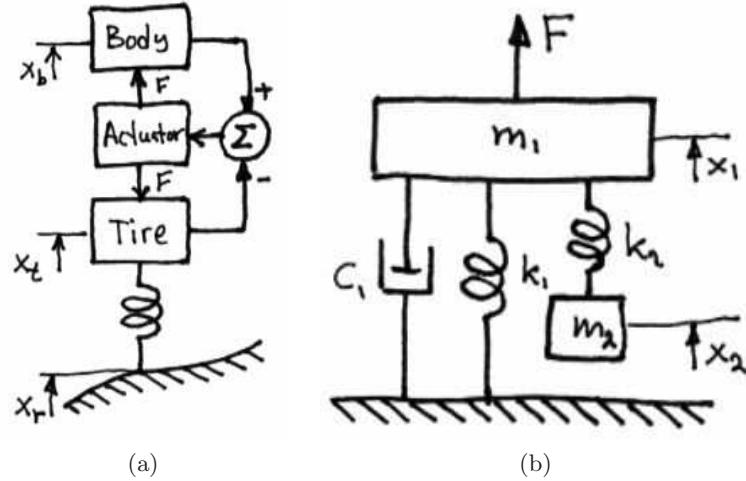


Figure 8.16: Schematic diagram of the *quarter car model* (a) and of a vibration absorber right (b).

Let λ be a zero of the polynomial

$$b(s) = b_1 s^{n-1} + b_2 s^{n-2} + \cdots + b_n$$

Show that if the input is $u(t) = e^{\lambda t}$ then there is a solution to the differential equation that is identically zero.

8. Active and passive damping is used in cars to give a smooth ride on a bumpy road. A schematic diagram of a car with a damping system is shown in Figure 8.16(a). The car is approximated with two masses, one represents a quarter of the car body and the other a wheel. The actuator exerts a force F between the wheel and the body based on feedback from the distance between body and the center of the wheel (the *rattle space*). A simple model of the system is given by Newton's equations for body and wheel

$$m_b \ddot{x}_b = F, \quad m_w \ddot{x}_w = -F + k_t(x_r - x_w),$$

where m_b is a quarter of the body mass, m_w is the effective mass of the wheel including brakes and part of the suspension system (the *unsprung mass*), and k_t is the tire stiffness. Furthermore x_b , x_w and x_r represent the heights of body, wheel, and road, measured from their equilibria. For a conventional damper consisting of a spring and a

damper we have $F = k(x_w - x_b) + c(\dot{x}_w - \dot{x}_b)$, for an active damper the force F can be more general and it can also depend on riding conditions. Rider comfort can be characterized by the transfer function G_{ax_r} from road height x_r to body acceleration $a = \ddot{x}_b$. Show that this transfer function has the property $G_{ax_r}(i\omega_t) = k_t/m_b$, where $\omega_t = \sqrt{k_t/m_w}$ (the *tire hop frequency*). The equation implies that there are fundamental limitations to the comfort that can be achieved with any damper. More details are given in [HB90].

9. Damping vibrations is a common engineering problem. A schematic diagram of a damper is shown in Figure 8.16(b). The disturbing vibration is a sinusoidal force acting on mass m_1 and the damper consists of mass m_2 and the spring k_2 . Show that the transfer function from disturbance force to height x_1 of the mass m_1 is

$$G_{x_1F} = \frac{m_2 s^2 + k_2}{m_1 m_2 s^4 + m_2 c_1 s^3 + (m_1 k_2 + m_2(k_1 + k_2))s^2 + k_2 c_1 s + k_1 k_2}$$

How should the mass m_2 and the stiffness k_2 be chosen to eliminate a sinusoidal oscillation with frequency ω_0 . More details are given on pages 87–93 in the classic text on vibrations [DH85].

10. Consider the linear state space system

$$\begin{aligned}\dot{x} &= Ax + Bu \\ y &= Cx.\end{aligned}$$

Show that the transfer function is

$$G(s) = \frac{b_1 s^{n-1} + b_2 s^{n-2} + \cdots + b_n}{s^n + a_1 s^{n-1} + \cdots + a_n}$$

where

$$\begin{aligned}b_1 &= CB \\ b_2 &= CAB + a_1 CB \\ b_3 &= CA^2B + a_1 CAB + a_2 CB \\ &\vdots \\ b_n &= CA^{n-1}B + a_1 CA^{n-1}B + \cdots + a_{n-1}CB\end{aligned}$$

and $\lambda(s) = s^n + a_1 s^{n-1} + \cdots + a_n$ is the characteristic polynomial for A .

11. Consider a closed loop system of the form of Figure 8.6 with $F = 1$ and P and C having a common pole. Show that if each system is written in state space form, the resulting closed loop system is not reachable and not observable.
12. The Physicist Ångström, who is associated with the length unit Å, used frequency response to determine thermal diffusivity of metals [Ång61]. Heat propagation in a metal rod is described by the partial differential equation

$$\frac{\partial T}{\partial t} = a \frac{\partial^2 T}{\partial x^2} - \mu T, \quad (8.25)$$

where $a = \frac{\lambda}{\rho C}$ is the thermal diffusivity, and the last term represents thermal loss to the environment. Show that the transfer function relating temperatures at points with the distance ℓ is

$$G(s) = e^{-\ell\sqrt{(s+\mu)/a}}, \quad (8.26)$$

and the frequency response is given by

$$\begin{aligned} \log |G(i\omega)| &= -\ell \sqrt{\frac{\mu + \sqrt{\omega^2 + \mu^2}}{2a}} \\ \arg G(i\omega) &= -\ell \sqrt{\frac{-\mu + \sqrt{\omega^2 + \mu^2}}{2a}}. \end{aligned}$$

Also derive the following equation

$$\log |G(i\omega)| \arg G(i\omega) = \frac{\ell^2 \omega}{2a}.$$

This remarkably simple formula shows that diffusivity can be determined from the value of the transfer function at one frequency. It was the key in Ångström's method for determining thermal diffusivity. Notice that the parameter μ which represents the thermal losses does not appear in the formula.

Chapter 9

Loop Analysis

Regeneration or feed-back is of considerable importance in many applications of vacuum tubes. The most obvious example is that of vacuum tube oscillators, where the feed-back is carried beyond the singing point. Another application is the 21-circuit test of balance, in which the current due to the unbalance between two impedances is fed back, the gain being increased until singing occurs. Still other applications are cases where portions of the output current of amplifiers are fed back to the input either unintentionally or by design. For the purpose of investigating the stability of such devices they may be looked on as amplifiers whose output is connected to the input through a transducer. This paper deals with the theory of stability of such systems.

Abstract for “Regeneration Theory”, Harry Nyquist, 1932 [Nyq32].

In this chapter we study how stability and robustness of closed loop systems can be determined by investigating how signals propagate around the feedback loop. The Nyquist stability theorem is a key result that provides a way to analyze stability and introduce measures of degrees of stability.

9.1 The Loop Transfer Function

The basic idea of loop analysis is to trace how a sinusoidal signal propagates in the feedback loop and explore the resulting stability by investigating if the signal grows or decays around the loop. This is easy to do because the transmission of sinusoidal signals through a (linear) dynamical system is characterized by the frequency response of the system. The key result is the Nyquist stability theorem, which provides a great deal of insight regarding the stability of a system. Unlike proving stability with Lyapunov functions,

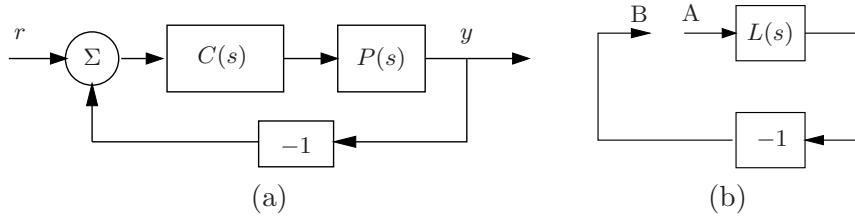


Figure 9.1: Block diagram of a (a) simple feedback system with (b) the loop opened at AB.

studied in Chapter 4, the Nyquist criterion allows us to determine more than just whether a system is stable or unstable. It provides a measure of the degree of stability through the definition of stability margins. The Nyquist theorem also indicates how an unstable system should be changed to make it stable, which we shall study in detail in Chapters 10–12.

Consider the system in Figure 9.1a. The traditional way to determine if the closed loop system is stable is to investigate if the closed loop characteristic polynomial has all its roots in the left half plane. If the process and the controller have rational transfer functions $P(s) = n_p(s)/d_p(s)$ and $C(s) = n_c(s)/d_c(s)$, then the closed loop system has the transfer function

$$G_{yr} = \frac{PC}{1 + PC} = \frac{n_p(s)n_c(s)}{d_p(s)d_c(s) + n_p(s)n_c(s)},$$

and the characteristic polynomial is

$$\lambda(s) = d_p(s)d_c(s) + n_p(s)n_c(s).$$

To check stability, we simply compute the roots of the characteristic polynomial and verify that they all have negative real part. This approach is straightforward but it gives little guidance for design: it is not easy to tell how the controller should be modified to make an unstable system stable.

Nyquist's idea was to investigate conditions under which oscillations can occur in a feedback loop. To study this, we introduce the *loop transfer function*,

$$L = PC,$$

which is the transfer function obtained by breaking the feedback loop, as shown in Figure 9.1. The loop transfer function is simply the transfer function from the input at position A to the output at position B.

We will first determine conditions for having a periodic oscillation in the loop. Assume that a sinusoid of frequency ω_0 is injected at point A. In steady state the signal at point B will also be a sinusoid with the frequency ω_0 . It seems reasonable that an oscillation can be maintained if the signal at B has the same amplitude and phase as the injected signal, because we could then connect A to B. Tracing signals around the loop we find that the signals at A and B are identical if

$$L(j\omega_0) = -1, \quad (9.1)$$

which provides a condition for maintaining an oscillation. The key idea of the Nyquist stability criterion is to understand when this can happen in a very general setting. As we shall see, this basic argument becomes more subtle when the loop transfer function has poles in the right half plane.

One of the powerful concepts embedded in Nyquist's approach to stability analysis is that it allows us to determine the stability of the feedback system by looking at properties of the open loop transfer function. This idea will turn out to be very important in how we approach designing transfer functions.

9.2 The Nyquist Criterion

In this section we present Nyquist's criterion for determining the stability of a feedback system through analysis of the loop transfer function. We begin by introducing a convenient graphical tool, the Nyquist plot, and showing how it can be used to ascertain stability.

The Nyquist Plot

The frequency response of the loop transfer function can be represented by plotting the complex number $L(j\omega)$ as a function of ω . Such a plot is called a *Nyquist plot* and the curve is called a *Nyquist curve*. An example of a Nyquist plot is given in Figure 9.2. The magnitude $|L(j\omega)|$ is called the *loop gain* because it tells how much the signal is amplified as it passes around the feedback loop.

The condition for oscillation given in equation (9.1) implies that the Nyquist curve of the loop transfer function goes through the point $L = -1$, which is called the *critical point*. Intuitively it seems reasonable that the system is stable if $|L(j\omega_c)| < 1$, which means that the critical point -1 is on the left hand side of the Nyquist curve, as indicated in Figure 9.2.

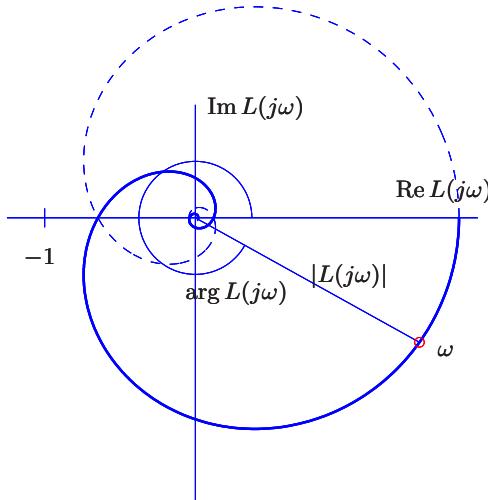


Figure 9.2: Nyquist plot of the transfer function $L(s) = 1.4e^{-s}/(s + 1)^2$. The gain and phase at the frequency ω are $g = |L(j\omega)|$ and $\varphi = \arg L(j\omega)$.

This means that the signal at point B will have smaller amplitude than the injected signal. This is essentially true, but there are several subtleties that require a proper mathematical analysis to clear up, and which we defer until the next section. For now we consider a simplified case, when the loop transfer function is stable.

For loop transfer functions that do not have poles in the right half plane, the precise stability condition is that the complete Nyquist plot does not encircle the critical point -1 . The complete Nyquist plot is obtained by adding the plot for negative frequencies shown in the dashed curve in Figure 9.2. This plot is the mirror image of the Nyquist curve about the real axis.

Theorem 9.1 (Simplified Nyquist criterion). *Let $L(s)$ be the loop transfer function for a negative feedback system (as shown in Figure 9.1) and assume that L has no poles in the closed right half plane ($\operatorname{Re} s \geq 0$). Then the closed loop system is stable if and only if the closed contour given by $\Omega = \{L(j\omega) : -\infty < \omega < \infty\} \subset \mathbb{C}$ has no net encirclements of $s = -1$.*

The following conceptual procedure can be used to determine that there are no encirclements: Fix a pin at the critical point $s = -1$ orthogonal to the plane. Attach a string with one end at the critical point and the other to the Nyquist plot. Let the end of the string attached to the Nyquist curve traverse the whole curve. There are no encirclements if the cord does not

wind up on the pin when the curve is encircled.

Example 9.1 (Cruise control). Consider the speed control system introduced in Section 3.1 and analyzed using state space techniques in Example 6.9. In this example, we study the stability of the system using the Nyquist criterion.

The linearized dynamics around the equilibrium speed v_e and throttle position u_e are given by

$$\begin{aligned}\dot{\tilde{v}} &= a\tilde{v} - g\theta + b\tilde{u} \\ y &= v = \tilde{v} + v_e,\end{aligned}$$

where $\tilde{v} = v - v_e$, $\tilde{u} = u - u_e$, m is the mass of the car and θ is the angle of the road. The constant $a < 0$ depends on the throttle characteristic and is given in Example 5.10.

The transfer function from throttle to speed is given by

$$P(s) = G_{yu}(s) = \frac{b}{s - \alpha}.$$

We consider a controller that is a modified version of the proportional-integral (PI) controller given previously. Assume that the transfer function of the controller is

$$C(s) = G_{ue}(s) = k_p + \frac{k_i}{s + \beta} = \frac{k_p s + k_i + k_p \beta}{s + \beta}$$

giving a loop transfer function of

$$L(s) = b \frac{k_p s + k_i + k_p \beta}{(s + a)(s + \beta)}.$$

The Nyquist plot for the system, using $a = 0.0101$, $b = 1.3203$, $k_p = 0.5$, $k_i = 0.1$ and $\beta = 0.1$, is shown in Figure 9.3. We see from the Nyquist plot that the closed loop system is stable, since there are no net encirclements of the -1 point. ∇

One nice property of the Nyquist stability criterion is that it can be applied to infinite dimensional systems, as is illustrated by the following example. 

Example 9.2 (Heat conduction). Consider a temperature control system where the heat conduction process has the transfer function

$$P(s) = e^{-\sqrt{s}}$$

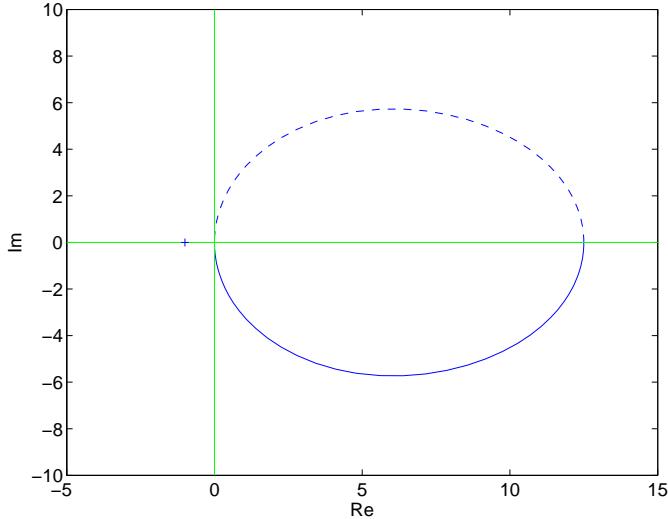


Figure 9.3: Nyquist plot for the speed control system.

and the controller is a proportional controller with gain k . The loop transfer function is $L(s) = ke^{-\sqrt{s}}$ and its Nyquist plot for $k = 1$ is shown in Figure 9.4. To compute the stability condition for the system as a function of the gain k , we analyze the transfer function a bit more carefully. We have

$$P(j\omega) = e^{-\sqrt{j\omega}} = e^{-\sqrt{\omega/2} - i\sqrt{\omega/2}}$$

and hence

$$\log P(j\omega) = -\sqrt{j\omega} = -\frac{\omega\sqrt{2}}{2} - i\frac{\omega\sqrt{2}}{2}$$

and

$$\arg L(j\omega) = -\frac{\omega\sqrt{2}}{2}.$$

The phase is $-\pi$ for $\omega = \omega_c = \pi/\sqrt{2}$ and the gain at that frequency is $ke^{-\pi} \approx 0.0432k$. The Nyquist plot for a system with gain k is obtained simply by multiplying the Nyquist curve in the figure by k . The Nyquist curve reaches the critical point $L = -1$ for $k = e^\pi = 23.1$. The complete Nyquist curve in Figure 9.4 shows that the Nyquist curve does not encircle the critical point if $k < e^\pi$, giving a stability condition for the system. ∇

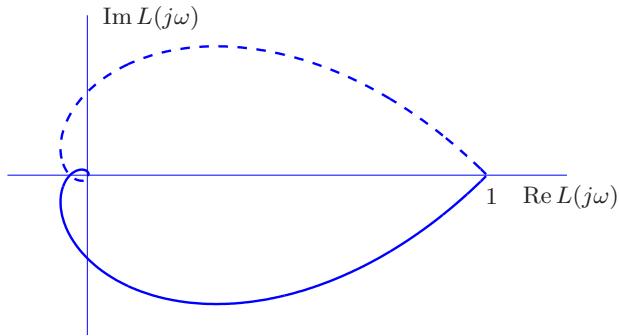


Figure 9.4: Nyquist plot of the transfer function $L(s) = e^{-\sqrt{s}}$

Nyquist's Stability Theorem



We will now state and prove the Nyquist stability theorem for a general loop transfer function $L(s)$. This requires some results from the theory of complex variables, for which the reader can consult [?] and the references therein. Since some precision is needed in stating Nyquist's criterion properly, we will also use a more mathematical style of presentation. The key result is the following theorem about functions of complex variables.

Theorem 9.2 (Principle of variation of the argument). *Let D be a closed region in the complex plane and let Γ be the boundary of the region. Assume the function $f : \mathbb{C} \rightarrow \mathbb{C}$ is analytic in D and on Γ , except at a finite number of poles and zeros. Then the winding number, w_n , is given by*

$$w_n = \frac{1}{2\pi} \Delta_\Gamma \arg f(z) = \frac{1}{2\pi i} \int_\Gamma \frac{f'(z)}{f(z)} dz = N - P,$$

where Δ_Γ is the net variation in the angle along the contour Γ , N is the number of zeros and P the number of poles in D . Poles and zeros of multiplicity m are counted m times.

Proof. Assume that $z = a$ is a zero of multiplicity m . In the neighborhood of $z = a$ we have

$$f(z) = (z - a)^m g(z),$$

where the function g is analytic and different from zero. The ratio of the derivative of f to itself is then given by

$$\frac{f'(z)}{f(z)} = \frac{m}{z-a} + \frac{g'(z)}{g(z)}$$

and the second term is analytic at $z = a$. The function f'/f thus has a single pole at $z = a$ with the residue m . The sum of the residues at the zeros of the function is N . Similarly we find that the sum of the residues of the poles of is $-P$. Furthermore we have

$$\frac{d}{dz} \log f(z) = \frac{f'(z)}{f(z)},$$

which implies that

$$\int_{\Gamma} \frac{f'(z)}{f(z)} dz = \Delta_{\Gamma} \log f(z),$$

where Δ_{Γ} again denotes the variation along the contour Γ . We have

$$\log f(z) = \log |f(z)| + i \arg f(z).$$

Since the variation of $|f(z)|$ around a closed contour is zero we have

$$\Delta_{\Gamma} \log f(z) = i \Delta_{\Gamma} \arg f(z)$$

and the theorem is proven. \square

This theorem is useful for determining the number of poles and zeros of a function of complex variables in a given region. By choosing an appropriate closed region D with boundary Γ , we can determine the difference between the number of poles and zeros through computation of the winding number.

Theorem 9.2 can be used to prove Nyquist's stability theorem by choosing Γ as the Nyquist contour shown in Figure 9.5, which encloses the right half plane. To construct the contour, we start with part of the imaginary axis $-iR \leq s \leq iR$, and a semicircle to the right with radius R . If the function f has poles on the imaginary axis we introduce small semicircles with radii r to the right of the poles as shown in the figure. The Nyquist contour is obtained by letting $R \rightarrow \infty$ and $r \rightarrow 0$. We call the contour Γ the full Nyquist contour, sometimes call the “ D contour”.

To see how we used this to compute stability, consider a closed loop system with the loop transfer function $L(s)$. The closed loop poles of the system are the zeros of the function

$$f(s) = 1 + L(s).$$

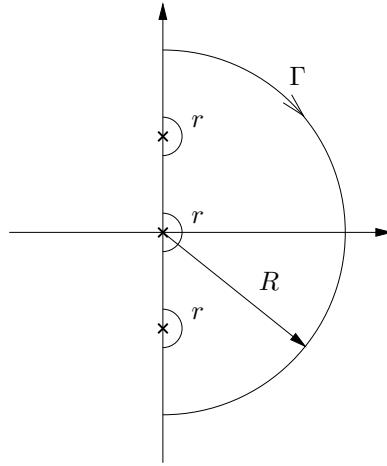


Figure 9.5: The Nyquist contour Γ .

To find the number of zeros in the right half plane, we investigate the winding number of the function $f(s) = 1 + L(s)$ as s moves along the Nyquist contour Γ in the clockwise direction. The winding number can conveniently be determined from the Nyquist plot. A direct application of the Theorem 9.2 gives the following result.

Theorem 9.3 (Nyquist's stability theorem). *Consider a closed loop system with the loop transfer function $L(s)$, which which has P poles in the region enclosed by the Nyquist contour. Let w_n be the winding number of the function $f(s) = 1 + L(s)$ when s encircles the Nyquist contour Γ . The closed loop system then has $w_n + P$ poles in the right half plane.*

Since the image of $1 + L(s)$ is simply a shifted version of $L(s)$, we usually restate the Nyquist criterion as net encirclements of the -1 point by the image of $L(s)$.

There is a subtlety with the Nyquist plot when the loop transfer function has poles on the imaginary axis because the gain is infinite at the poles. This means that the map of the small semicircles are infinitely large half circles. When plotting Nyquist curves on the computer, one must be careful to see that the such poles are properly handled and often one must sketch those portions of the Nyquist plot by hand, being careful to loop the right way around the poles.

We illustrate Nyquist's theorem by a series of examples.

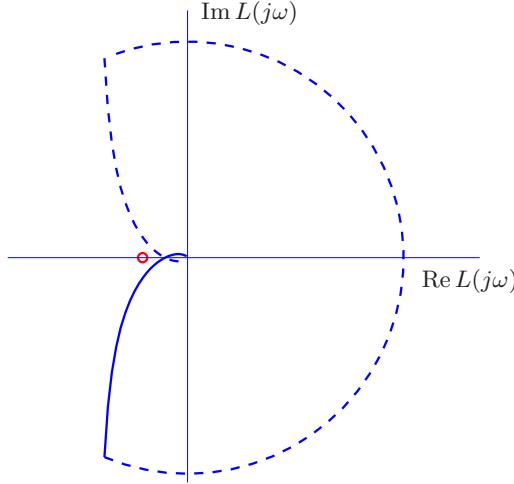


Figure 9.6: The complete Nyquist curve for the loop transfer function $L(s) = \frac{k}{s(s+1)^2}$. The curve is drawn for $k < 2$. The map of the positive imaginary axis is shown in full lines, the map of the negative imaginary axis and the small semi circle at the origin in dashed lines.

Example 9.3. Consider a closed loop system with the loop transfer function

$$L(s) = \frac{k}{s(s+1)^2}.$$

Figure 9.6 shows the image of the contour Γ under the map L . The loop transfer function does not have any poles in the region enclosed by the Nyquist contour. By computing the phase of L , one can show that the Nyquist plot intersects the imaginary axis for $\omega = 1$ and the intersection is at $-k/2$. It follows from Figure 9.6 that the winding number is zero if $k < 2$ and 2 if $k > 2$. We can thus conclude that the closed loop system is stable if $k < 2$ and that the closed loop system has two roots in the right half plane if $k > 2$. ∇

Next we will consider a case where the loop transfer function has a pole inside the Nyquist contour.

Example 9.4 (Loop transfer function with RHP pole). Consider a feedback system with the loop transfer function

$$L(s) = \frac{k}{s(s-1)(s+5)}.$$

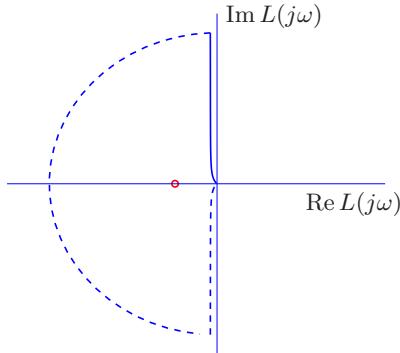


Figure 9.7: Complete Nyquist plot for the loop transfer function $L(s) = \frac{k}{s(s-1)(s+5)}$. The map of the positive imaginary axis is shown in full lines, the map of the negative imaginary axis and the small semi circle at the origin in dashed lines.

This transfer function has a pole at $s = 1$ which is inside the Nyquist contour. The complete Nyquist plot of the loop transfer function is shown in Figure 9.7. Traversing the contour Γ in clockwise we find that the winding number is $w_n = 1$. It follows from the principle of the variation of the argument that the closed loop system has $w_n + P = 2$ poles in the right half plane and hence is unstable. ∇

Normally, we find that unstable systems can be stabilized simply by reducing the loop gain. There are however situations where a system can be stabilized by increasing the gain. This was first encountered by electrical engineers in the design of feedback amplifiers who coined the term *conditional stability*. The problem was actually a strong motivation for Nyquist to develop his theory. We will illustrate by an example.

Example 9.5 (Conditional stability). Consider a feedback system with the loop transfer function

$$L(s) = \frac{3(s+1)^2}{s(s+6)^2}. \quad (9.2)$$

The Nyquist plot of the loop transfer function is shown in Figure 9.8. Notice that the Nyquist curve intersects the negative real axis twice. The first intersection occurs at $L = -12$ for $\omega = 2$ and the second at $L = -4.5$ for $\omega = 3$. The intuitive argument based on signal tracing around the loop in Figure 9.1 is strongly misleading in this case. Injection of a sinusoid with frequency 2 rad/s and amplitude 1 at A gives, in steady state, an oscillation

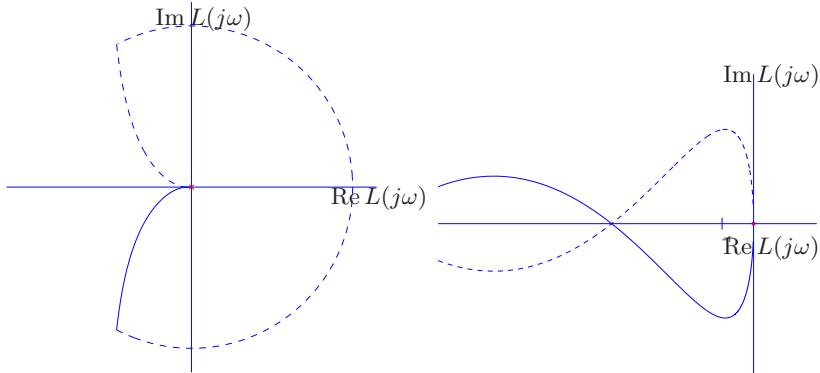


Figure 9.8: Nyquist curve for the loop transfer function $L(s) = \frac{3(s+1)^2}{s(s+6)^2}$. The plot on the right is an enlargement of the area around the origin of the plot on the left.

at B that is in phase with the input and has amplitude 12. Intuitively it is seems unlikely that closing of the loop will result a stable system. It follows from Nyquist's stability criterion that the system is stable because the critical point is to the left of the Nyquist curve when it is traversed for increasing frequencies. ∇

9.3 Stability Margins

In practice it is not enough that a system is stable. There must also be some margins of stability that describe how stable the system is and its robustness to perturbations. There are many ways to express this, but one of the most common is the use of gain and phase margins, inspired by Nyquist's stability criterion. The key idea is that it is easy to plot of the loop transfer function $L(s)$. An increase of controller gain simply expands the Nyquist plot radially. An increase of the phase of the controller twists the Nyquist plot clockwise. Hence from the Nyquist plot we can easily pick off the amount of gain or phase that can be added without causing the system to go unstable.

Let ω_{180} be the *phase crossover frequency*, which is the smallest frequency where the phase of the loop transfer function $L(s)$ is -180° . The *gain margin* is defined as

$$g_m = \frac{1}{|L(j\omega_{180})|}. \quad (9.3)$$

It tells how much the controller gain can be increased before reaching the stability limit.

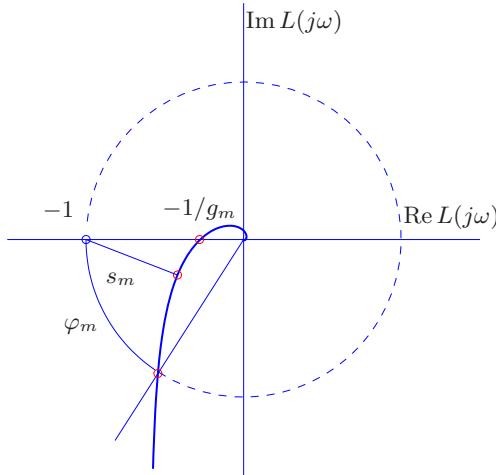


Figure 9.9: Nyquist plot of the loop transfer function L with gain margin g_m , phase margin φ_m and stability margin s_m .

Similarly, let ω_{gc} be the gain crossover frequency, the lowest frequency where the loop transfer function $L(s)$ has unit magnitude. The phase margin is

$$\varphi_m = \pi + \arg L(j\omega_{gc}), \quad (9.4)$$

the amount of phase lag required to reach the stability limit. The margins have simple geometric interpretations in the Nyquist diagram of the loop transfer function as is shown in Figure 9.9.

A drawback with gain and phase margins is that it is necessary to give both of them in order to guarantee that the Nyquist curve not is close to the critical point. An alternative way to express margins is by a single number, the *stability margin*, s_m , which is the shortest distance from the Nyquist curve to the critical point. This number also has other nice interpretations as will be discussed in Chapter 12.

When we are designing feedback systems, it will often be useful to define the robustness of the system using gain, phase and stability margins. These numbers tell us how much the system can vary from our nominal model and still be stable. Reasonable values of the margins are phase margin $\varphi_m = 30^\circ - 60^\circ$, gain margin $g_m = 2 - 5$, and stability margin $s_m = 0.5 - 0.8$.

There are also other stability measures, such as the *delay margin*, which is the smallest time delay required to make the system unstable. For loop transfer functions that decay quickly the delay margin is closely related to

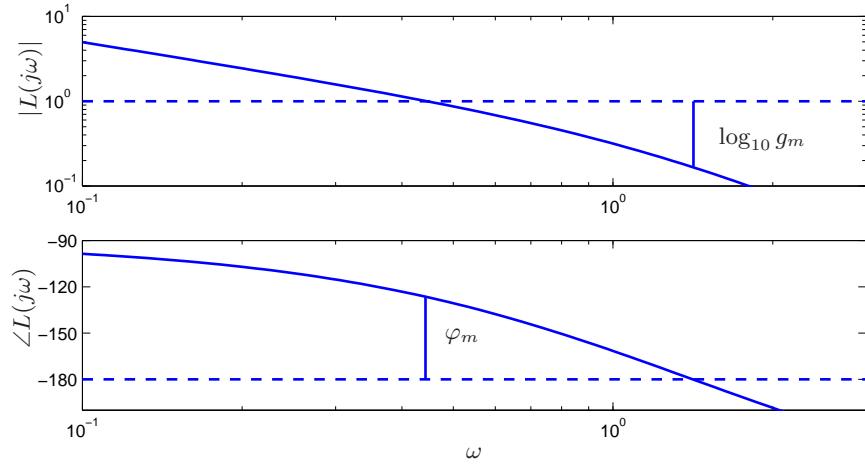


Figure 9.10: Finding gain and phase margins from the Bode plot of the loop transfer function. The loop transfer function is $L(s) = 1/(s(s+1)(s+2))$, the gain margin is $g_m = 6.0$, the gain crossover frequency $\omega_{gc} = 1.42$, the phase margin is $\varphi_m = 53^\circ$ at the phase crossover frequency $\omega = 0.44$.

the phase margin but for systems where the amplitude ratio of the loop transfer function has several peaks at high frequencies the delay margin is a more relevant measure. A more detailed discussion of robustness measures is given in Chapter 12.

Gain and phase margins can also be determined from the Bode plot of the loop transfer function. A change of controller gain translates the gain curve vertically and it has no effect on the phase curve. To determine the gain margin we first find the phase crossover frequency ω_{180} where the phase is -180° . The gain margin is the inverse of the gain at that frequency. To determine the phase margin we first determine the gain crossover frequency ω_{gc} , i.e. the frequency where the gain of the loop transfer function is one. The phase margin is the phase of the loop transfer function at that frequency plus 180° . Figure 9.10 illustrates how the margins are found in the Bode plot of the loop transfer function. The stability margin cannot easily be found from the Bode plot of the loop transfer function. There are however other Bode plots that will give s_m ; these will be discussed in Chapter 12.

Example 9.6 (Vehicle steering). Consider the linearized model for vehicle steering with a controller based on state feedback. The transfer function of

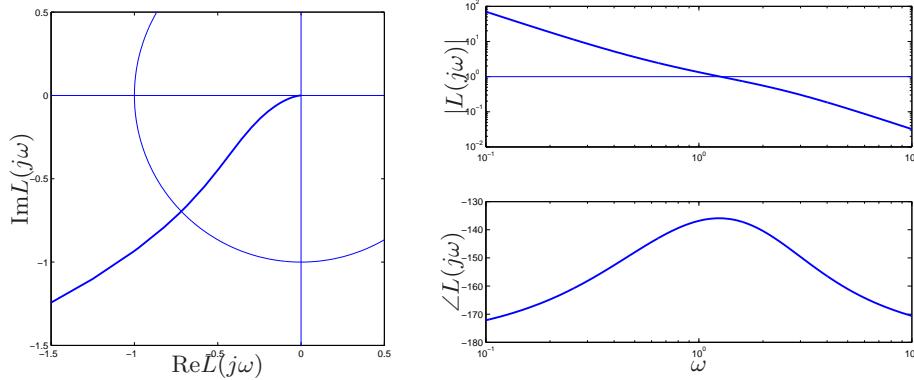


Figure 9.11: Nyquist (left) and Bode (right) plots of the loop transfer function for vehicle steering with a controller based on state feedback and an observer.

the process is

$$P = \frac{\alpha s + 1}{s^2}.$$

and the controller has the transfer function

$$C = \frac{s(k_1 l_1 + k_2 l_2) + k_1 l_2}{s^2 + s(\alpha k_1 + k_2 + l_1) + k_1 + l_2 + k_2 l_1 - \alpha k_2 l_2},$$

as computed in Example 8.4. The Nyquist and Bode plots of the loop transfer function $L = PC$ for the process parameter $a = 0.5$, and a controller characterized by $\omega_c = 1$, $\zeta_c = 0.707$, $\omega_o = 2$, $\zeta_o = 0.707$ are shown in Figure 9.11. The gains of the state feedback are $k_1 = 1$ and $k_2 = 0.914$, and the observer gains are $l_1 = 2.828$ and $l_2 = 4$. The phase margin of the system is 44° and the gain margin is infinite since the phase lag is never greater than 180° , indicating that the closed loop system is robust. ∇

Example 9.7 (Pupillary light reflex dynamics). The pupillary light reflex dynamics was discussed in Example 8.7. Stark found a clever way to artificially increase the loop gain by focusing a narrow beam at the boundary of the pupil. It was possible to increase the gain so much that the pupil started to oscillate. The Bode plot in Figure 9.12b shows that the phase crossover frequency is $\omega_{gc} = 8$ rad/s. This is in good agreement with Stark's experimental investigations which gave an average frequency of 1.35 Hz or 8.5 rad/s. ∇

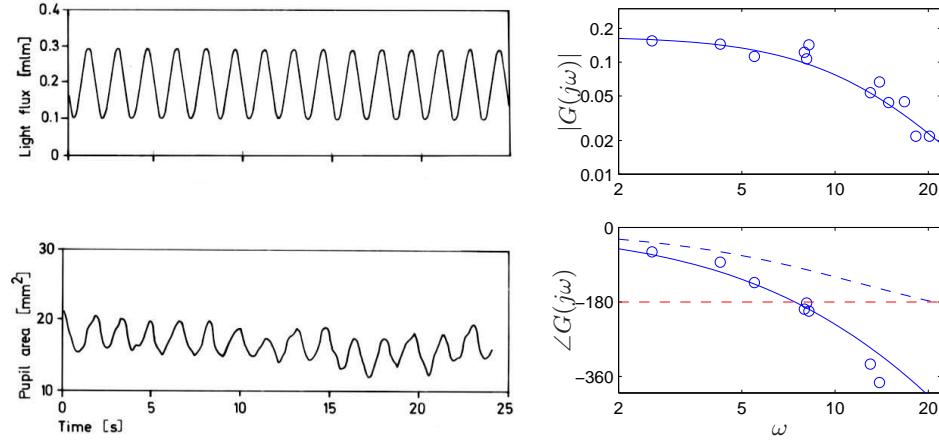


Figure 9.12: Sample curves from open loop frequency response of the eye (left) and Bode plot for the open loop dynamics (right). See Example 8.7 for a detailed description.

9.4 Bode's Relations

An analysis of Bode plots reveals that there appears to be a relation between the gain curve and the phase curve. Consider for example the Bode plots for the differentiator and the integrator (shown in Figure 8.10). For the differentiator the slope is +1 and the phase is constant $\pi/2$ radians. For the integrator the slope is -1 and the phase is $-\pi/2$. For the first order system $G(s) = s + a$, the amplitude curve has the slope 0 for small frequencies and the slope +1 for high frequencies and the phase is 0 for low frequencies and $\pi/2$ for high frequencies.

Bode investigated the relations between the curves for systems with no poles and zeros in the right half plane. He found that the phase was uniquely given by the gain and vice versa:

$$\begin{aligned} \arg G(j\omega_0) &= \frac{1}{\pi} \int_0^\infty \frac{d \log |G(j\omega)|}{d \log \omega} \log \left| \frac{\omega + \omega_0}{\omega - \omega_0} \right| d \log \omega \\ &\quad \frac{\pi}{2} \int_0^\infty f(\omega) \frac{d \log |G(j\omega)|}{d \log \omega} d \log \omega \approx \frac{\pi}{2} \frac{d \log |G(j\omega)|}{d \log \omega}, \end{aligned} \quad (9.5)$$

where f is the weighting kernel

$$f(\omega) = \frac{2}{\pi^2} \log \left| \frac{\omega + \omega_0}{\omega - \omega_0} \right| = \frac{2}{\pi^2} \log \left| \frac{\frac{\omega}{\omega_0} + 1}{\frac{\omega}{\omega_0} - 1} \right|.$$

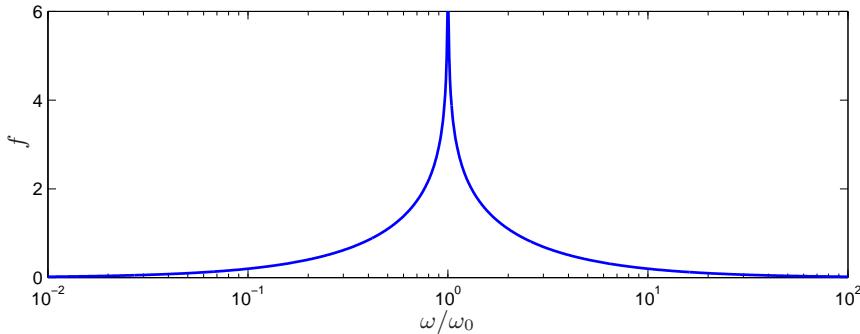


Figure 9.13: The weighting kernel f in Bode's formula for computing the phase curve from the gain curve for minimum phase systems.

The phase curve is thus a weighted average of the derivative of the gain curve. The weight w is shown in Figure 9.13. Notice that the weight falls off rapidly and it is practically zero when the frequency has changed by a factor of ten. It follows from equation (9.5) that a slope of +1 corresponds to a phase of $\pi/2$ or 90° . Compare with Figure 8.10, where the Bode plots have constant slopes -1 and $+1$.

Non-Minimum Phase Systems

Bode's relations hold for systems that do not have poles and zeros in the left half plane. Such systems are called *minimum phase systems* because systems with poles and zeros in the right half plane have larger phase lag. The distinction is important in practice because minimum phase systems are easier to control than systems with larger phase lag. We will now give a few examples of non-minimum phase transfer functions.

Example 9.8 (Time delay). The transfer function of a time delay of T units is $G(s) = e^{-sT}$. This transfer function has unit gain, $|G(j\omega)| = 1$, and the phase is

$$\arg G(j\omega) = -\omega T.$$

The corresponding minimum phase system with unit gain has the transfer function $G(s) = 1$. The time delay thus has an additional phase lag of ωT . Notice that the phase lag increases linearly with frequency. Figure 9.14 shows the Bode plot of the transfer function. (Because we use a log scale for frequency, the phase falls off much faster than linearly in the plot.) ∇

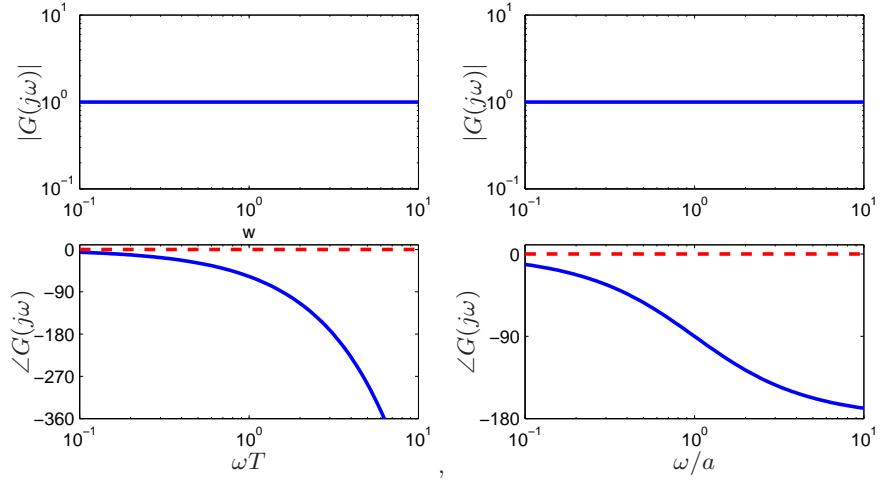


Figure 9.14: Bode plots of a time delay $G(s) = e^{-sT}$ (left) and a system with a right half plane zero $G(s) = (a - s)/(a + s)$ (right). The dashed lines show the phase curves of the corresponding minimum phase systems.

It seems intuitively reasonable that it is impossible to make a system with a time delay respond faster than without the time delay. The presence of a time delay will thus limit the response speed of a system.

Example 9.9 (System with a RHP zero). Consider a system with the transfer function

$$G(s) = \frac{a - s}{a + s}, \quad a > 0,$$

which has a zero $s = a$ in the right half plane. The transfer function has unit gain, $|G(j\omega)| = 1$, and

$$\arg G(j\omega) = -2 \arctan \frac{\omega}{a}.$$

The corresponding minimum phase system with unit gain has the transfer function $G(s) = 1$. Figure 9.14 shows the Bode plot of the transfer function. The Bode plot resembles the Bode plot for a time delay, which is not surprising because the exponential function e^{-sT} can be approximated by

$$e^{-sT} \approx \frac{1 - sT/2}{1 + sT/2}.$$

As far as minimum phase properties are concerned, a right half plane zero at $s = a$ is thus similar to a time delay of $T = 2/a$. Since long time delays

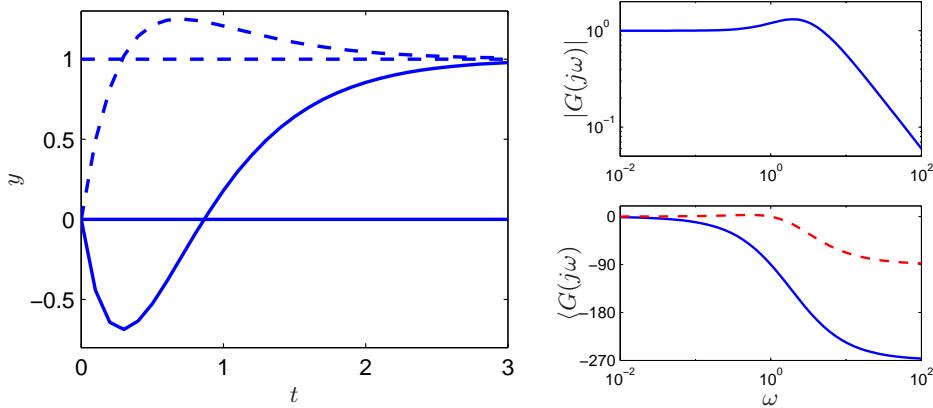


Figure 9.15: Step responses (left) and Bode plots (right) of a system with a zero in the right half plane (full lines) and the corresponding minimum phase system (dashed).

create difficulties in controlling a system we may expect that systems with zeros close to the origin are also difficult to control. ∇

Figure 9.15 shows the step response of a system with the transfer function

$$G(s) = \frac{6(-s+1)}{s^2 + 5s + 6},$$

which has a zero in the right half plane. Notice that the output goes in the wrong direction initially, which is also referred to as an *inverse response*. The figure also shows the step response of the corresponding minimum phase system, which has the transfer function

$$G(s) = \frac{6(s+1)}{s^2 + 5s + 6}.$$

The curves show that the minimum phase system responds much faster. It thus appears that a the non-minimum phase system is more difficult to control. This is indeed the case, as will be shown in Section 11.4.

The presence of poles and zeros in the right half plane imposes severe limitations on the achievable performance. Dynamics of this type should be avoided by redesign of the system, whenever possible. While the poles are intrinsic properties of the system and they do not depend on sensors and actuators, the zeros depend on how inputs and outputs of a system are coupled to the states. Zeros can thus be changed by moving sensors

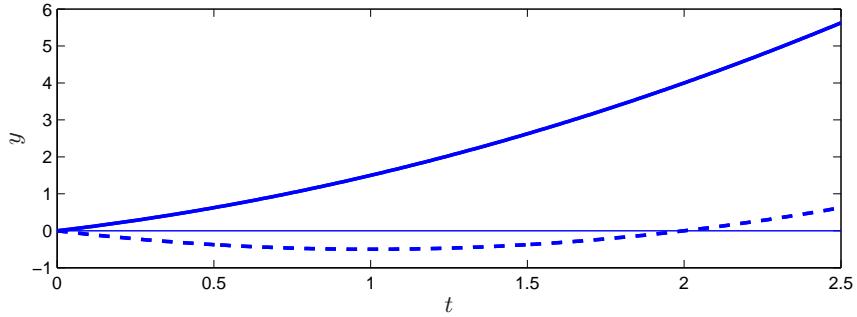


Figure 9.16: Step responses from steer angle to lateral translation for simple kinematics model when driving forward (full) and reverse (dashed).

and actuators or by introducing new sensors and actuators. Non-minimum phase systems are unfortunately not uncommon in practice.

The following example gives a system theoretic interpretation of the common experience that it is more difficult to drive in reverse gear and illustrates some of the properties of transfer functions in terms of their poles and zeros.

Example 9.10 (Vehicle steering). The un-normalized transfer function from steer angle to lateral translation for the simple vehicle model is

$$P(s) = G_{y\delta}(s) = \frac{av_0s + v_0^2}{bs^2}$$

The transfer function has a zero at $s = v_0/a$. In normal driving this zero is in the left half plane but when reversing the zero moves to the right half plane, which makes the system more difficult to control. Figure 9.16 shows the step response for forward and reverse driving, the parameters are $a = b = 1$, $v_0 = 1$ for forward driving and $v_0 = -1$ for reverse driving. The figure shows that with reverse driving the lateral motion is initially opposite to the desired motion. The action of the zero can also be interpreted as a delay of the control action. ∇



9.5 The Notion of Gain

A key idea in loop analysis is to trace the behavior of signals through a system. The concepts of gain and phase represented by the magnitude and the angle of a transfer function are strongly intuitive because they describe

how sinusoidal signals are transmitted. We will now show that the notion of gain can be defined in a much more general way. Something has to be given up to do this and it turns out that it is difficult to define gain for transmission of general signal but that it is easy to define the maximum gain. For this purpose we first define appropriate classes of input and output signals, $u \in \mathcal{U}$ and $y \in \mathcal{Y}$, where \mathcal{U} and \mathcal{Y} are spaces where a notion of magnitude is defined. The gain of a system is defined as

$$\gamma = \sup_{u \in \mathcal{U}} \frac{\|y\|}{\|u\|}, \quad (9.6)$$

where sup is the *supremum*, defined as the smallest number that is larger than its argument. The reason for using supremum is that the maximum may not be defined for $u \in \mathcal{U}$. A correct treatment requires considerable care and space so will will only give a few examples.

Example 9.11 (Linear systems with square integrable inputs). Let the input space \mathcal{U} be square integrable functions, and consider a stable linear system with transfer function $G(s)$. The norm of a signal is given by

$$\|u\|_2 = \sqrt{\int_0^\infty u^2(\tau) d\tau}$$

where the subscript 2 refers to the fact that \mathcal{U} is the set of square integrable functions. Using the same norm for \mathcal{Y} , the gain of the system can be shown to be

$$\gamma = \sup_{\omega} |G(j\omega)| := \|G\|_\infty. \quad (9.7)$$

∇

Example 9.12 (Static nonlinear system). Consider a nonlinear static system with scalar inputs and outputs described by $y = f(u)$. The gain obtained γ is a number such that $-\gamma u \leq |f(u)| \leq \gamma u$. The gain thus defines a sector that encloses the function. ∇

Example 9.13 (Multivariable static system). Consider a static multivariable system $y = Au$, where A is a matrix, whose elements are complex numbers. The matrix does not have to be square. Let the and inputs and outputs be vectors whose elements are complex numbers and use the Euclidean norm

$$\|u\| = \sqrt{\sum |u_i|^2}.$$

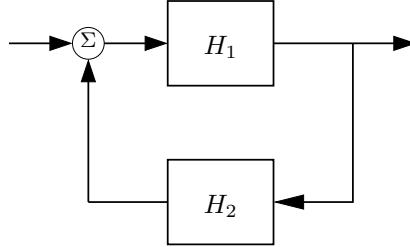


Figure 9.17: A simple feedback loop.

The norm of the output is

$$\|y\|^2 = u^* A^* A u,$$

where $*$ denotes the complex conjugate transpose. The matrix $A^* A$ is symmetric and positive semidefinite, and the right hand side is a quadratic form. The eigenvalues $\lambda(A)$ of the matrix $A^* A$ are all real and we have

$$\|y\|^2 \leq \lambda_{\max}(A^* A) \|u\|^2.$$

The gain is thus

$$\gamma = \sqrt{\lambda_{\min}(A^* A)} \quad (9.8)$$

The eigenvalues of the matrix $A^* A$ are called the *singular values* of the matrix and the largest singular value is denoted $\bar{\sigma}(A)$ respectively. ∇

Example 9.14 (Linear multivariable dynamic system). For a linear system multivariable system with a real rational transfer function matrix $G(s)$. Let the input be square integrable functions. The gain of the system is then we have

$$\gamma = \|G(j\omega)\|_\infty = \inf_\omega \bar{\sigma}(G(j\omega)). \quad (9.9)$$

∇

For linear systems it follows from Nyquist's theorem that the closed loop is stable if the gain of the loop transfer function is less than one for all frequencies. This result can be extended to much larger class of systems by using the concept of the gain of a system. Consider the closed loop system in Figure 9.17. Let the gains of the systems H_1 and H_2 be γ_1 and γ_2 . The *small gain theorem* says that the closed loop system is input/output stable if $\gamma_1 \gamma_2 < 1$, and the gain of the closed loop system is

$$\gamma = \frac{\gamma_1}{1 - \gamma_1 \gamma_2}$$

Notice that if systems H_1 and H_2 are linear it follows from the Nyquist stability theorem that the closed loop is stable, because if $\gamma_1\gamma_2 < 1$ the Nyquist curve is always inside the unit circle. The small gain theorem is thus an extension of the Nyquist stability theorem.

It also follows from the Nyquist stability theorem that a closed loop system is stable if the phase of the loop transfer function is between $-\pi$ and π . This result can also be extended to nonlinear systems as well. It is called the *passivity theorem* and is closely related to the small gain theorem.

Additional applications of the small gain theorem and its application to robust stability are given in Chapter 12.

9.6 Further Reading

Nyquist's original paper giving his now famous stability criterion was published in the Bell Systems Technical Journal in 1932 [Nyq32].

9.7 Exercises

1. Use the Nyquist theorem to analyze the stability of the speed control system in Example 9.1, but using the original PI controller from Example 6.9.
2. Discrete time Nyquist
3. Example systems:

Chapter 10

PID Control

Based on a survey of over eleven thousand controllers in the refining, chemicals and pulp and paper industries, 97% of regulatory controllers utilize PID feedback.

Desborough Honeywell, 2000, see [DM02].

PID control is by far the most common way of using feedback in natural and man-made systems. PID controllers are commonly used in industry and a large factory may have thousands of them, in instruments and laboratory equipment. In engineering applications the controllers appear in many different forms: as a stand alone controller, as part of hierarchical, distributed control systems, or built into embedded components. Most controllers do not use derivative action. In this chapter we discuss the basic ideas of PID control and the methods for choosing the parameters of the controllers. Many aspects of control can be understood based on linear analysis. However, there is one nonlinear effect, that has to be considered in most control systems namely that actuators saturate. In combinations with controllers having integral actions saturations give rise to an effect called *integral windup*. This phenomenon that occurs in practically all control systems will be discussed in depth for PID controllers. Methods to avoid windup will also be presented. Finally we will also discuss implementation of PID controllers, similar methods can be used to implement many other controllers.

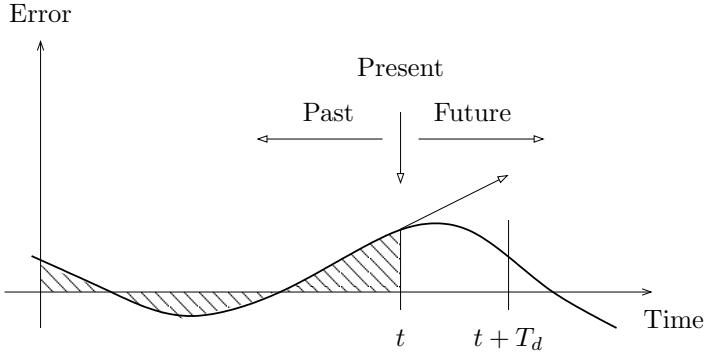


Figure 10.1: A PID controller takes control action based on past, present and prediction of future control errors.

10.1 The Controller

The ideal version of the PID controller is given by the formula

$$u(t) = k_p e(t) + k_i \int_0^t e(\tau) d\tau + k_d \frac{de}{dt}, \quad (10.1)$$

where u is the control signal and e is the control error ($e = r - y$). The reference value, r , is also called the *setpoint*. The control signal is thus a sum of three terms: a proportional term that is proportional to the error, an integral term that is proportional to the integral of the error, and a derivative term that is proportional to the derivative of the error. The controller parameters are proportional gain k_p , integral gain k_i and derivative gain k_d . The controller can also be parameterized as

$$u(t) = k_p \left(e(t) + \frac{1}{T_i} \int_0^t e(\tau) d\tau + T_d \frac{de(t)}{dt} \right), \quad (10.2)$$

where T_i is the integral time constant and T_d the derivative time constant. The proportional part acts on the present value of the error, the integral represents an average of past errors and the derivative can be interpreted as a prediction of future errors based on linear extrapolation, as illustrated in Figure 10.1. Note that the control signal u is formed entirely from the error e , there is no feedforward term (which would correspond to $k_r r$ in the state feedback case). In Section 10.5 we will introduce a modification which also uses feedforward.

We begin our analysis by considering pure proportional feedback. Figure 10.2a shows the responses of the output to a unit step in the command

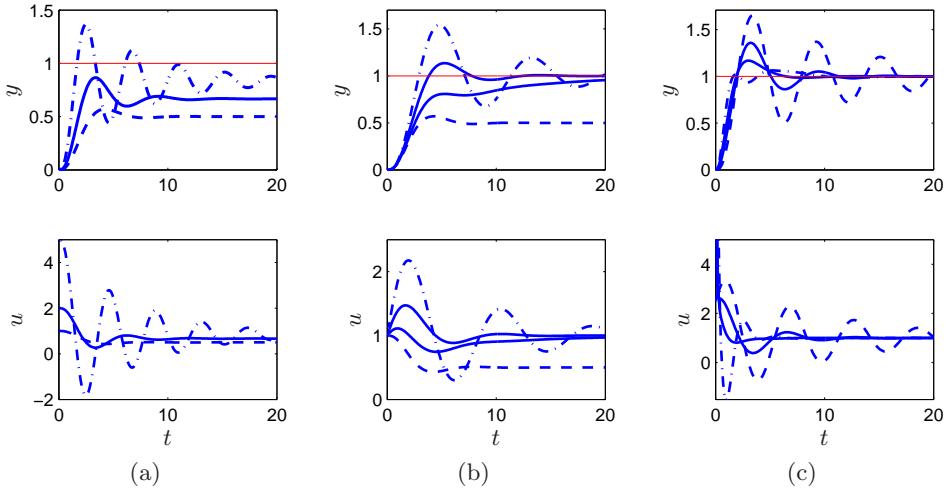


Figure 10.2: Responses to step changes in the command signal for a proportional controller (left), PI controller (center) and PID controller (right). The process has the transfer function $P(s) = 1/(s + 1)^3$, the proportional controller (left) had parameters $k_p = 1$ (dashed), 2 and 5 (dash-dotted), the PI controller has parameters $k_p = 1$, $k_i = 0$ (dashed), 0.2, 0.5 and 1 (dash-dotted), and the PID controller has parameters are $k_p = 2.5$, $k_i = 1.5$ and $k_d = 0$ (dashed), 1, 2, 3 and 4 (dash-dotted).

signal for a system with pure proportional control at different gain settings. In the absence of a feedforward term, the output never reaches the reference and hence we are left with non-zero steady state error. Letting the process and the controller have transfer functions $P(s)$ and $C(s)$, the transfer function from reference to output is

$$G_{yr} = \frac{PC}{1 + PC}. \quad (10.3)$$

The zero frequency gain with proportional control $C(s) = k_p$ is

$$G_{yr}(0) = \frac{P(0)k_p}{1 + P(0)k_p}$$

and thus the steady state error for a unit step is $1 - G_{yr}(0) = 1/(1 + k_p P(0))$. For the system in Figure 10.2a with gains $k_p = 1, 2$ and 5 , the steady state error is $0.5, 0.33$ and 0.17 . The error decreases with increasing gain, but the system also becomes more oscillatory. Notice in the figure that the initial value of the control signal equals the controller gain.

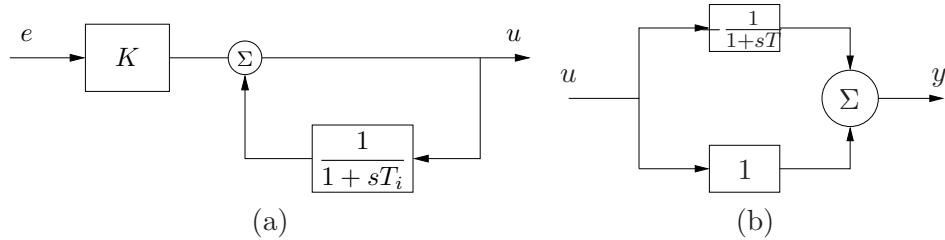


Figure 10.3: Implementation of integral action (left) and derivative action (right) by combining simple blocks.

To avoid having a steady state error, the proportional controller can be changed to

$$u(t) = k_p e(t) + u_d, \quad (10.4)$$

where u_d is a feedforward term that is adjusted to give the desired steady state value. If we choose $u_d = r/P(0) = k_r r$, then the output will be exactly equal to the reference value, as it was in the state space case. However, this requires exact knowledge of the process dynamics, which is usually not available. In early controllers the term u_d , which was also called the reset, was adjusted manually to obtain the desired steady state.

As we saw in Sections 1.5 and 6.4, integral action guarantees that the process output agrees with the reference in steady state and provides an alternative to including a feedforward term. To see the effect of integral action in the frequency domain, we consider a proportional-integral (PI) controller, which has a transfer function

$$C(s) = k_p e + \frac{k_i}{s}.$$

We see that the controller has infinite zero frequency gain ($C(0) = \infty$) and it then follows from equation (10.3) that $G_{yr}(0) = 1$, which implies that there is no steady-state error.

Integral action can also be viewed as a method for generating the feed-forward term u_d in the proportional controller (10.4) automatically. An alternative way to represent this action is shown in Figure 10.3a, where the low pass part of the control action of a proportional controller is filtered and feed back with positive gain. This implementation, called *automatic reset*, was one of the early inventions of integral control. Integral action is often realized in this way in biological systems.

The transfer function of the system in Figure 10.3 is obtained by loop tracing: assuming exponential signals, we have

$$u = k_p e + \frac{1}{1+sT} u,$$

and solving for u gives

$$u = k_p \frac{1+sT}{sT} e = k_p + \frac{k_p}{sT},$$

which is the transfer function for a PI controller.

The properties of integral action are illustrated in Figure 10.2b. The proportional gain is constant, $k_p = 1$, and the integral gains are $k_i = 0, 0.2, 0.5$ and 1 . The case $k_i = 0$ corresponds to pure proportional control, with a steady state error of 50%. The steady state error is removed when integral gain action is used. The response creeps slowly towards the reference for small values of k_i , but faster for larger integral gains, but the system also becomes more oscillatory.

We now return to the general PID controller and consider the use of the derivative term, k_d . Recall that the original motivation for derivative feedback was to provide predictive action. The input-output relation of a controller with proportional and derivative action is

$$u = k_p e + k_d \frac{de}{dt} = k \left(e + T_d \frac{de}{dt} \right),$$

where $T_d = k_d/k_p$ is the derivative time constant. The action of a controller with proportional and derivative action can be interpreted as if the control is made proportional to the *predicted* process output, where the prediction is made by extrapolating the error T_d time units into the future using the tangent to the error curve (see Figure 10.1).

Derivative action can also be implemented by taking the difference between the signal and its low-pass filtered version as shown in Figure 10.3a. The transfer function for the system is

$$C(s) = \left(1 - \frac{1}{1+sT} \right) = \frac{sT}{1+sT} U(s).$$

The system thus has the transfer function $G(s) = sT/(1+sT)$, which approximates a derivative for low frequencies. Notice that this implementation gives filtering automatically.

Figure 10.2c illustrates the behavior of a system with a PID controller: the system is oscillatory when no derivative action is used and it becomes

more damped as derivative gain is increased. A comparison of the systems with P, PI and PID control in Figure 10.2 shows that the steady-state error is removed by introducing integral action and that the response speed can be improved by introducing derivative action.

10.2 Tuning

Users of control systems are frequently faced with the task of adjusting the controller parameters to obtain a desired behavior. There are many different ways to do this. One way to do this is to go through the steps of modeling and control design. Since the PID controller has so few parameters a number of special empirical methods have also been developed. A simple idea is to connect a controller, increase the gain until the system starts to oscillate, and then reduce the gains by an appropriate factor. Another is to measure some features of the open loop response and to determine controller parameters based on these features. We will present the Ziegler-Nichols methods which are the most celebrated tuning rules.

Ziegler-Nichols' Tuning

Ziegler and Nichols developed two techniques for controller tuning in the 1940s. The idea was to tune the controller based on the following idea: Make a simple experiment, extract some features of process dynamics from the experimental data, and determine controller parameters from the features.

One method is based on direct adjustment of the controller parameters. A controller is connected to the process, integral and derivative gain are set to zero and the proportional gain is increased until the system starts to oscillate. The critical value of the proportional gain k_c is observed together with the period of oscillation T_c . The controller parameters are then given by Table 10.1. The values in the table were obtained based on many simulations and experiments on processes that are normally encountered in process industry. There are many variations of the method which are widely used in industry.

Another method proposed by Ziegler and Nichols is based on determination of the open loop step response of the process, as shown Figure 10.4a. The step response is measured by applying a step input to the process and recording the response. The response is scaled to correspond to a unit step input and characterized by parameters a and T_{del} , which are the intercepts of the steepest tangent of the step response with the coordinate axes. The parameter T_{del} is an approximation of the time delay of the system and

Table 10.1: Controller parameters for the Ziegler-Nichols frequency response method which gives controller parameters in terms of critical gain k_c and critical period T_c . Parameter T_p is an estimate of the period of damped oscillations of the closed loop system.

Controller	k_p/k_c	T_i/T_c	T_d/T_c	T_p/T_c
P	0.5			1.0
PI	0.4	0.8		1.4
PID	0.6	0.5	0.125	0.85

a/T_{del} is the steepest slope of the step response. Notice that it is not necessary to wait until steady state to find the parameters, it suffices to wait until the response has had an inflection point. The controller parameters are given in Table 10.2. The parameters were obtained by extensive simulation of a range of representative processes.

Improved Ziegler-Nichols Rules

There are two drawbacks with the Ziegler-Nichols rules: too little process information is used and the closed loop systems that are obtained lack robustness. Substantially better tuning is obtained by fitting the model

$$P(s) = \frac{K}{1+sT} e^{-sT_{\text{del}}} \quad (10.5)$$

to the step response. A simple way to do this is illustrated in Figure 10.4b. The zero frequency gain of the process K is determined from the steady state value of the step response. The time delay T_{del} is determined from the

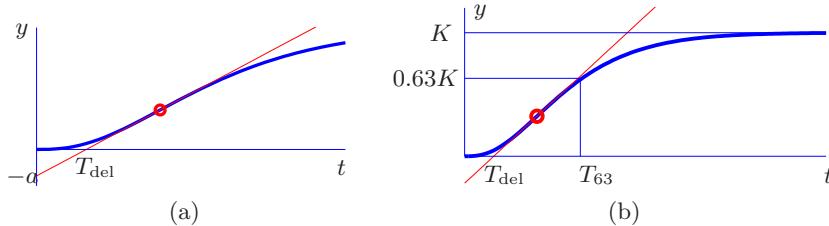


Figure 10.4: Characterization of the unit step response by two (left) and three parameters (right). The point where the tangent is steepest is marked with a small circle.

Table 10.2: Controller parameters for the Ziegler-Nichols step response method. Parameter T_p is an estimate of the period of damped oscillations of the closed loop system.

Controller	ak_p	T_i/T_{del}	T_d/T_{del}	T_p/T_{del}
P	1			4
PI	0.9	3		5.7
PID	1.2	2	$T_{\text{del}}/2$	3.4

intercept of the steepest tangent to the step response and the time T_{63} is the time where the output has reached 63% of its steady state value. The parameter T is then given by $T = T_{63} - T_{\text{del}}$. Notice that the experiment takes longer time than the experiment in Figure 10.4a because it is necessary to wait until the steady state has been reached. The following tuning formulas have been obtained by tuning controllers to a large set of processes typically encountered in process control

$$\begin{aligned} k_p K &= \min(0.4 T/L, 0.25) \\ T_i &= \max(T, 0.5T_{\text{del}}). \end{aligned} \quad (10.6)$$

Notice that the improved formulas typically give lower controller gain than the Ziegler-Nichols method, and that integral gain is higher, particularly for systems with dynamics that are delay dominated, i.e. $T_{\text{del}} > 2T$.

Relay Feedback

The experiment used in the Ziegler-Nichols frequency response method, where the gain of a proportional controller is increased until the system reaches instability, gives the frequency ω_{180} where the process has a phase lag of 180° and the process gain K_{180} at that frequency. Another way to obtain this information is to connect the process in a feedback loop with a relay as shown in Figure 10.5a. For many systems there will then be an oscillation, as shown in Figure 10.5b, where the relay output u is a square wave and the process output y is close to a sinusoid. Notice that the process input and output have opposite phase and that an oscillation with constant period is established quickly.

To provide some analysis, we assume that the relay output is expanded in a Fourier series and that the process attenuates higher harmonics effectively. It is then sufficient to consider only the first harmonic component of the

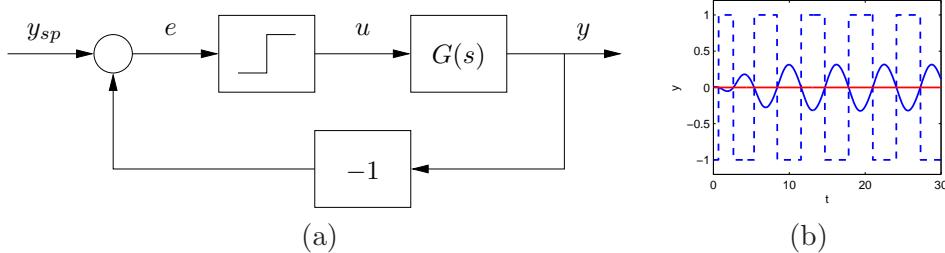


Figure 10.5: Block diagram of a process with relay feedback (left) and typical signals (right). The process output y is solid and the relay output u is dashed. Notice that the signals u and y are out of phase.

input. The input and the output then have opposite phase, which means that the frequency of the oscillation ω_{180} is such that the process has a phase lag of 180° . If d is the relay amplitude, the first harmonic of the square wave input has amplitude $4d/\pi$. Let a be the amplitude of the process output. The process gain at ω_{180} is then given by

$$K_{180} = |P(i\omega_{180})| = \frac{\pi a}{4d}. \quad (10.7)$$

The relay experiment is easily automated. Since the amplitude of the oscillation is proportional to the relay output, it is easy to control it by adjusting the relay output. The amplitude and the period can be determined after about 20 s, in spite of the fact that the system is started so far from the equilibrium that it takes about 8 s to reach the correct level. The settling time for the step response of the system is 40 s.

Automatic tuning based on relay feedback is used in many commercial PID controllers. Tuning is accomplished simply by pushing a button which activates relay feedback. The relay amplitude is automatically adjusted to keep the oscillations sufficiently small, the relay feedback is switched to a PID controller as soon as the tuning is accomplished.

10.3 Modeling and Control Design

Parameters of PID controllers can also be determined by modeling process dynamics and applying some method for control design. Since the complexity of the controller is directly related to the complexity of the model it is necessary to have models of low order.

To illustrate the ideas we will consider the case where a process dynamics

is approximated by a first order transfer function

$$P(s) = \frac{b}{s + a}.$$

The approximation is reasonable for systems where storage of mass, momentum and energy can be captured by one state variable. Typical examples are the velocity of a car on the road, control of the velocity of a rotating system, electric systems where energy is essentially stored in one component, incompressible fluid flow in a pipe, level control of a tank, pressure control in a gas tank and temperature in a body with uniform temperature distribution.

A PI controller has the transfer function

$$C(s) = k_p + \frac{k_i}{s},$$

and the transfer function of the closed loop system from reference to output is

$$G_{yr} = \frac{PC}{1 + PC} = \frac{b(k_p s + k_i)}{s^2 + (a + bk_p)s + bk_i}.$$

The closed loop system has the characteristic polynomial

$$s^2 + (a + bk_p)s + bk_i.$$

Assuming that the desired characteristic polynomial is

$$s^2 + 2\zeta\omega_0 s + \omega_0^2, \quad (10.8)$$

we find that the controller parameters are given by

$$\begin{aligned} k_p &= \frac{2\zeta\omega_0 - a}{b} = \frac{2\zeta\omega_0 T - 1}{K} \\ k_i &= \frac{\omega_0^2}{b} = \frac{\omega_0^2 T}{K}. \end{aligned} \quad (10.9)$$

The parameter ω_0 determines the response speed and ζ determines the damping. Notice that controller gain becomes negative if $\zeta\omega_0 < 0.5$, which gives a closed loop system with bad properties, as will be discussed in Section 12.5.

The same approach can be used to find the parameters of a PID controller for a process with dynamics of second order (Exercise 1).

Example 10.1 (Cruise control design). Consider the problem of maintaining the speed of a car as it goes up a hill. In Example 5.14 we found that there was very little difference between the linear and nonlinear models when investigating PI control provided that the throttle does not reach the saturation limits. We will now use a linear model to design a controller and to investigate the effects of design parameters. A simple linear model of a car was given in Example 5.10:

$$\frac{d(v - v_e)}{dt} = a(v - v_e) + b(u - u_e) - g\theta, \quad (10.10)$$

where v is the velocity of the car, u is the input from the engine and θ is the slope of the hill. The parameters were $a = -0.101$, $b = 1.3203$, $g = 9.8$, $v_e = 20$, and $u_e = 0.1616$. This model will be used to find suitable parameters of a vehicle speed controller. To investigate the behavior of the closed loop system we start with the linearized process model (10.10) and we assume that the cruise controller is PI controller is described by

$$u = k_p(v_e - v) + k_i \int_0^t (v_e - v(\tau)) d\tau. \quad (10.11)$$

To compute the error dynamics, introduce the error $e = v_e - v$, differentiate equations (10.10) and (10.11), and eliminate u . The error is then given by the differential equation

$$\frac{d^2e}{dt^2} + (-a + bk_p)\frac{de}{dt} + bk_i e = 9.8 \frac{d\theta}{dt}. \quad (10.12)$$

We notice that the steady state error is zero if θ and e are constant, which is no surprise since the controller has integral action.

To understand the effects of the controller parameters K and k_i we can compare equation (10.12) with the standard second order system

$$\ddot{q} + 2\zeta\omega_0\dot{q} + \omega_0^2 q = ku.$$

This gives

$$k_p = \frac{a + 2\zeta\omega_0}{b} \quad k_i = \frac{\omega_0^2}{b}$$

where ζ denotes relative damping and ω_0 is the undamped natural frequency. The parameter ω_0 gives response speed and ζ determines the shape of the response. Since it is desirable that a cruise control system should respond to changes smoothly without oscillations we choose $\zeta = 1$, which corresponds to critical damping.

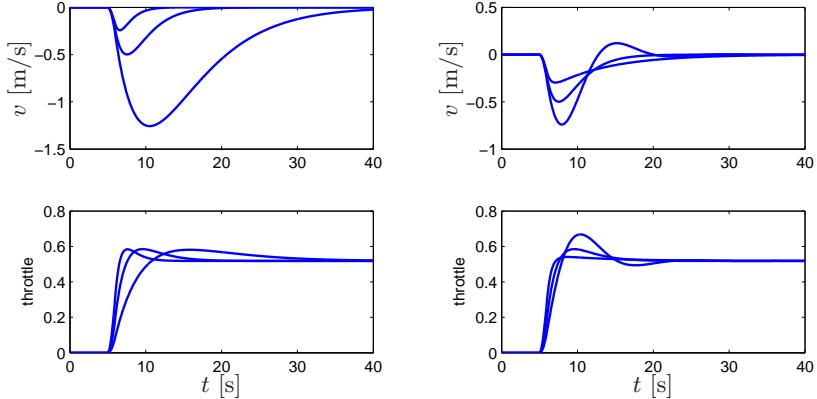


Figure 10.6: Illustrates the effect of parameters ω_0 (left) and ζ_0 (right) on the response of a car with cruise control.

The consequences of different choices of ω_0 and ζ_0 are illustrated in Figure 10.6. The figure shows the velocity and throttle for a car that first moves on a horizontal road and encounters a hill with slope 4° at time 6. Between time 5 and 6 the slope increases linearly. The choice of ω_0 is a compromise between response speed and control actions. The compromise is illustrated in Figure 10.6, which shows the velocity error and the control signal for a simulation where the slope of the road suddenly changes by 4° . The largest velocity error decreases with increasing ω_0 , but the control signal also changes more rapidly. In the simple model (10.10) it was assumed that the force responds instantaneously to throttle commands. For rapid changes there may be additional dynamics that has to be accounted for. There are also physical limitations to the rate of change of the force, which also restrict the admissible value of ω_0 . A reasonable choice of ω_0 is in the range of 0.2 to 1.0. Notice in Figure 10.6 that even with $\omega_0 = 0.1$ the largest velocity error is only 1 m/s.

Another interpretation of the effect of the integral action can be given by returning to the basic force balance model of the car

$$m \frac{dv}{dt} = F - F_d,$$

where m is the mass of the car, F is the applied force (from the engine) and F_d is the disturbance force (aerodynamic drag and force of gravity). Since zero steady state error implies that v is constant, we see that the PI controller generates an output force F that in steady state is equal to the

drag force F_d . Since the error is zero in steady state the controller output equals the output of the integrator of the PI controller. The output of the integrator in the PI controller can thus be interpreted as an estimator of the drag force. ∇

10.4 Integrator Windup

Many aspects of a control system can be understood from linear models. There are, however, some nonlinear phenomena that must be taken into account. These are typically limitations in the actuators: a motor has limited speed, a valve cannot be more than fully opened or fully closed, etc. For a system which operates over a wide range of conditions, it may happen that the control variable reaches the actuator limits. When this happens the feedback loop is broken and the system runs in open loop because the actuator will remain at its limit independently of the process output as long as the actuator remains saturated. The integral term will also build up since the error typicallys zero. The integral term and the controller output may then become very large. The control signal will then remain saturated even when the error changes and it may take a long time before the integrator and the controller output comes inside the saturation range. The consequence is that there are large transients. This situation is colloquially referred to as *integrator windup* which is illustrated by the following example.

Example 10.2 (Cruise control). The windup effect is illustrated in Figure 10.7, which shows what happens when a car encounters a hill that is so steep (6°) that the throttle saturates when the cruise controller attempts to maintain speed. When encountering the slope at time $t = 5$ the velocity decreases and the throttle increases to generate more torque. The torque required is however so large that the throttle saturates. The error decreases slowly because the torque generated by the engine is just a little larger than the torque required to compensate for the gravity. The error is large and the integral continues to build up until the error reaches zero at time 30, but but the controller output is still much larger than the saturation limit and the actuator remains saturated. The integral term starts to decrease and at time 45 and the velocity settles to quickly to the desired value. Notice that it takes considerable time before the controller output comes in the range where it does not saturate resulting in a large overshoot. ∇

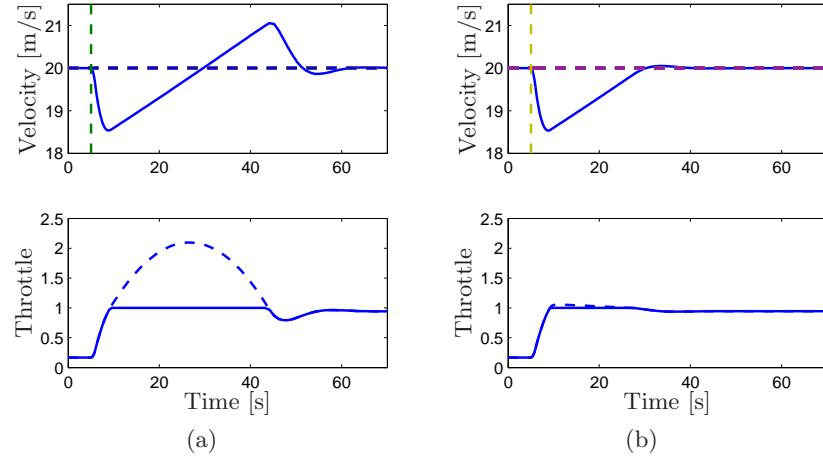


Figure 10.7: Simulation of windup (left) and anti-windup (right). The figure shows the speed v and the throttle u for a car that encounters a slope that is so steep that the throttle saturates. The controller output is dashed. The controller parameters are $k_p = 0.5$ and $k_i = 0.1$.

Avoiding Windup

There are many ways to avoid windup. One method is illustrated in Figure 10.8: the system has an extra feedback path that is generated by measuring the actual actuator output, or the output of a mathematical model of the saturating actuator, and forming an error signal (e_s) as the difference between the output of the controller (v) and the actuator output (u). The signal e_s is fed to the input of the integrator through gain k_t . The signal e_s is zero when there is no saturation and the extra feedback loop has no effect on the system. When the actuator saturates, the signal e_s is feedback to the integrator in such a way that e_s goes towards zero. This implies that controller output is kept close to the saturation limit. The controller output will then change as soon as the error changes sign and integral windup is avoided.

The rate at which the controller output is reset is governed by the feedback gain, k_t , a large value of k_t give a short reset time. The parameter k_t can, however, not be too large because measurement error can then cause an undesirable reset. A reasonable compromise is to choose $k_t \approx 1/T_i$ for PI control and as $k_t \approx 1/\sqrt{T_i T_d}$ for PID control. We illustrate how integral windup can be avoided by investigating the cruise control system.

Example 10.3 (Cruise control). Figure 10.7b shows what happens when

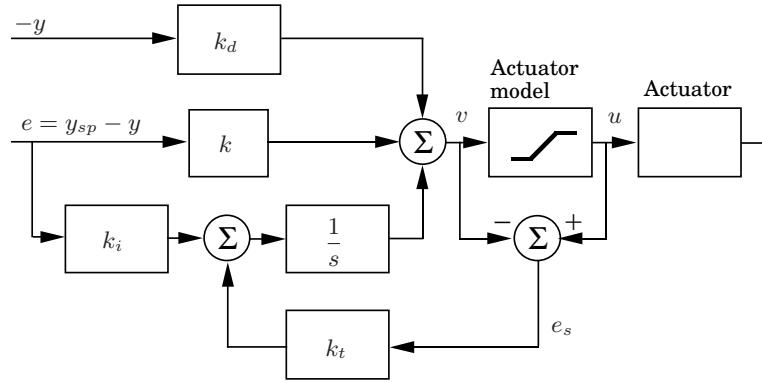


Figure 10.8: PID controller with anti-windup.

a controller with anti-windup is applied to the system simulated in Figure 10.7a. Because of the feedback from the actuator model the output of the integrator is quickly reset to a value such that the controller output is at the saturation limit. The behavior is drastically different from that in Figure 10.7a and the large overshoot is avoided. The tracking gain $k_t = 2$ in the simulation. ∇

10.5 Implementation

There are many practical issues that have to be considered when implementing PID controllers. They have been developed over time based on practical experiences. In this section we consider some of the most common. Similar considerations also apply to other types of controllers.

Filtering the Derivative

A drawback with derivative action is that an ideal derivative has very high gain for high frequency signals. This means that high frequency measurement noise will generate large variations of the control signal. The effect of measurement noise be reduced by replacing the term $k_d s$ by

$$D_a = -\frac{k_d s}{1 + sT_f}. \quad (10.13)$$

This can be interpreted as an ideal derivative that is filtered using a first-order system with the time constant T_f . For small s the transfer function is

approximately $k_d s$ and for large s it is equal to k_d/T_f . The approximation acts as a derivative for low-frequency signals and as a constant gain for the high frequency signals. The filtering time is chosen as $T_f = (k_d/k)/N$, with N in the range of 2 to 20. Filtering is obtained automatically if the derivative is implemented by taking difference between the signal and a its filtered version as shown in Figure 10.2.

The transfer function of a PID controller with a filtered derivative is

$$C(s) = k_p \left(1 + \frac{1}{sT_i} + \frac{sT_d}{1 + sT_d/N} \right). \quad (10.14)$$

The high-frequency gain of the controller is $K(1 + N)$. Instead of filtering just the derivative it is also possible to use an ideal controller and filter the measured signal. The transfer function of such a controller with the filter is then

$$C(s) = k_p \left(1 + \frac{1}{sT_i} + sT_d \right) \frac{1}{(1 + sT_f)^2}. \quad (10.15)$$

where a second order filter is used.

Setpoint Weighting

The control system in equation (10.1) is called a system with *error feedback* because the controller acts on the error, which is the difference between the reference and the output. In the simulation of PID controllers in Figure 10.1 there is a large initial peak of the control signal, which is caused by the derivative of the reference signal. The peak can be avoided by modifying the controller equation (10.1) to

$$u = k_p(\beta r - y) + k_i \int_0^\infty (r(\tau) - y(\tau)) d\tau + k_d \left(\gamma \frac{dr}{dt} - \frac{dy}{dt} \right) \quad (10.16)$$

In this controller, proportional and derivative actions act on fractions β and γ of the reference. Integral action has to act on the error to make sure that the error goes to zero in steady state. The closed loop systems obtained for different values of β and γ respond to load disturbances and measurement noise in the same way. The response to reference signals is different because it depends on the values of β and γ , which are called *reference weights* or *setpoint weights*.

Figure 10.9 illustrates the effects of setpoint weighting on the step response. The figure shows clearly the effect of changing β . The overshoot for reference changes is smallest for $\beta = 0$, which is the case where the reference is only introduced in the integral term, and increases with increasing

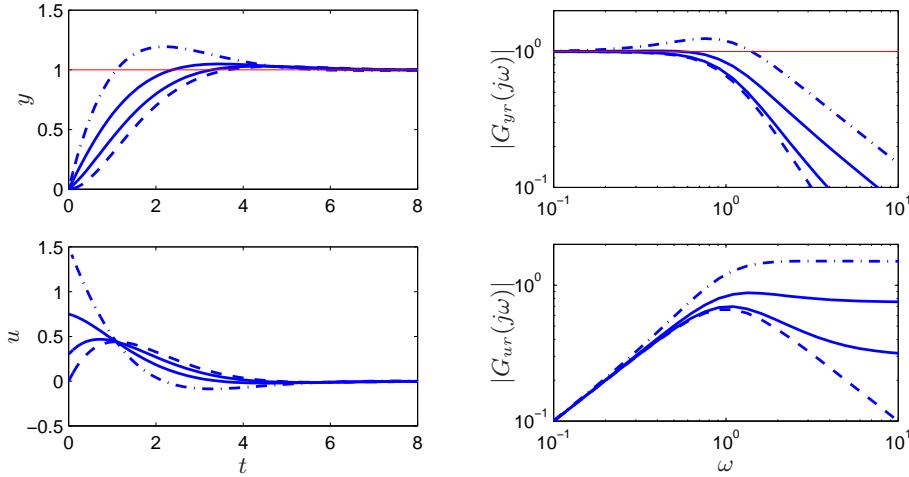


Figure 10.9: Time and frequency responses for system with PI controller and set-point weighting. The curves on the left show responses in process output y and control signal and the curves on the right show the gain curves for the transfer functions $G_{yr}(s)$ and $G_{ur}(s)$. The process transfer function is $P(s) = 1/s$, the controller gains are $k = 1.5$ and $k_i = 1$, and the setpoint weights are $\beta = 0$ (dashed) 0.2, 0.5 and 1 (dash dotted).

β . Parameter β it typically in the range of 0 to 1 and γ is normally zero to avoid large transients in the control signal when the reference is changed.

The controller given by equation (10.16) is a special case of controller with two degrees which will be discussed in Section 11.1.

Implementation based Operational Amplifiers

PID controllers have been implemented in many different technologies. Figure 10.10 shows how they can be implemented by feedback around operational amplifiers.

To show that the circuit in Figure 10.10b is a PID controller we will use the approximate relation between the input voltage e and the output voltage u of an operational amplifier in Section 3.3:

$$u = -\frac{Z_1}{Z_0}e,$$

where Z_0 is the impedance between the negative input of the amplifier and the input voltage e , and Z_1 is the impedance between the zero input of the

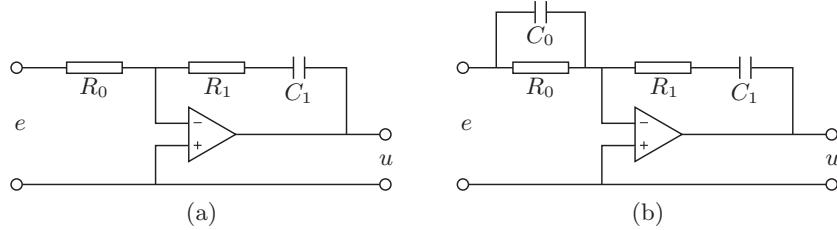


Figure 10.10: Schematic diagram of an electronic PI (left) and PID controllers (right) based on feedback around an operational amplifier.

amplifier and the output voltage u . The impedances are given by

$$Z_0 = \frac{R_0}{1 + R_0 C_0 p} \quad Z_1 = R_1 + \frac{1}{C_1 p},$$

and we find the following relation between the input voltage e and the output voltage u :

$$u = -\frac{Z_1}{Z_0} e = -\frac{R_1}{R_0} \frac{(1 + R_0 C_0 p)(1 + R_1 C_1 p)}{R_1 C_1 p} e.$$

This is the input-output relation for a PID controller on the form (10.2) with parameters

$$k_p = \frac{R_1}{R_0} \quad T_i = R_1 C_1 \quad T_d = R_0 C_0.$$

The corresponding results for a PI controller is obtained by setting $C_0 = 0$.

Computer Implementation

In this section we briefly describe how a PID controller may be implemented using a computer. The computer typically operates periodically, with signals from the sensors sampled and converted to digital form by the A/D converter, the control signal computed and then converted to analog form for the actuators. The sequence of operation is as follows:

1. Wait for clock interrupt
2. Read input from sensor
3. Compute control signal
4. Send output to the actuator
5. Update controller variables

6. Repeat

Notice that an output is sent to the actuators as soon as it is available. The time delay is minimized by making the calculations in Step 3 as short as possible and performing all updates after the output is commanded.

As an illustration we consider the PID controller in Figure 10.8, which has a filtered derivative, setpoint weighting and protection against integral windup. The controller is a continuous time dynamical system. To implement it using a computer, the continuous time system has to be approximated by a discrete time system.

The signal v is the sum of the proportional, integral and derivative terms

$$v(t) = P(t) + I(t) + D(t) \quad (10.17)$$

and the controller output is $u(t) = \text{sat}(v(t))$ where sat is the saturation function that models the actuator. The proportional term is

$$P = k_p(\beta y_{sp} - y).$$

This term is implemented simply by replacing the continuous variables with their sampled versions. Hence

$$P(t_k) = k_p(\beta y_r(t_k) - y(t_k)), \quad (10.18)$$

where $\{t_k\}$ denotes the sampling instants, i.e., the times when the computer reads its input. The integral term is

$$I(t) = k_i \int_0^t e(s) ds + \frac{1}{T_t} (\text{sat}(v) - v)$$

and approximating the integral by a sum gives

$$I(t_{k+1}) = I(t_k) + k_i h e(t_k) + \frac{h}{T_t} (\text{sat}(v) - v). \quad (10.19)$$

The derivative term D is given by the differential equation

$$T_f \frac{dD}{dt} + D = -k_d y.$$

Approximating this equation with a backward difference we find

$$T_f \frac{D(t_k) - D(t_{k-1})}{h} + D(t_k) = -k_d \frac{y(t_k) - y(t_{k-1})}{h},$$

which can be rewritten as

$$D(t_k) = \frac{T_f}{T_f + h} D(t_{k-1}) - \frac{k_d}{T_f + h} (y(t_k) - y(t_{k-1})). \quad (10.20)$$

The advantage of using a backward difference is that the parameter $T_f/(T_f + h)$ is nonnegative and less than one for all $h > 0$, which guarantees that the difference equation is stable.

Reorganizing equations (10.17)–(10.20), the PID controller can be described by the following pseudo code:

```
% Precompute controller coefficients
bi=ki*h
ad=Tf/(Tf+h)
bd=kd/(Tf+h)
br=h/Tt

% Control algorithm - main loop
while (running) {
    r=adin(ch1)                      % read setpoint from ch1
    y=adin(ch2)                      % read process variable from ch2
    P=kp*(b*r-y)                     % compute proportional part
    D=ad*D-bd*(y-yold)               % update derivative part
    v=P+I+D                          % compute temporary output
    u=sat(v,ulow,uhigh)              % simulate actuator saturation
    daout(ch1)                        % set analog output ch1
    I=I+bi*(r-y)+br*(u-v)           % update integral
    yold=y                            % update old process output
    sleep(h)   % wait until next update interval
}
```

Precomputation of the coefficients **bi**, **ad**, **bd** and **br** saves computer time in the main loop. These calculations have to be done only when controller parameters are changed. The main loop is executed once every sampling period. The program has three states: **yold**, **I**, and **D**. One state variable can be eliminated at the cost of a less readable code. Notice that the code includes computing the derivative of the process output, proportional action on a portion of the error ($b \neq 1$), and modeling of the actuator saturation in the integral computation to give protection against windup.

10.6 Further Reading

The history of PID control is a very rich one and stretches back to the beginning of the foundation of control theory. A very readable treatment is

given by Mindel [Min02]. A comprehensive presentation of PID control is given in [ÅH95].

10.7 Exercises

1. Consider a second order process with transfer function

$$P(s) = \frac{b}{s^2 + a_1 s + a_2}.$$

Find the gains for a PID controller that gives the closed loop system a characteristic polynomial of the form

$$s^2 + 2\zeta\omega_0 s + \omega_0^2.$$

2. (Vehicle steering) Design a proportion-integral controller for the vehicle steering system that gives closed loop characteristic equation

$$s^3 + 2\omega_0 s^2 + 2\omega_0 s + \omega_0^3.$$

Chapter 11

Loop Shaping

Quotation

Authors, citation.

In this chapter we continue to explore the use of frequency domain techniques for design of feedback systems. We begin with a more thorough description of the performance specifications for control systems, and then introduce the concept of “loop shaping” as a mechanism for designing controllers in the frequency domain. We also introduce some fundamental limitations to performance for systems with right half plane poles and zeros.

11.1 A Basic Feedback Loop

In the previous chapter, we considered the use of PID feedback as a mechanism for designing a feedback controller for a given process. In this chapter we will expand our approach to include a richer repertoire of tools for shaping the frequency response of the closed loop system.

One of the key ideas in this chapter is that we can design the behavior of the closed loop system by studying the open loop transfer function. This same approach was used in studying stability using the Nyquist criterion: we plotted the Nyquist plot for the *open* loop transfer function to determine the stability of the *closed* loop system. From a design perspective, the use of loop analysis tools is very powerful: since the loop transfer function is $L = PC$, if we can specify the desired performance in terms of properties of L , we can directly see the impact of changes in the controller C . This is much easier, for example, than trying to reason directly about the response

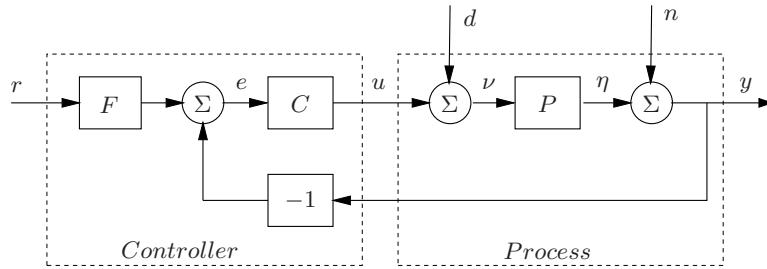


Figure 11.1: Block diagram of a basic feedback loop.

of the closed loop system, whose transfer function is given by

$$G_{yr} = \frac{PC}{1 + PC}$$

(assuming $F = 1$).

We will start by investigating some key properties of the feedback loop. A block diagram of a basic feedback loop is shown in Figure 11.1. The system loop is composed of two components, the process and the controller, and the controller has two blocks: the feedback block C and the feedforward block F . There are two disturbances acting on the process, the *load disturbance*, d , and the *measurement noise*, n . The load disturbance represents disturbances that drive the process away from its desired behavior, while the measurement noise represents the uncertainty in sensing the output of the system. In the figure, the load disturbance is assumed to act on the process input. This is a simplification, since disturbances often enter the process in many different ways, but allows us to streamline the presentation without significant loss of generality.

The process output η is the real physical variable that we want to control. Control is based on the measured signal y , where the measurements are corrupted by measurement noise n . The process is influenced by the controller via the control variable u . The process is thus a system with three inputs—the control variable u , the load disturbance d and the measurement noise n —and one output—the measured signal. The controller is a system with two inputs and one output. The inputs are the measured signal y and the reference signal r and the output is the control signal u . Note that the control signal u is an input to the process and the output of the controller, and that the measured signal is the output of the process and an input to the controller.

The feedback loop in Figure 11.1 is influenced by three external signals, the reference r , the load disturbance d and the measurement noise n . There are at least three signals, η , y and u that are of great interest for control, giving nine relations between the input and the output signals. Since the system is linear, these relations can be expressed in terms of the transfer functions. The following relations are obtained from the block diagram in Figure 11.1:

$$\begin{pmatrix} w \\ y \\ u \end{pmatrix} = \begin{pmatrix} \frac{P}{1+PC} & -\frac{PC}{1+PC} & \frac{PCF}{1+PC} \\ \frac{P}{1+PC} & \frac{1}{1+PC} & \frac{PCF}{1+PC} \\ -\frac{PC}{1+PC} & -\frac{C}{1+PC} & \frac{CF}{1+PC} \end{pmatrix} \begin{pmatrix} d \\ n \\ r \end{pmatrix}. \quad (11.1)$$

To simplify notations we have dropped the arguments of all transfer functions.

There are several interesting conclusions we can draw from these equations. First we can observe that several transfer functions are the same and that all relations are given by the following set of six transfer functions, which we call the *Gang of Six*:

$$\begin{array}{ccc} \frac{PCF}{1+PC} & \frac{PC}{1+PC} & \frac{P}{1+PC} \\ \frac{CF}{1+PC} & \frac{C}{1+PC} & \frac{1}{1+PC} \end{array} \quad (11.2)$$

The transfer functions in the first column give the response of the process output and control signal to the setpoint. The second column gives the same signals in the case of pure error feedback when $F = 1$. The transfer function $P/(1 + PC)$, in the third column, tells how the process variable reacts to load disturbances and the transfer function $C/(1 + PC)$, in the second column, gives the response of the control signal to measurement noise. Notice that only four transfer functions are required to describe how the system reacts to load disturbances and the measurement noise, and that two additional transfer functions are required to describe how the system responds to setpoint changes.

The linear behavior of the system is determined by six transfer functions in equation (11.2) and specifications can be expressed in terms of these transfer functions. The special case when $F = 1$ is called a system with (pure) error feedback. In this case all control actions are based on feedback from the error only and the system is completely characterized by four transfer functions, namely the four rightmost transfer functions in equation (11.2),

which have specific names:

$$\begin{aligned}
 S &= \frac{1}{1+PC} && \text{sensitivity function} \\
 T &= \frac{PC}{1+PC} && \text{complementary sensitivity function} \\
 PS &= \frac{P}{1+PC} && \text{load sensitivity function} \\
 CS &= \frac{C}{1+PC} && \text{noise sensitivity function}
 \end{aligned} \tag{11.3}$$

These transfer functions and their equivalent systems are called the *Gang of Four*. The load disturbance sensitivity function is sometimes called the input sensitivity function and the noise sensitivity function is sometimes called the output sensitivity function. These transfer functions have many interesting properties that will be discussed in detail in the rest of the chapter and good insight into these properties is essential for understanding feedback systems.

The procedure for designing a controller for the system in Figure 11.1 can be divided into two independent steps:

1. Design the feedback controller C that reduces the effects of load disturbances and the sensitivity to process variations without introducing too much measurement noise into the system.
2. Design the feedforward F to give the desired response to the reference signal (or setpoint).

The properties of the system can be expressed in terms of properties of the transfer functions (11.3), as illustrated in the following example.

Example 11.1. Consider the process

$$P(s) = \frac{1}{(s+1)^4}$$

with a PI feedback controller

$$C(s) = 0.775 + \frac{1}{2.05s}$$

and a feedforward controller

$$F(s) = \frac{1}{(0.5s+1)^4}.$$

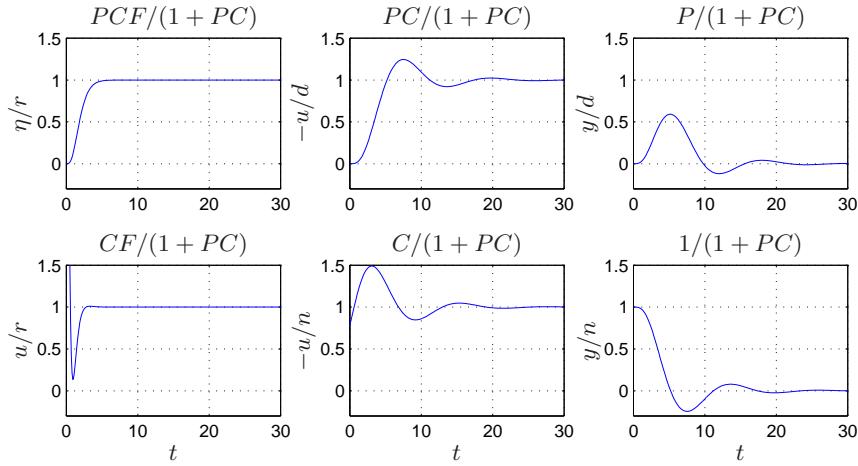


Figure 11.2: Step responses of the Gang of Six for PI control $k = 0.775$, $T_i = 2.05$ of the process $P(s) = (s + 1)^{-4}$. The feedforward is designed to give the transfer function $(0.5s + 1)^{-4}$ from reference r to output y .

Figures 11.2 and 11.3 show the step and frequency responses for the Gang of Six and give useful insight into the properties of the closed loop system.

The time responses in Figure 11.2 show that the feedforward gives a substantial improvement of the response speed as seen by the differences between the first and second columns. The settling time is substantially shorter with feedforward, 4 s versus 25 s, and there is no overshoot. This is also reflected in the frequency responses in Figure 11.3, which show that the transfer function with feedforward has higher bandwidth and that it has no resonance peak.

The transfer functions $CF/(1 + PC)$ and $-C/(1 + PC)$ represent the signal transmission from reference to control and from measurement noise to control. The time responses in Figure 11.2 show that the reduction in response time by feedforward requires a substantial control effort. The initial value of the control signal is out of scale in Figure 11.2 but the frequency response in Figure 11.3 shows that the high frequency gain of $PCF/(1+PC)$ is 16, which can be compared with the value 0.78 for the transfer function $C/(1 + PC)$. The fast response thus requires significantly larger control signals.

There are many other interesting conclusions that can be drawn from Figures 11.2 and 11.3. Consider for example the response of the output to load disturbances expressed by the transfer function $P/(1 + PC)$. The

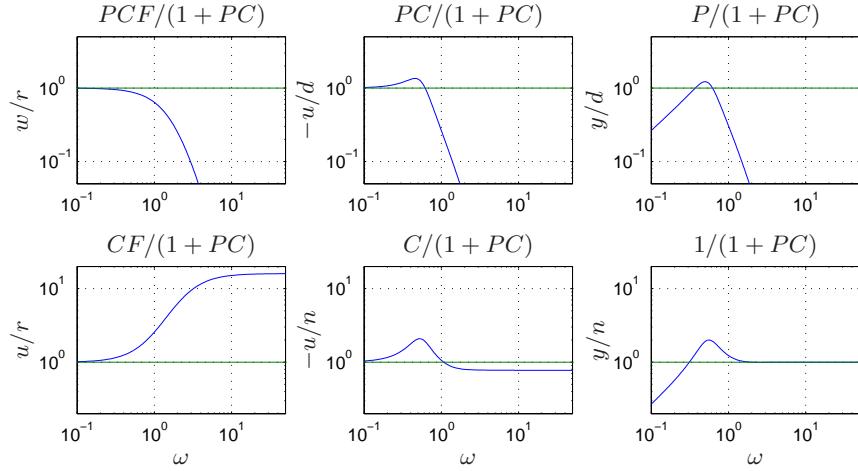


Figure 11.3: Gain curves of frequency responses of the Gang of Six for PI control $k = 0.775$, $T_i = 2.05$ of the process $P(s) = (s + 1)^{-4}$ where the feedforward has been designed to give the transfer function $(0.5s + 1)^{-4}$ from reference to output.

frequency response has a pronounced peak 1.22 at $\omega_{max} = 0.5$ and the corresponding time function has its maximum 0.59 at $t_{max} = 5.2$. Notice that the peaks are of the same magnitude and that the product of $\omega_{max}t_{max} = 2.6$. Similar relations hold for the other responses. ∇

11.2 Performance Specifications

A key element of the control design process is how we specify the desired performance of the system. Inevitably the design process requires a tradeoff between different features of the closed loop system and specifications are the mechanism by which we describe the desired outcome of those tradeoffs.

Frequency Domain Specifications

One of the main methods of specifying the performance of a system is through the frequency response of various input/output pairs. Since specifications were originally focused on setpoint response, it was natural to consider the transfer function from reference input to process output. For a system with error feedback, the transfer function from reference to output is equal to the complementary transfer function, $T = PC/(1+PC)$. A typical gain curve for this response is shown in Figure 11.4. Good performance

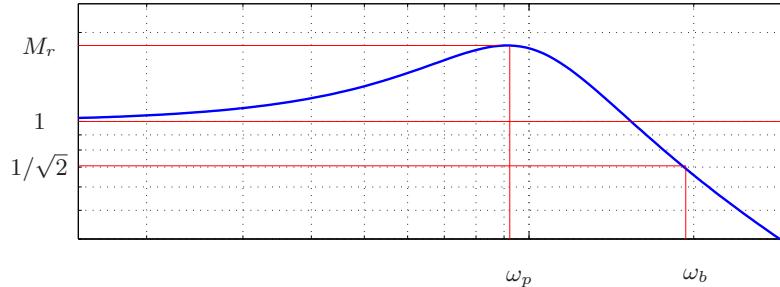


Figure 11.4: Gain curve for transfer function from setpoint to output.

requires that the zero frequency gain is one (so that the output tracks the reference). Typical specification measures include:

- The *resonance peak*, M_r , is the largest value of the frequency response.
- The *peak frequency*, ω_p , is the frequency where the maximum occurs.
- The *bandwidth*, ω_b , is the frequency where the gain has decreased to $1/\sqrt{2}$.

Specifications can also be related to the loop transfer function, $L = PC$. Useful features that have been discussed previously are:

- The *gain crossover frequency*, ω_{gc} , is the lowest frequency where the loop transfer function L has unit magnitude. This is roughly equal to the frequency where the closed loop gain drops to below $1/\sqrt{2}$.
- The *gain margin*, g_m , is the amount that the loop gain can be increased before reaching the stability limit. A high gain margin insures that errors in modeling the gain of the system do not lead to instability.
- The *phase margin*, φ_m , is the amount of phase lag required to reach the stability limit. A phase margin of 30° to 60° is typically required for robustness to modeling errors and non-oscillatory response.

These concepts were given in more detail in Section 9.3.

In addition to specifications on the loop transfer function, there are also a number of useful specifications on the sensitivity function and the complementary sensitivity function:

- The *maximum sensitivity*, M_s , is the peak value of the magnitude of sensitivity function and indicates the maximum amplification from the reference to the error signal.

- The *maximum sensitivity frequency*, ω_{ms} , is the frequency where the sensitivity function has its maximum.
- The *sensitivity crossover frequency*, ω_{sc} , is the frequency where the sensitivity function becomes greater than 1 for the first time. Disturbances are attenuated below this frequency and can be amplified above this frequency.
- The *maximum complementary sensitivity*, M_t , is the peak value of the magnitude of the complementary sensitivity function. It provides the maximum amplification from the reference signal to the output signal.
- The *maximum complementary sensitivity frequency*, ω_{mt} , is the frequency where the complementary sensitivity function has its maximum.

As we will see in the rest of the chapter, these various measures can be used to gain insights into the performance of the closed loop system and are often used to specify the desired performance for a control design.

Although we have defined different specifications for the loop transfer function L , the sensitivity function S and the complementary sensitivity function T , these transfer functions are all related through a set of algebraic relationships:

$$S = \frac{1}{1+L} \quad T = \frac{L}{1+L} \quad S + T = 1.$$

These relationships can limit the ability to independently satisfy specifications for the quantities listed above and may require tradeoffs, as we shall see.

Relations between Time and Frequency Domain Features

In Section 5.3 we described some of the typical parameters that described the step response of a system. These included the rise time, steady state error, and overshoot. For many applications, it is natural to provide these time domain specifications and we can relate these to the eigenvalues of the closed loop system, which are equivalent to the poles of the transfer function $T = PC/(1 + PC)$.

There are approximate relations between specifications in the time and frequency domain. Let $G(s)$ be the transfer function from reference to output. In the time domain the response speed can be characterized by the rise time T_r and the settling time T_s . In the frequency domain the response time

can be characterized by the closed loop bandwidth ω_b , the gain crossover frequency ω_{gc} , the sensitivity frequency ω_{ms} . The product of bandwidth and rise time is approximately constant $T_r\omega_b \approx 2$, so decreasing the rise time corresponds to increasing the closed loop bandwidth.

The overshoot of the step response M_p is related to the resonant peak M_r of the frequency response in the sense that a larger peak normally implies a larger overshoot. Unfortunately there is no simple relation because the overshoot also depends on how quickly the frequency response decays. For $M_r < 1.2$ the overshoot M_p in the step response is often close to $M_r - 1$. For larger values of M_r the overshoot is typically less than $M_r - 1$. These relations do not hold for all systems: there are systems with $M_r = 1$ that have a positive overshoot. These systems have transfer functions that decay rapidly around the bandwidth. To avoid overshoot in systems with error feedback it is advisable to require that the maximum of the complementary sensitivity function is small, say $M_t = 1.1 - 1.2$.

Response to Load Disturbances

The sensitivity function in equation (11.3) shows how feedback influences disturbances. Disturbances with frequencies that are lower than the sensitivity crossover frequency ω_{sc} are attenuated by feedback and those with $\omega > \omega_{sc}$ are amplified by feedback. The largest amplification is the maximum sensitivity M_s .

Consider the system in Figure 11.1. The transfer function from load disturbance d to process output w is

$$G_{wd} = \frac{P}{1 + PC} = PS = \frac{T}{C}. \quad (11.4)$$

Since load disturbances typically have low frequencies, it is natural that the criterion emphasizes the behavior of the transfer function at low frequencies. Filtering of the measurement signal has only marginal effect on the attenuation of load disturbances because the filter typically only attenuates high frequencies. For a system with $P(0) \neq 0$ and a controller with integral action, the controller gain goes to infinity for small frequencies and we have the following approximation for small s :

$$G_{wd} = \frac{T}{C} \approx \frac{1}{C} \approx \frac{s}{k_i}. \quad (11.5)$$

Figure 11.5 gives the gain curve for a typical case and shows that the approximation is very good for low frequencies.

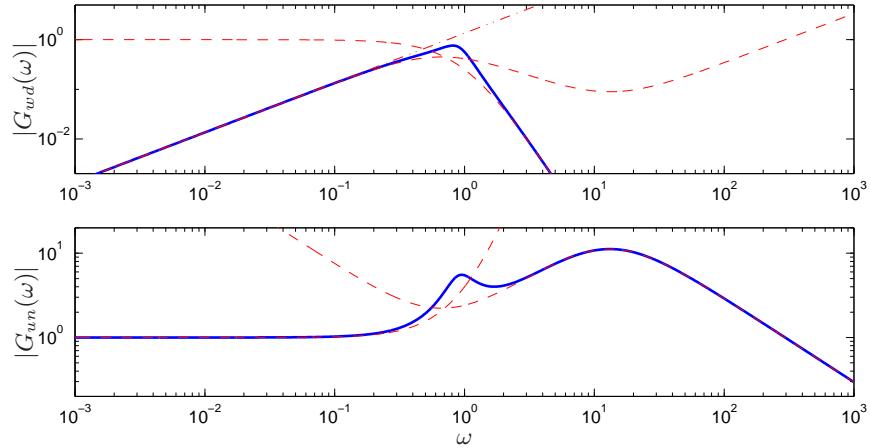


Figure 11.5: Gains of the transfer functions G_{wd} and G_{un} for PID control ($k = 2.235$, $T_i = 3.02$, $T_i = 0.756$ and $T_f = Td/5$) of the process $P = (s + 1)^{-4}$. The gain of the transfer functions P , C , $1/C$ are shown with dashed lines and s/k_i with dash-dotted lines.

Measurement noise, which typically has high frequencies, generates rapid variations in the control variable that are detrimental because they cause wear in many actuators and they can even saturate the actuator. It is thus important to keep the variations in the control signal at reasonable levels—a typical requirement is that the variations are only a fraction of the span of the control signal. The variations can be influenced by filtering and by proper design of the high frequency properties of the controller.

The effects of measurement noise are captured by the transfer function from measurement noise to the control signal,

$$G_{un} = \frac{C}{1 + PC} = CS = \frac{T}{P}. \quad (11.6)$$

Figure 11.5 shows the gain curve of G_{un} for a typical system. For low frequencies the transfer function the sensitivity function equals 1 and equation (11.6) can be approximated by $1/P$. For high frequencies it is approximated as $G_{un} \approx C$. A simple measure of the effect of measurement noise is the high frequency gain of the transfer function G_{un} ,

$$M_{un} := \|G_{un}\|_\infty = \sup_\omega |G_{un}(j\omega)|. \quad (11.7)$$

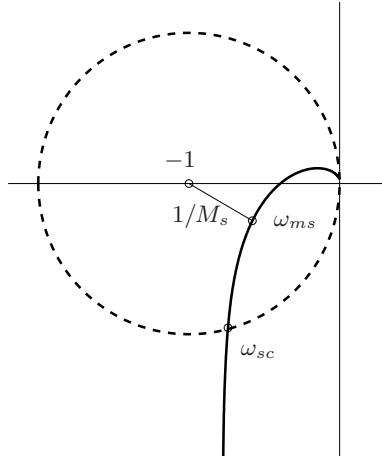


Figure 11.6: Nyquist curve of loop transfer function showing graphical interpretation of maximum sensitivity. The sensitivity crossover frequency ω_{sc} and the frequency ω_{ms} where the sensitivity has its largest value are indicated in the figure. All points inside the dashed circle have sensitivities greater than 1.

The sensitivity function can be written as

$$S = \frac{1}{1 + PC} = \frac{1}{1 + L}. \quad (11.8)$$

Since it only depends on the loop transfer function it can also be visualized graphically using the Nyquist plot of the loop transfer function. This is illustrated in Figure 11.6. The complex number $1+L(j\omega)$ can be represented as the vector from the point -1 to the point $L(j\omega)$ on the Nyquist curve. The sensitivity is thus less than one for all points outside a circle with radius 1 and center at -1 . Disturbances of these frequencies are attenuated by the feedback. If a control system has been designed based on a given model, it is straightforward to estimate the potential disturbance reduction simply by recording a typical output and filtering it through the sensitivity function.

Example 11.2. Consider the same system as the previous example

$$P(s) = \frac{1}{(s + 1)^4},$$

with a PI controller. Figure 11.7 shows the gain curve of the sensitivity function for $k = 0.8$ and $k_i = 0.4$. The figure shows that the sensitivity crossover frequency is 0.32 and that the maximum sensitivity 2.1 occurs at

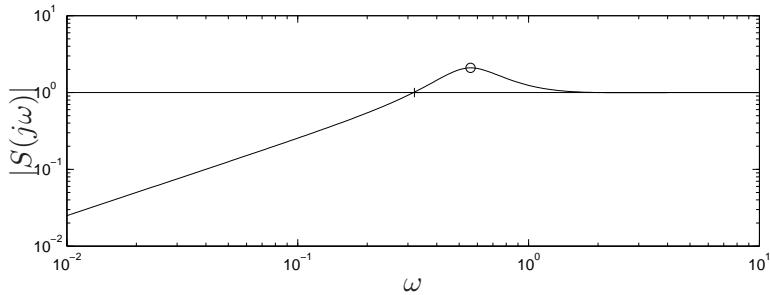


Figure 11.7: Gain curve of the sensitivity function for PI control ($k = 0.8$, $k_i = 0.4$) of process with the transfer function $P(s) = (s + 1)^{-4}$. The sensitivity crossover frequency is indicated by + and the maximum sensitivity by o.

$\omega_{ms} = 0.56$. Feedback will thus reduce disturbances with frequencies less than 0.32 rad/s, but it will amplify disturbances with higher frequencies. The largest amplification is 2.1. ∇

11.3 Feedback Design via Loop Shaping

One advantage the the Nyquist stability theorem is that it is based on the loop transfer function, which is related to the controller transfer function through $L = PC$. It is thus easy to see how the controller influences the loop transfer function. To make an unstable system stable we simply have to bend the Nyquist curve away from the critical point.

This simple idea is the basis of several different design methods, collectively called *loop shaping*. The methods are based on the idea of choosing a compensator that gives a loop transfer function with a desired shape. One possibility is to start with the loop transfer function of the process and modify it by changing the gain and adding poles and zeros to the controller until the desired shape is obtained.

Design Considerations

We will first discuss suitable forms of a loop transfer function that give good performance and good stability margins. Good robustness requires good gain and phase margins. This imposes requirements on the loop transfer function around the crossover frequencies ω_{pc} and ω_{gc} . The gain of L at low frequencies must be large in order to have good tracking of command signals and good rejection of low frequency disturbances. This can be

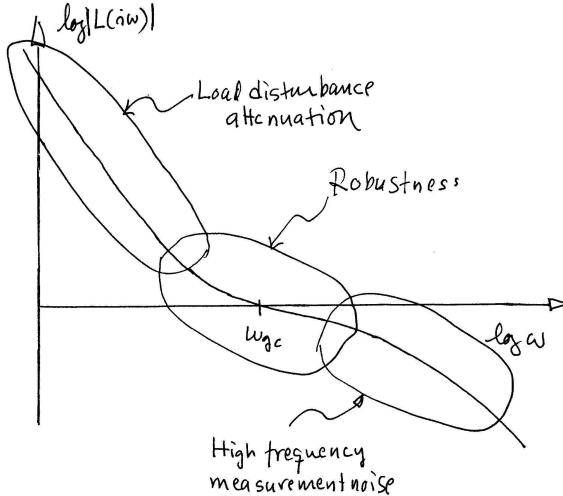


Figure 11.8: Gain curve of the Bode plot for a typical loop transfer function. The gain crossover frequency ω_{gc} and the slope n_{gc} of the gain curve at crossover are important parameters.

achieved by having a large crossover frequency and a steep slope of the gain curve for the loop transfer function at low frequencies. To avoid injecting too much measurement noise into the system it is desirable that the loop transfer function have a low gain at frequencies higher than the crossover frequencies. The loop transfer function should thus have the shape indicated in Figure 11.8.

Bode's relations (see Section 9.4) impose restrictions on the shape of the loop transfer function. Equation (9.5) implies that the slope of the gain curve at gain crossover cannot be too steep. If the gain curve is constant, we have the following relation between slope n_{gc} and phase margin φ_m :

$$n_{gc} = -2 + \frac{2\varphi_m}{\pi}. \quad (11.9)$$

This formula holds approximately when the gain curve does not deviate too much from a straight line. It follows from equation (11.9) that the phase margins 30° , 45° and 60° corresponds to the slopes $-5/3$, $-3/2$ and $-4/3$.

There are many specific design methods that are based on loop shaping. We will illustrate the basic approach by the design of a PI controller.

Example 11.3 (Design of a PI controller). Consider a system with the

transfer function

$$P(s) = \frac{1}{(s+1)^4}. \quad (11.10)$$

A PI controller has the transfer function

$$C(s) = k + \frac{k_i}{s} = k \frac{1 + sT_i}{sT_i}.$$

The controller has high gain at low frequencies and its phase lag is negative for all parameter choices. To have good performance it is desirable to have high gain and a high gain crossover frequency. Since a PI controller has negative phase, the gain crossover frequency must be such that the process has phase lag smaller than $180 - \varphi_m$, where φ_m is the desired phase margin. For the process (11.10) we have

$$\angle P(j\omega) = -4 \arctan \omega$$

If a phase margin of $\pi/3$ or 60° is required, we find that the highest gain crossover frequency that can be obtained with a proportional controller is $\omega_{gc} = \tan \pi/6 = 0.577$. The gain crossover frequency must be lower with a PI controller.

A simple way to design a PI controller is to specify the gain crossover frequency to be ω_{gc} . This gives

$$L(j\omega) = P(j\omega)C(j\omega) = \frac{kP(j\omega) \sqrt{1 + \omega_{gc}^2 T_i^2}}{\omega_{gc} T_i} = 1,$$

which implies

$$k_p = \frac{\sqrt{1 + \omega_{gc}^2 T_i^2}}{\omega_{gc} T_i P(j\omega_{gc})}.$$

We have one equation for the unknowns k and T_i . An additional condition can be obtained by requiring that the PI controller have a phase lag of 45° at the gain crossover, hence $\omega T_i = 0.5$. Figure 11.9 shows the Bode plot of the loop transfer function for $\omega_{gc} = 0.1, 0.2, 0.3, 0.4$ and 0.5 . The phase margins corresponding to these crossover frequencies are $94^\circ, 71^\circ, 49^\circ, 29^\circ$ and 11° . The gain crossover frequency must be less than 0.26 to have the desired phase margin 60° . Figure 11.9 shows that the controller increases the low frequency gain significantly at low frequencies and that the phase lag decreases. The figure also illustrates the tradeoff between performance and robustness. A large value of ω_{gc} gives a higher low frequency gain and

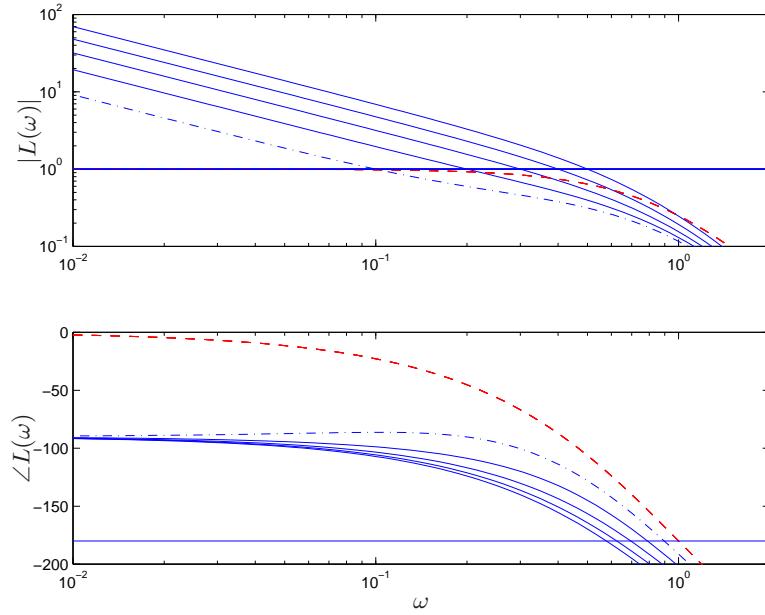


Figure 11.9: Bode plot of the loop transfer function for PI control of a process with the transfer function $P(s) = 1/(s + 1)^4$ with $\omega_{gc} = 0.1$ (dash-dotted), 0.2, 0.3, 0.4 and 0.5. The dashed line in the figure is the Bode plot of the process.

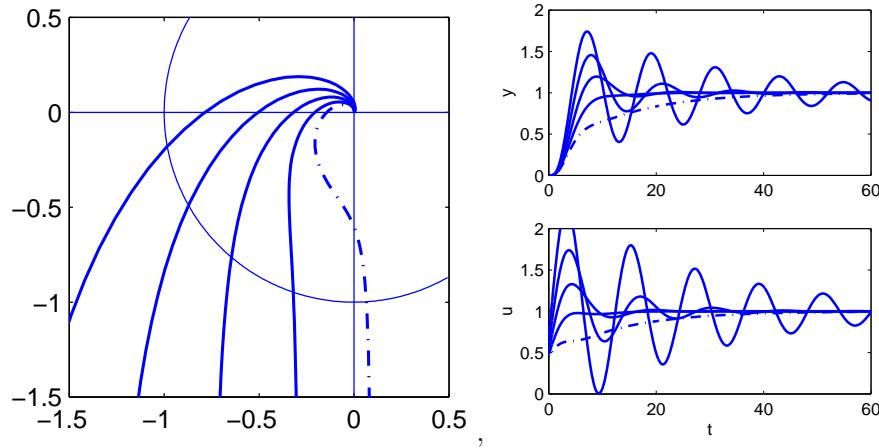


Figure 11.10: Nyquist plot of the loop transfer function for PI control of a process with the transfer function $P(s) = 1/(s + 1)^4$ with $\omega_{gc} = 0.1$ (dash-dotted), 0.2, 0.3, 0.4 and 0.5 (left) and corresponding step responses of the closed loop system (right).

a lower phase margin. Figure 11.10 shows the Nyquist plots of the loop transfer functions and the step responses of the closed loop system. The responses to command signals show that the designs with large ω_{gc} are too oscillatory. A reasonable compromise between robustness and performance is to choose ω_{gc} in the range 0.2 to 0.3. For $\omega_{gc} = 0.25$, the controller parameters are $k = 0.50$ and $T_i = 2.0$. Notice that the Nyquist plot of the loop transfer function is bent towards the left for low frequencies. This is an indication that integral action is too weak. Notice in Figure 11.10 that the corresponding step responses are also very sluggish. ∇

Lead Compensation

A common problem in design of feedback systems is that the phase lag of the system at the desired crossover frequency is not high enough to allow either proportional or integral feedback to be used effectively. Instead, one may have a situation where you need to add phase *lead* to the system, so that the crossover frequency can be increased.

A standard way to accomplish this is to use a *lead compensator*, which has the form

$$C(s) = k \frac{s + a}{s + b} \quad a < b. \quad (11.11)$$

The transfer function corresponding to this controller is shown in Figure 11.11. A key feature of the lead compensator is that it adds phase *lead* in the frequency range between the pole/zero pair (and extending approximately 10X in frequency in each direction). By appropriately choosing the location of this phase lead, we can provide additional phase margin at the gain crossover frequency.

Because the phase of a transfer function is related to the slope of the magnitude, increasing the phase requires increasing the gain of the loop transfer function over the frequency range in which the lead compensation is applied. Hence we can also think of the lead compensator as changing the slope of the transfer function and thus shaping the loop transfer function in the crossover region (although it can be applied elsewhere as well).

Example 11.4 (Pitch control for a ducted fan). Consider the control of the pitch (angle) of a vertically oriented ducted fan, as shown in Figure 11.12. We model the system with a second order transfer function of the form

$$P = \frac{r}{Js^2 + ds + mgl},$$

with the parameters given in Table 11.1. We take as our performance

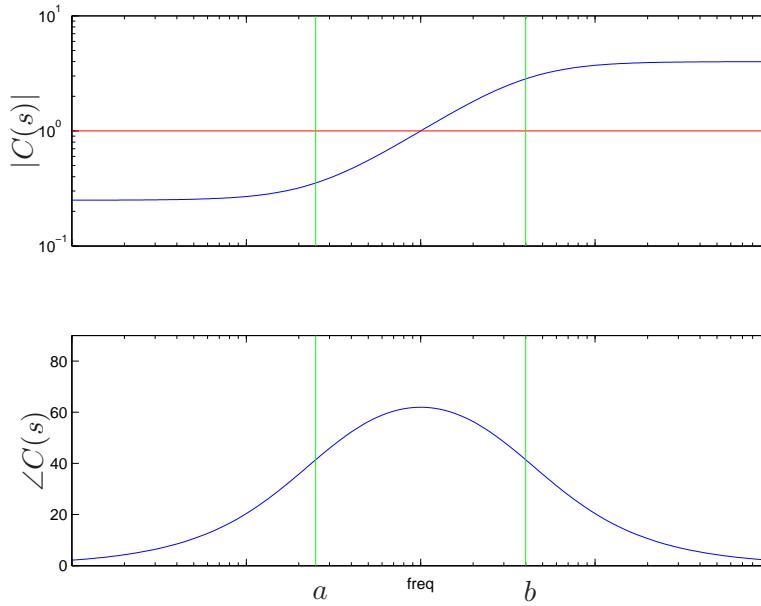


Figure 11.11: Frequency response for a lead compensator, $C(s) = k(s + a)/(s + b)$.

specification that we would like less than 1% error in steady state and less than 10% tracking error up to 10 rad/sec.

The open loop transfer function is shown in Figure 11.13a. To achieve our performance specification, we would like to have a gain of at least 10 at a frequency of 10 rad/sec, requiring the gain crossover frequency to be at a higher frequency. We see from the loop shape that in order to achieve the

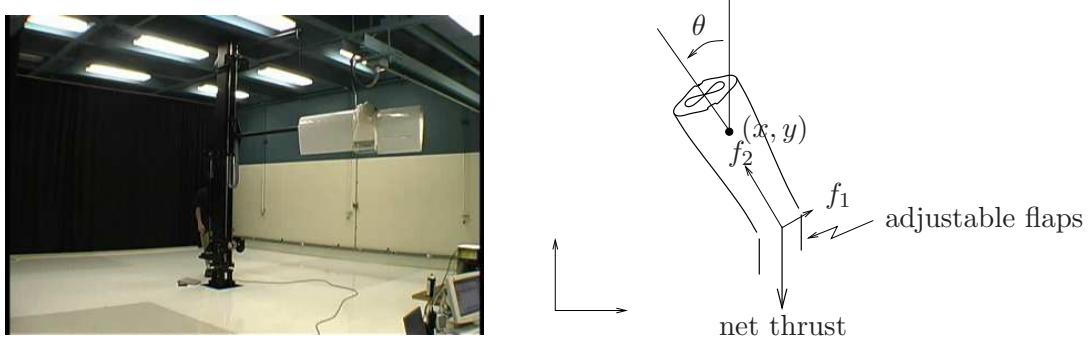


Figure 11.12: Caltech ducted fan with support stand.

Symbol	Description	Value	
m	inertial mass of fan, x axis	4.0	kg
J	fan moment of inertia, φ_3 axis	0.0475	kg m^2
r	nominal distance of flaps from fan pivot	26.0	cm
d	angular damping factor	0.001	kg m/s
g	gravitational constant	9.8	m/sec^2

Table 11.1: Parameter values for the planar ducted fan model which approximate the dynamics of the Caltech ducted fan.

desired performance we cannot simply increase the gain, since this would give a very low phase margin. Instead, we must increase the phase at the desired crossover frequency.

To accomplish this, we use a lead compensator (11.11) with $a = 2$ and $b = 50$. We then set the gain of the system to provide a large loop gain up to the desired bandwidth, as shown in Figure 11.13b. We see that this system has a gain of greater than 10 at all frequencies up to 10 rad/sec and that it has over 40° degrees of phase margin. ∇

The action of a lead compensator is essentially the same as that of the derivative portion of a PID controller. As described in Section 10.5, we often use a filter for the derivative action of a PID controller to limit the high frequency gain. This same effect is present in a lead compensator through the pole at $s = b$.

Equation (11.11) is a first order lead compensator and can provide up to 90° of phase lead. Higher levels of phase lead can be provided by using a second order lead compensator:

$$C = k \frac{(s + a)^2}{(s + b)^2} \quad a < b.$$



11.4 Fundamental Limitations

Although loop shaping gives us a great deal of flexibility in designing the closed loop response of a system, there are certain fundamental limits on what can be achieved. We consider here some of the primary performance limitations that can occur; additional limitations having to do with robustness are considered in the next chapter.

One of the key limitations of loop shaping occurs when we have the possibility of cancellation of right half plane poles and zeros. The canceled

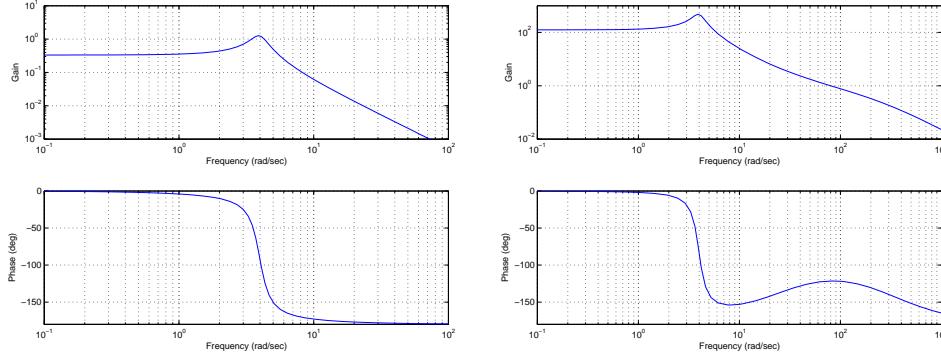


Figure 11.13: Control design using a lead compensator: (a) Bode plot for P and (b) Bode plot for $L = PC$ using a lead compensator.

poles and zeros do not appear in the loop transfer function but they can appear in the transfer functions from disturbances to outputs or control signals. Cancellations can be disastrous if the canceled factors are unstable, as was shown in Section 7.5. This implies that there is a major difference between minimum phase and non-minimum phase systems.

To explore the limitations caused by poles and zeros in the right half plane we factor the process transfer function as

$$P(s) = P_{mp}(s)P_{nmp}(s), \quad (11.12)$$

where P_{mp} is the minimum phase part and P_{nmp} is the non-minimum phase part. The factorization is normalized so that $|P_{nmp}(j\omega)| = 1$ and the sign is chosen so that P_{nmp} has negative phase. Requiring that the phase margin is φ_m we get

$$\arg L(j\omega_{gc}) = \arg P_{nmp}(j\omega_{gc}) + \arg P_{mp}(j\omega_{gc}) + \arg C(j\omega_{gc}) \geq -\pi + \varphi_m, \quad (11.13)$$

where C is the controller transfer function. Let n_{gc} be the slope of the gain curve at the crossover frequency; since $|P_{nmp}(j\omega)| = 1$ it follows that

$$n_{gc} = \frac{d \log |L(j\omega)|}{d \log \omega} \Bigg|_{\omega=\omega_{gc}} = \frac{d \log |P_{mp}(j\omega)C(j\omega)|}{d \log \omega} \Bigg|_{\omega=\omega_{gc}}.$$

The slope n_{gc} is negative and larger than -2 if the system is stable. It follows from Bode's relations, equation (9.5), that

$$\arg P_{mp}(j\omega) + \arg C(j\omega) \approx n_{gc} \frac{\pi}{2}$$

Combining this with equation (11.13) gives the following inequality for the allowable phase lag

$$\varphi_\ell = -\arg P_{nmp}(j\omega_{gc}) \leq \pi - \varphi_m + n_{gc} \frac{\pi}{2}. \quad (11.14)$$

This condition, which we call the *crossover frequency inequality*, shows that the gain crossover frequency must be chosen so that the phase lag of the non-minimum phase component is not too large. To find numerical values we will consider some reasonable design choices. A phase margin of 45° ($\varphi_m = \pi/4$), and a slope $n_{gc} = -1/2$ gives an admissible phase lag of $\varphi_\ell = \pi/2 = 1.57$ rad and a phase margin of 45° and $n_{gc} = -1$ gives an admissible phase lag $\varphi_\ell = \pi/4 = 0.78$ rad. It is thus reasonable to require that the phase lag of the non-minimum phase part is in the range of 0.5 to 1.6 radians, or roughly 30° to 90° .

The crossover frequency inequality shows that non-minimum phase components impose severe restrictions on possible crossover frequencies. It also means that there are systems that cannot be controlled with sufficient stability margins. The conditions are more stringent if the process has an uncertainty $\Delta P(j\omega_{gc})$. As we shall see in the next chapter, the admissible phase lag is then reduced by $\arg \Delta P(j\omega_{gc})$.

A straightforward way to use the crossover frequency inequality is to plot the phase of the transfer function of the process and the phase of the corresponding minimum phase system. Such a plot, shown in Figure 11.14, will immediately show the permissible gain crossover frequencies.

As an illustration we will give some analytical examples.

Example 11.5 (Zero in the right half plane). The non-minimum phase part of the plant transfer function for a system with a right half plane zero is

$$P_{nmp}(s) = \frac{z-s}{z+s}. \quad (11.15)$$

where $z > 0$. The phase lag of the non-minimum phase part is

$$\varphi_\ell = -\arg P_{nmp}(j\omega) = 2 \arctan \frac{\omega}{z}$$

Since the phase of P_{nmp} decreases with frequency, the inequality (11.14) gives the following bound on the crossover frequency:

$$\frac{\omega_{gc}}{z} \leq \tan \frac{\varphi_\ell}{2}. \quad (11.16)$$

With reasonable values of φ_ℓ we find that the gain crossover frequency must be smaller than the right half plane zero. It also follows that systems with slow zeros are more difficult to control than systems with fast zeros. ∇

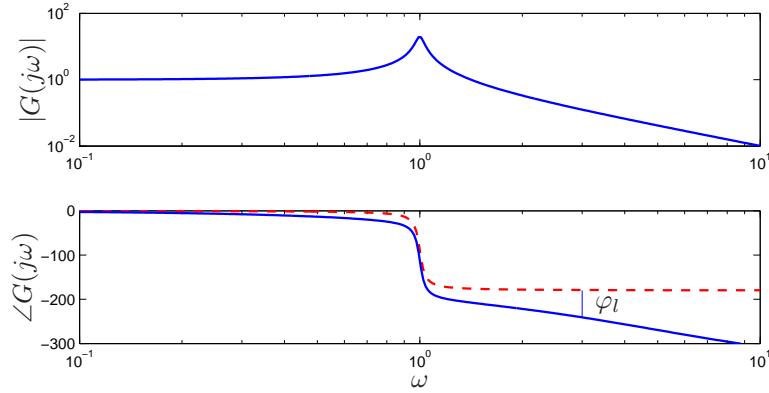


Figure 11.14: Bode plot of process transfer function (full lines) and corresponding minimum phase transfer function (dashed). The permissible gain crossover frequencies are those for which the difference in phase between the two curves satisfies equation (11.14).

Example 11.6 (Time delay). The transfer function of a time delay is

$$P(s) = e^{-sT}. \quad (11.17)$$

This is also the non-minimum phase part P_{nmp} and the corresponding phase lag is

$$\varphi_\ell = -\arg P_{nmp}(j\omega) = \omega T \quad \implies \quad w_{gc} \leq \frac{\varphi_\ell}{T}.$$

If the transfer function for the time delay is approximated by

$$e^{-sT} \approx \frac{1 - sT/2}{1 + sT/2},$$

we find that a time delay T corresponds to a right half plane zero $z = 2/T$. A slow zero thus corresponds to a long time delay. ∇

Example 11.7 (Pole in the right half plane). The non-minimum phase part of the transfer function for a system with a pole in the right half plane is

$$P_{nmp}(s) = \frac{s + p}{s - p}, \quad (11.18)$$

where $p > 0$. The phase lag of the non-minimum phase part is

$$\varphi_\ell = -\arg P_{nmp}(j\omega) = 2 \arctan \frac{p}{\omega}$$

Table 11.2: Achievable phase margin for $\varphi_m = \pi/4$ and $n_{gc} = -1/2$ and different pole-zero ratios p/z .

p/z	0.45	0.24	0.20	0.17	0.12	0.10	0.05
z/p	2.24	4.11	5.00	5.83	8.68	10	20
φ_m	0	30	38.6	45	60	64.8	84.6

and the crossover frequency inequality becomes

$$\omega_{gc} > \frac{p}{\tan(\varphi_\ell/2)}.$$

With reasonable values of φ_ℓ we find that the gain crossover frequency should be larger than the unstable pole. ∇

Example 11.8 (Pole and a zero in the right half plane). The non-minimum phase part of the transfer function for a system with both poles and zeros in the right half plane is

$$P_{nmp}(s) = \frac{(z-s)(s+p)}{(z+s)(s-p)}. \quad (11.19)$$

The phase lag of this transfer function is

$$\varphi_\ell = -\arg P_{nmp}(j\omega) = 2\arctan \frac{\omega}{z} + 2\arctan \frac{p}{\omega} = 2\arctan \frac{\omega_{gc}/z + p/\omega_{gc}}{1 - p/z}.$$

The minimum value of the right hand side is given by

$$\min_{\omega_{gc}} \left(2\arctan \frac{\omega_{gc}/z + p/\omega_{gc}}{1 - p/z} \right) = 2\arctan \frac{2\sqrt{p/z}}{1 - p/z} = 4\arctan \sqrt{\frac{p}{z}},$$

which is achieved at $\omega = \sqrt{pz}$. The crossover frequency inequality (11.14) becomes

$$\varphi_\ell = -\arg P_{nmp}(j\omega) \leq 4\arctan \sqrt{\frac{p}{z}},$$

or

$$\frac{p}{z} \leq \tan \frac{\varphi_\ell}{4}.$$

The design choices $\varphi_m = \pi/4$ and $n_{gc} = -1/2$ gives $p < 0.17z$. Table 11.2 shows the admissible pole-zero ratios for different phase margins. The

phase-margin that can be achieved for a given ratio p/z is

$$\varphi_m < \pi + n_{gc} \frac{\pi}{2} - 4 \arctan \sqrt{\frac{p}{z}}. \quad (11.20)$$

A pair of poles and zeros in the right half plane thus imposes severe constraints on the gain crossover frequency. The best gain crossover frequency is the geometric mean of the unstable pole and zero. A robust controller does not exist unless the pole/zero ratio is sufficiently small. ∇

Avoiding Difficulties with RHP Poles and Zeros

As the examples above show, right half plane poles and zeros significantly limit the achievable performance of a system, hence one would like to avoid these whenever possible. The poles of a system depend on the intrinsic dynamics of the system and are given by the eigenvalues of the dynamics matrix A of a linear system. Sensors and actuators have no effect on the poles. The only way to change poles is to redesign the system. Notice that this does not imply that unstable systems should be avoided. Unstable system may actually have advantages; one example is high performance supersonic aircraft.

The zeros of a system depend on the how sensors and actuators are coupled to the states. The zeros depend on all the matrices A , B , C and D in a linear system. The zeros can thus be influenced by moving sensors and actuators or by adding sensors and actuators. Notice that a fully actuated system $B = I$ does not have any zeros.

11.5 Design Example

In this section we carry out a detailed design example that illustrates the main techniques in this chapter.

11.6 Further Reading

A more complete description of the material in this chapter is available in the text by Doyle, Francis and Tannenbaum [DFT92] (out of print, but available online).

11.7 Exercises

1. Regenerate the controller for the system in Example 11.4 and use the frequency responses for the Gang of Four to show that the performance specification is met.

Chapter 12

Robust Performance

However, by building an amplifier whose gain is deliberately made, say 40 decibels higher than necessary (10000 fold excess on energy basis), and then feeding the output back on the input in such a way as to throw away that excess gain, it has been found that extraordinary improvements in constancy of amplification and freedom from non-linearity.

Harold S. Black, “Stabilized Feedback Amplifiers”, 1934 [Bla34].

The above quote illustrates that one the key uses of feedback is to provide robustness to uncertainty. It is one of the most useful properties of feedback and is what makes it possible to design feedback systems based on strongly simplified models. This chapter focuses on the analysis of robustness of feedback systems. We consider the stability and performance of systems who process dynamics are uncertain and derive fundamental limits for robust stability and performance. To do this we develop ways to model uncertainty, both in the form of parameter variations and in the form of neglected dynamics. We also discuss how to design controllers to achieve robust performance. One limitation of the tools we present here is that they are usually restricted to linear systems, although some nonlinear extensions have been developed.

12.1 Modeling Uncertainty

One form of uncertainty in dynamical systems is that the parameters describing the system are unknown, which is called *parametric uncertainty*. A typical example is the variation of the mass of a car, which changes with the number of passengers and the weight of the baggage. When linearizing a nonlinear system, the parameters of the linearized model also depend on

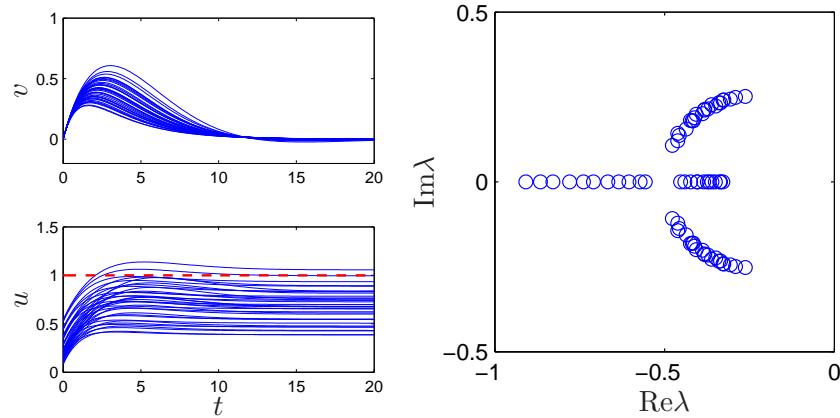


Figure 12.1: Responses of the cruise control system to a slope increase of 3° (left) and the eigenvalues of the closed loop system (right). Model parameters are swept over a wide range.

the operating condition. It is straightforward to investigate effects of parametric uncertainty simply by evaluating the performance criteria for a range of parameters. Such a calculation will directly reveal the consequences of parameter variations. We illustrate by a simple example.

Example 12.1 (Cruise control). The cruise control problem was described in Section 3.1 and a PI controller was designed in Example 10.1. To investigate the effect of parameter variations we will choose a controller designed for a nominal operating condition corresponding to mass $m = 1600$, fourth gear $\alpha = 12$ and speed $v = 25$ m/s, the controller gains are $k = 0.72$ and $k_i = 0.18$. Figure 12.1 shows the velocity v and the throttle u when encountering a hill with a 3° slope with masses in the range $1600 < m < 2000$, gear ratios $10 \leq \alpha \leq 16$ and velocity $10 \leq v \leq 40$ m/s. The simulations were done using models that were linearized around the different operating conditions. The figure shows that there are variations in the response but that they are quite reasonable. The largest velocity error is in the range of 0.2 to 0.6 m/s, and the response time is about 15 s. The control signal is marginally larger than 1 in some cases which implies that the throttle is fully open. A full nonlinear simulation using a controller with windup protection is required if we want to explore these cases in more detail. Figure 12.1 also shows the eigenvalues of the closed loop system for the different operating conditions. The figure shows that the closed loop system is well damped in all cases. ∇

This example indicates that at least as far as parametric variations are concerned, the design based on a simple nominal model will give satisfactory control. The example also indicates that a controller with fixed parameters can be used in all cases. Notice however that we have not considered operating conditions in low gear and at low speed.

Unmodeled Dynamics

It is generally fairly easy to investigate the effects of parametric variations. There are however other uncertainties that also are important. The simple model of the cruise control system only captures the dynamics of the forward motion of the vehicle and the torque characteristics of the engine and transmission. It does not, for example, include a detailed model of the engine dynamics (whose combustion processes are extremely complex), nor the slight delays that can occur in modern electronically controlled engines (due to the processing time of the embedded computers). These neglected mechanisms that are called *unmodeled dynamics*.

Unmodeled dynamics can be accounted for by developing a more complex model. Such models are commonly used for controller development but is a substantial effort to develop the models. An alternative is to investigate if the closed loop system is sensitive to generic forms of unmodeled dynamics. The basic idea is to describe the “unmodeled” dynamics by including a transfer function in the system description whose frequency response is bounded, but otherwise unspecified. For example, we might model the engine dynamics in the speed control example as a system that very quickly provides the torque that is requested through the throttle, giving a small deviation from the simplified model, which assumed the torque response was instantaneous. This technique can also be used in many instances to model parameter variations, allowing a quite general approach to uncertainty management.

In particular we wish to explore if additional linear dynamics may cause difficulties. A simple way is to assume that the transfer function of the process is $P(s) + \Delta P(s)$ where $P(s)$ is the nominal simplified transfer function and $\delta_a = \Delta P(s)$ represents the unmodeled dynamics. This case is called *additive uncertainty*. Figure 12.2 shows some other cases to represent uncertainties in a linear system.

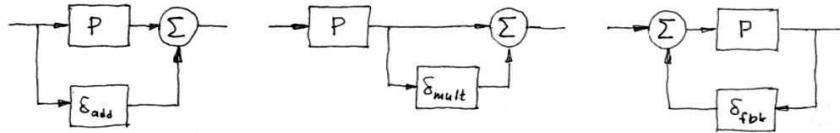


Figure 12.2: Representation of system with additive (left), multiplicative (middle) and feedback uncertainties (right). The nominal system is P systems and δ represents the uncertainties.

When are Two Systems Similar

A fundamental issue is to determine when two systems are close. This seemingly innocent problem is not as simple as it may appear. A naive idea is to say that two systems are close if their open loop responses are close. Even if this appears natural, there are complications as is illustrated by the following examples.

Example 12.2 (Similar in open loop but large differences in closed loop). The systems with the transfer functions

$$P_1(s) = \frac{100}{s+1}, \quad P_2(s) = \frac{100}{(s+1)(sT+1)^2}$$

have very similar open loop responses for small values of T , as illustrated in the top left corner of Figure 12.3, where $T = 0.025$. The differences between the step responses are barely noticeable in the figure. The step responses with unit gain error feedback are shown in the figure to the right. Notice that one closed loop system is stable and the other one is unstable. The transfer functions from reference to output are

$$T_1 = \frac{100}{s+101} \quad T_2 = \frac{1161600}{(s+83.93)(s^2 - 2.92s + 1925.37)}.$$

∇

Example 12.3 (Different in open loop but similar in closed loop). Consider the systems

$$P_1(s) = \frac{100}{s+1}, \quad P_2(s) = \frac{100}{s-1}.$$

The open loop responses have very different because P_1 is stable and P_2 is unstable, as shown in the bottom left plot in Figure 12.3. Closing a feedback

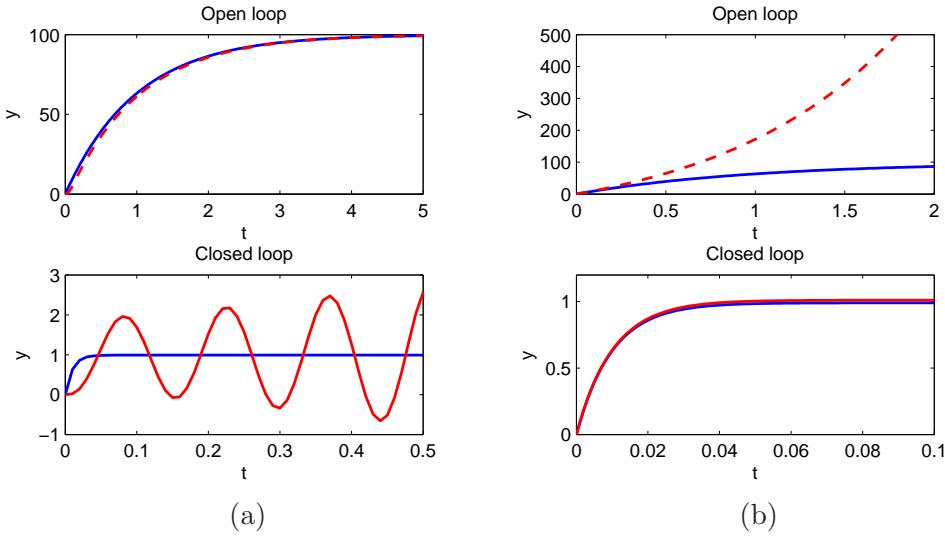


Figure 12.3: Open loop step responses and corresponding closed loop step responses for (a) Example 12.2 and (b) Example 12.3.

loop with unit gain around the systems we find that the closed loop transfer functions are

$$T_1(s) = \frac{100}{s+101} \quad T_2(s) = \frac{100}{s+99}$$

which are very close as is also shown in Figure 12.3. ∇

These examples show that if our goal is to close a feedback loop it may be very misleading to compare the open loop responses of the system. Inspired by the examples we will introduce a distance measure that is more appropriate for closed loop operation. Consider two systems with the rational transfer functions

$$P_1(s) = \frac{n_1(s)}{d_1(s)} \quad \text{and} \quad P_2(s) = \frac{n_2(s)}{d_2(s)},$$

where \$n_1(s)\$, \$n_2(s)\$, \$d_1(s)\$ and \$d_2(s)\$ are polynomials. Let

$$p(s) = d_1(s)n_2(-s) - n_1(s)d_2(-s)$$

and define the *chordal distance* between the transfer functions is defined as

$$d_\nu(P_1, P_2) = \begin{cases} \sup_{\omega} \frac{|P_1(j\omega) - P_2(j\omega)|}{\sqrt{(1+|P_1(j\omega)|^2)(1+|P_2(j\omega)|^2)}} & \text{if } p(s) \text{ has no RHP zeros} \\ 1 & \text{otherwise.} \end{cases} \quad (12.1)$$

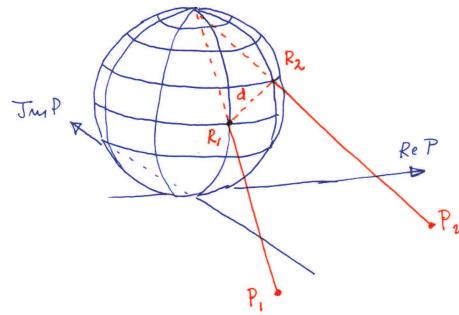


Figure 12.4: Geometric interpretation of the distance $d(P_1, P_2)$ between two transfer functions.

The distance has a nice geometric interpretation, as shown in Figure 12.4, where the Nyquist plots of P_1 and P_2 are projected on the Riemann sphere. The Riemann sphere is located above the complex plane. It has diameter 1 and its south pole is at the origin of the complex plane. Points in the complex plane are projected onto the sphere by a line through the point and the north pole (Figure 12.4). The distance $d_\nu(P_1, P_2)$ is simply the shortest chordal distance between the projections of the Nyquist curves. Since the diameter of the Riemann sphere is 1, it follows that the distance is never larger than 1.

The distance $d_\nu(P_1, P_2)$ is similar to $|P_1 - P_2|$ when the transfer functions are small, but very different when $|P_1|$ and $|P_2|$ are large. It is also related to the behavior of the systems under unit feedback as will be discussed in Section 12.6.

12.2 Stability in the Presence of Uncertainty

We begin by considering the problem of robust stability: when can we show that the stability of a system is robust with respect to process variations. This is an important question since the potential for instability is one of the main drawbacks of feedback. Hence we want to ensure that even if we have small inaccuracies in our model, we can still guarantee stability and performance.

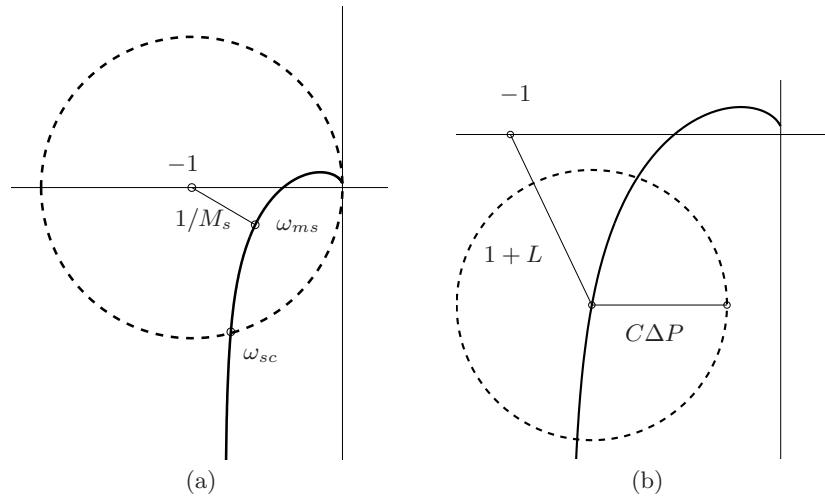


Figure 12.5: The left figure shows that the distance to the critical point $1/M_s$ is a robustness measure. The right figure shows the Nyquist curve of a nominal loop transfer function and its uncertainty caused by additive process variations ΔP .

Using Nyquist's Stability Criterion

The Nyquist criterion provides a powerful and elegant way to study the effects of uncertainty for linear systems. A simple criterion is that the Nyquist curve is sufficiently far from the critical point -1 . Recall that the shortest distance from the Nyquist curve is $1/M_s$ where M_s is the maximum of the sensitivity function. The maximum sensitivity M_s is thus a good robustness measure, as illustrated Figure 12.5a.

We will now derive explicit conditions for permissible process uncertainties. Consider a feedback system with a process P and a controller C . If the process is changed from P to $P + \Delta P$, the loop transfer function changes from PC to $PC + C\Delta P$, as illustrated in Figure 12.5b. If we have a bound on the size of ΔP (represented by the dashed circle in the figure), then the system remains stable as long as the process variations never overlap the -1 point, since this leaves the number of encirclements of -1 unchanged.

Some additional assumptions required for the analysis to hold. Most importantly, we require that the process perturbations ΔP be stable so that we do not introduce any new right half plane poles that would require additional encirclements in the Nyquist criterion. Also, we note that this condition is conservative: it allows for any perturbation that satisfies the given bounds,

while in practice we may have more information about possible perturbations.

The distance from the critical point -1 to the loop transfer function L is $|1 + L|$. This means that the perturbed Nyquist curve will not reach the critical point -1 provided that

$$|C\Delta P| < |1 + L|,$$

which implies

$$|\Delta P| < \left| \frac{1 + PC}{C} \right| \quad \text{or} \quad \left| \frac{\Delta P}{P} \right| < \frac{1}{|T|}. \quad (12.2)$$

This condition must be valid for all points on the Nyquist curve, i.e. pointwise for all frequencies. The condition for stability can thus be written as

$$\left| \frac{\Delta P(j\omega)}{P(j\omega)} \right| < \frac{1}{|T(j\omega)|} \quad \text{for all } \omega \geq 0. \quad (12.3)$$

This condition allows us to reason about uncertainty without exact knowledge of the process perturbations. Namely, we can verify stability for *any* uncertainty ΔP that satisfies the given bound. From an analysis perspective, this gives us a measure of the robustness of a given design. Conversely, if we require robustness of a given level, we can attempt to choose our controller C such that the desired level of robustness is available (by asking T to be small).

The formula given by equation (12.3) is one of the reasons why feedback systems work so well in practice. The mathematical models used to design control system are often strongly simplified. There may be model errors and the properties of a process may change during operation. Equation (12.3) implies that the closed loop system will at least be stable for substantial variations in the process dynamics.

It follows from equation (12.3) that the variations can be large for those frequencies where T is small and that smaller variations are allowed for frequencies where T is large. A conservative estimate of permissible process variations that will not cause instability is given by

$$\left| \frac{\Delta P(j\omega)}{P(j\omega)} \right| < \frac{1}{M_t},$$

where M_t is the largest value of the complementary sensitivity

$$M_t = \sup_{\omega} |T(j\omega)| = \left\| \frac{PC}{1 + PC} \right\|_{\infty}. \quad (12.4)$$

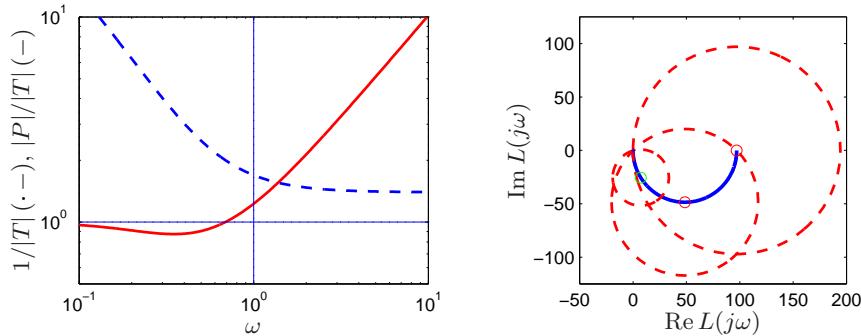


Figure 12.6: Illustration of the robustness for a cruise controller. The left figure shows the maximum relative error ($1/|T|$, dot-dashed) and absolute error ($|P|/|T|$, solid) for the process uncertainty ΔP . The Nyquist curve is shown in the right figure, as a solid line. The dashed circles show permissible perturbations in the process dynamics, $|\Delta P| = |P|/|T|$, at the frequencies $\omega = 0, 0.0142$ and 0.05 .

The value of M_t is influenced by the design of the controller. For example, if $M_t = 2$ then pure gain variations of 50% or pure phase variations of 30° are permitted without making the closed loop system unstable.

Example 12.4 (Cruise control). Consider the cruise control system discussed in Section 3.1. The model of the car in fourth gear at speed 25 m/s is

$$P(s) = \frac{1.38}{s + 0.0142},$$

and the controller is a PI controller with gains $k = 0.72$ and $k_i = 0.18$. Figure 12.6 plots the allowable size of the process uncertainty using the bound in equation (12.3). At low frequencies, $T(0) = 1$ and so the perturbations can be as large as the original process ($|\Delta P/P| < 1$). The complementary sensitivity has its maximum $M_t = 1.14$ at $\omega_{mt} = 0.35$ and hence this gives the minimum allowable process uncertainty, with $|\Delta P/P| < 0.87$ or $|\Delta P| < 3.47$. Finally, at high frequencies $T \rightarrow 0$ and hence the relative error can get very large. For example, at $\omega = 5$ we have $|T(j\omega)| = 0.195$ which means that the stability requirement is $|\Delta P/P| < 5.1$. The analysis clearly indicates that the system has good robustness and that the high frequency properties of the transmission system are not important for the design of the cruise controller.

Another illustration of the robustness of the system is given in the right diagram of Figure 12.6, which shows the Nyquist curve of the transfer func-

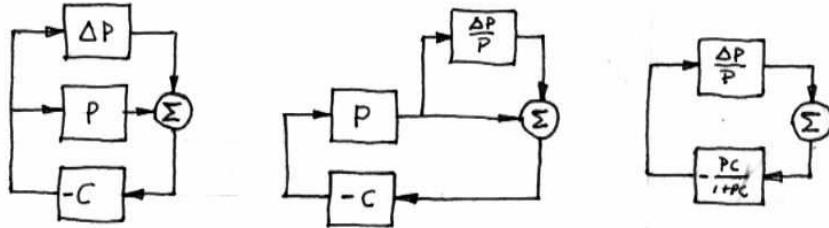


Figure 12.7: Illustration of robustness to process perturbations.

tion of the process and the uncertainty bounds $\Delta P = |P|/|T|$ for a few frequencies. Note that the controller can tolerate very large amounts of uncertainty and still maintain stability of the closed loop. ∇

The situation illustrated in the previous example is typical for many processes: moderately small uncertainties are only required around the gain crossover frequencies, but large uncertainties can be permitted at higher and lower frequencies. A consequence of this is that a simple model that describes the process dynamics well around the crossover frequency is often sufficient for design. Systems with many resonance peaks are an exception to this rule because the process transfer function for such systems may have large gains also for higher frequencies.

Notice that the results we have given can be very conservative. Referring to Figure 12.5, the critical perturbations, which were the basis for our analysis, are in the direction towards the critical point. It is possible to have much larger perturbations in the opposite direction.



The Small Gain Theorem

The robustness result given by equation (12.3) can be given another interpretation by using the small gain theorem, introduced in Section 9.5. It is convenient to choose a particular form of the small gain theorem where the gain of a system is defined in terms of the maximum amplitude of the frequency response. We first define the gain of a system as the H_∞ norm of its transfer function $H(s)$:

$$\|H\|_\infty = \sup_{\omega} |H(j\omega)|.$$

The small gain theorem can now be written as follows.

Table 12.1: Conditions for robust stability for different types of uncertainty

Process	Type	Robust Stability
$P + \Delta P$	Additive	$ CS\Delta P _\infty < 1$
$P(1 + \Delta P)$	Multiplicative	$\ S\Delta P\ _\infty < 1$
$P/(1 + \Delta P \cdot P)$	Feedback	$\ PS\Delta P\ _\infty < 1$

Theorem 12.1 (Small gain theorem). *Consider two stable, linear time invariant processes with transfer functions $P_1(s)$ and $P_2(s)$. The feedback interconnection of these two systems is stable if $\|P_1 P_2\|_\infty < 1$.*

The proof of this theorem follows directly from the Nyquist criterion applied to the loop transfer functions $L = P_1 P_2$.

The application of this theorem is illustrated in Figure 12.7, which shows a sequence of block diagrams of a closed loop system with a perturbed process. Using block diagram manipulation, we can isolate the uncertainty from the remaining dynamics and obtain the two block interconnection shown in Figure 12.7c. The loop transfer function of the resulting system is

$$L = \frac{PC}{1+PC} \frac{\Delta P}{P} = T\Delta P = CS\Delta P.$$

Equation (12.3) implies that the largest loop gain is less than one and hence the system is stable via the small gain theorem.

The small gain theorem can be used to check robust stability for uncertainty in a variety of situations. Table 12.1 summarizes a few of the common cases; the proofs (all via the small gain theorem) are left to the exercises.

Youla Parameterization



Since stability is such an essential property it is useful to characterize all controller that will stabilize a given process. Consider a stable process with the rational transfer function P , to simplify the writing we drop the arguments of the functions. A system with the complementary sensitivity function T can be obtained by feedforward control with the stable transfer function Q if

$$T = PQ \tag{12.5}$$

Notice that T must have the same RHP zeros as P since Q is stable. Now assume that we want to obtain the complementary transfer function T by

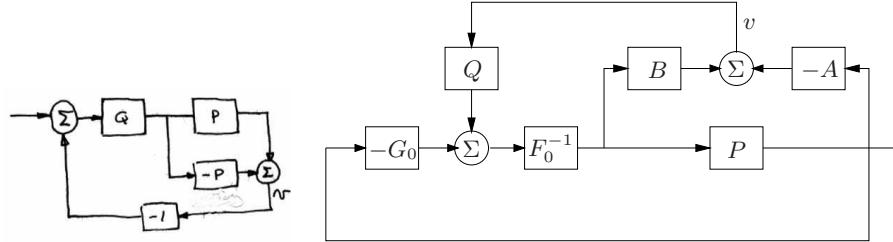


Figure 12.8: Block diagrams of Youla parameterizations of stable (left) and unstable systems (right). Notice that the signal v is zero.

using unit feedback with the controller C . Since $T = PC/(1 + PC) = PQ$ we find that the controller transfer function is

$$C = \frac{Q}{1 - QP}. \quad (12.6)$$

A straight forward calculation gives

$$\frac{1}{1 + PC} = 1 - T, \quad \frac{P}{1 + PC} = P - PT, \quad \frac{C}{1 + PC} = Q, \quad \frac{PC}{1 + PC} = T$$

which are all stable. All stabilizing controller are thus given by equation (12.6). Equation (12.6) is called a *Youla parameterization* because it characterizes all controllers that stabilizes a stable process. The parameterization is be illustrated by the block diagrams in Figure 12.8.

The feedforward controller (12.5) is given by $Q = P^{-1}T$. In particular if it is desired to have T close to one it follows that the feedforward controller is the inverse of the process transfer function. Comparing with the feedback controller (12.6) we find that the feedback controller obtains the desired result by using high gain feedback.

A similar characterization can be obtained also for unstable systems. Consider a process with a rational transfer function $P = a/b$ where a and b are polynomials, by introducing a stable polynomial c we can write

$$P(s) = \frac{a}{b} = \frac{A}{B},$$

where $A = a/c$ and $B = b/c$ are stable rational functions. We have

$$\begin{aligned} \frac{1}{1 + PC_0} &= \frac{AF_0}{AF_0 + BG_0} = S_0 & \frac{P}{1 + PC_0} &= \frac{BF_0}{AF_0 + BG_0} = PS_0 \\ \frac{C_0}{1 + PC_0} &= \frac{AG_0}{AF_0 + BG_0} = CS_0 & \frac{PC_0}{1 + PC_0} &= \frac{BG_0}{AF_0 + BG_0} = T_0 \end{aligned}$$

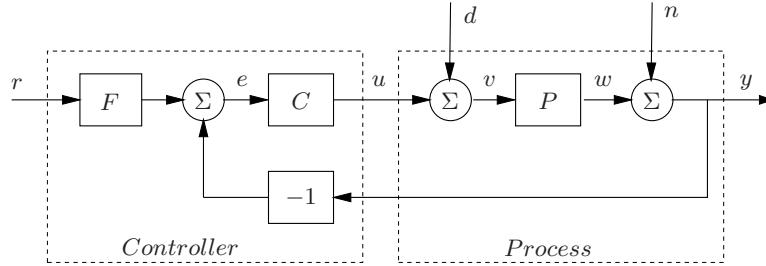


Figure 12.9: Block diagram of a basic feedback loop.

Since C is a stabilizing controller the function $AF_0 + BG_0$ must have all its zeros in the left half plane. All stabilizing controllers are now given by

$$C = \frac{G_0 + QA}{F_0 - QB}. \quad (12.7)$$

We have

$$\begin{aligned} \frac{1}{1 + PC} &= \frac{A(F_0 - QG)}{AF_0 + BG_0} & \frac{P}{1 + PC} &= \frac{BF_0 - QB^2}{AF_0 + BG_0} \\ \frac{C}{1 + PC} &= \frac{AG_0 + QA^2}{AF_0 + BG_0} & \frac{PC}{1 + PC} &= \frac{AF_0 + BG_0}{AF_0 + BG_0}. \end{aligned}$$

All these transfer functions are stable and equation(12.7) is therefore a Youla parameterization. Notice that equation (12.7) reduces to equation(12.6) for $F_0 = 1$ and $G_0 = 0$.

12.3 Performance in the Presence of Uncertainty

So far we have investigated the risk for instability and robustness to process uncertainty. We will now explore how responses to load disturbances, measurement noise and command signal following are influenced by process variations. To do this we will analyze the system in Figure 12.9.

Disturbance Attenuation

A simple criterion for disturbance attenuation is to compare the output of the closed loop system in Figure 12.9 with the output of the corresponding open loop system. If we let the disturbances for the open and closed loop systems be identical, the output of the closed loop system is then obtained

simply by passing the open loop output through a system with the transfer function S . The sensitivity function thus tells how the variations in the output are influenced by feedback. Disturbances with frequencies such that $|S(j\omega)| < 1$ are attenuated but disturbances with frequencies such that $|S(j\omega)| > 1$ are amplified by feedback. The maximum sensitivity M_s and the sensitivity crossover frequency ω_{sc} are simple performance measures.

The sensitivity function S gives a gross characterization of the effect of feedback on disturbances. A more detailed characterization is given by the transfer function from load disturbances to process output:

$$G_{yd} = \frac{P}{1 + PC} = PS. \quad (12.8)$$

Load disturbances typically have low frequencies and it is therefore important that the transfer function is small for low frequencies. For processes with constant low frequency gain and a controller with integral action we have $G_{yd} \approx s/k_i$. Integral gain k_i is thus a simple measure of attenuation of load disturbances.

To find how the transfer function G_{yd} is influenced by small variations in the process transfer function we differentiate equation (12.8) which gives

$$\frac{dG_{yd}}{G_{yd}} = S \frac{dP}{P}. \quad (12.9)$$

The response to load disturbances is thus insensitive to process variations for frequencies where $|S(j\omega)|$ is small, i.e. for those frequencies where load disturbances are important.

A drawback with feedback is that the controller feeds measurement noise into the system. In addition to the load disturbance rejection, it thus is also important that the control actions generated by measurement noise are not too large. It follows from Figure 12.9 that the transfer function G_{un} from measurement noise to controller output is given by

$$G_{un} = -\frac{C}{1 + PC} = -\frac{T}{P} \quad (12.10)$$

Since measurement noise typically has high frequencies it is important that the transfer function G_{un} is not too large for high frequencies. The loop transfer function PC is typically small for high frequencies, which implies that $G_{un} \approx C$ for large s . To avoid injecting too much measurement noise it is therefore important that $C(s)$ is small for large s . This property is called high frequency roll-off. Filtering of the measured signal in a PID controller is done to reduce injection of measurement noise, see Section 10.5.

To find how the transfer function G_{un} is influenced by small variations in the process transfer function we differentiate equation (12.10) which gives

$$\frac{dG_{un}}{G_{un}} = T \frac{dP}{P}. \quad (12.11)$$

Measurement noise typically has high frequencies. Since the complementary sensitivity function also is small for high frequencies we find that process uncertainty has little influence on the transfer function G_{un} for frequencies where measurement are important.

Command Signal Following

The transfer function from reference to output is given by

$$G_{yr} = \frac{PCF}{1 + PC} = T, \quad (12.12)$$

which is the complementary sensitivity function. To see how variations in P affect the performance of the system, we differentiate equation (12.12) with respect to the process transfer function:

$$\frac{dG_{yr}}{dP} = \frac{CF}{1 + PC} - \frac{PCFC}{(1 + PC)^2} = \frac{CF}{(1 + PC)^2} = S \frac{G_{yr}}{P}.$$

and it follows that

$$\frac{dG_{yr}}{G_{yr}} = S \frac{dP}{P}. \quad (12.13)$$

The relative error in the closed loop transfer function thus equals the product of the sensitivity function and the relative error in the process. In particular, it follows from equation (12.13) that the relative error in the closed loop transfer function is small when the sensitivity is small. This is one of the very useful properties of feedback.

When analyzing robust stability we were able to deal with large disturbances. In this section we have limited the analysis to small (differential) perturbations. There are some additional assumptions required for the analysis to hold. Most importantly, we require that the process perturbations dP be stable so that we do not introduce any new right half plane poles that would require additional encirclements in the Nyquist criterion. Also, we note that this condition is conservative: it allows for any perturbation that satisfies the given bounds, while in practice we have more information about possible perturbations.

12.4 Limits on the Sensitivities

The sensitivity function S and the complementary sensitivity function T tell us a great deal about the feedback loop. Disturbance rejection and sensitivity to process uncertainties are low for frequencies where S is small and tracking performance is good when T is close to 1. In this section we explore some of the limitations on robust performance by looking at algebraic and integral constraints on the functions.

Since

$$S = \frac{1}{1 + PC} \quad \text{and} \quad T = \frac{PC}{1 + PC}$$

it follows that the sensitivity functions are related through

$$S + T = 1. \quad (12.14)$$

A useful design goal is to make S close to zero and T close to one, a design goal that is compatible with equation (12.14). The loop transfer function L is typically large for small values of s and it goes to zero as s goes to infinity. This means that S is typically small for small s and close to 1 for large s . The complementary sensitivity function is close to 1 for small s and it goes to 0 as s goes to infinity.

Bode's Integral Formula

A basic problem is to investigate if S can be made small over a large frequency range. We will start by investigating an example.

Example 12.5 (System that admits small sensitivities). Consider a closed loop system consisting of a first order process and a proportional controller. Let the loop transfer function

$$L = PC = \frac{k}{s + 1}$$

where parameter k is the controller gain. The sensitivity function is

$$S = \frac{s + 1}{s + 1 + k}$$

and we have

$$|S(j\omega)| = \sqrt{\frac{1 + \omega^2}{1 + 2k + k^2 + \omega^2}}$$

This implies that $|S(j\omega)| < 1$ for all finite frequencies and that the sensitivity can be made arbitrary small for any finite frequency by making k sufficiently large. ∇

The system in Example 12.5 is unfortunately an exception. The key feature of the system is that the Nyquist curve of the process is completely contained in the right half plane. Such systems are called *positive real*. For these systems the Nyquist curve never enters the region shown in Figure 11.6 where the sensitivity is greater than one.

For typical control systems there are unfortunately severe constraints on the sensitivity function. The following theorem, due to Bode, provides fundamental insights into the limits of performance under feedback.

Theorem 12.2 (Bode's integral formula). *Let $S(s)$ be the sensitivity function for a feedback system and assume that it goes to zero faster than $1/s$ for large s . If the loop transfer has poles p_k in the right half plane then the sensitivity function satisfies the following integral:*

$$\int_0^\infty \log |S(j\omega)| d\omega = \int_0^\infty \log \frac{1}{|1 + L(j\omega)|} d\omega = \pi \sum \operatorname{Re} p_k. \quad (12.15)$$

Equation (12.15) implies that there are fundamental limitations to what can be achieved by control and that control design can be viewed as a redistribution of disturbance attenuation over different frequencies. This equation shows that if the sensitivity function is made smaller for some frequencies it must increase at other frequencies. This means that if disturbance attenuation is improved in one frequency range it will be worse in other. This is called the *waterbed effect*. It also follows that systems with poles in the right half plane have larger sensitivity.

For a loop transfer function without poles in the right half plane equation (12.15) reduces to

$$\int_0^\infty \log |S(j\omega)| d\omega = 0.$$

This formula can be given a nice geometric interpretation as shown in Figure 12.10, which shows $\log |S(j\omega)|$ as a function of ω . The area over the horizontal axis must be equal to the area under the axis when frequency is plotted on a *linear* scale.

There is an analogous result for the complementary sensitivity function which tells that

$$\int_0^\infty \log |T(\frac{1}{j\omega})| d\omega = \pi \sum \frac{1}{z_i},$$

where the summation is over all right half plane zeros. Notice that small right half plane zeros are worse than large ones and that large right half plane poles are worse than small ones.

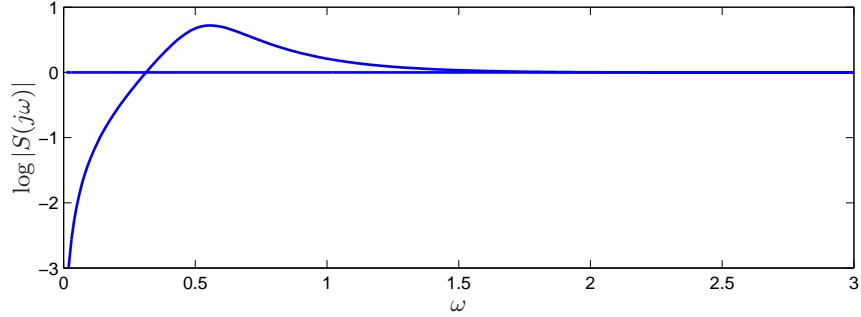


Figure 12.10: Geometric interpretation of the *waterbed effect* given by Bode's integral formula (12.15).

Derivation of Bode's Formula

This is a technical section which requires some knowledge of the theory of complex variables, in particular contour integration. Assume that the loop transfer function has distinct poles at $s = p_k$ in the right half plane and that $L(s)$ goes to zero faster than $1/s$ for large values of s .

Consider the integral of the logarithm of the sensitivity function $S(s) = 1/(1 + L(s))$ over the contour shown in Figure 12.11.

The contour encloses the right half plane except the points $s = p_k$ where the loop transfer function $L(s) = P(s)C(s)$ has poles and the sensitivity function $S(s)$ has zeros. The direction of the contour is counter clockwise.

The integral of the log of the sensitivity function around this contour is given by

$$\begin{aligned} \int_{\Gamma} \log(S(s)) ds &= \int_{jR}^{-jR} \log(S(s)) ds + \int_R \log(S(s)) ds + \sum_k \int_{\gamma} \log(S(s)) ds \\ &= I_1 + I_2 + I_3 = 0, \end{aligned}$$

where R is a large semi circle on the right and γ_k is the contour starting on the imaginary axis at $s = \text{Im} p_k$ and a small circle enclosing the pole p_k . The integral is zero because the function $\log S(s)$ is regular inside the contour. We have

$$I_1 = -j \int_{-jR}^{jR} \log(S(j\omega)) d\omega = -2j \int_0^{jR} \log(|S(j\omega)|) d\omega$$

because the real part of $\log S(j\omega)$ is an even function and the imaginary

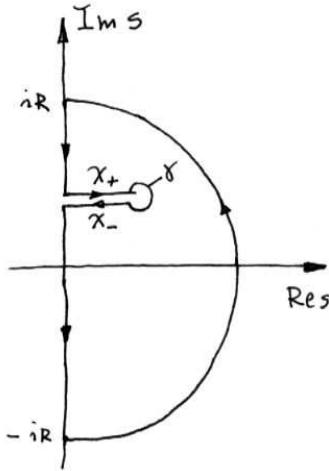


Figure 12.11: Contour used to prove Bode's theorem. To avoid clutter we have shown only one of the paths that enclose the right half plane.

part is an odd function. Furthermore we have

$$I_2 = \int_R \log(S(s)) ds = \int_R \log(1 + L(s)) ds \approx \int_R L(s) ds.$$

Since $L(s)$ goes to zero faster than $1/s$ for large s the integral goes to zero when the radius of the circle goes to infinity.

Next we consider the integral I_3 , for this purpose we split the contour into three parts X_+ , γ and X_- as indicated in Figure 12.11. We can then write the integral as

$$I_3 = \int_{X_+} \log S(s) ds + \int_\gamma \log S(s) ds + \int_{X_-} \log S(s) ds.$$

The contour γ is a small circle with radius r around the pole p_k . The magnitude of the integrand is of the order $\log r$ and the length of the path is $2\pi r$. The integral thus goes to zero as the radius r goes to zero. Furthermore, making use of the fact that X_- is oriented oppositely from X_+ , we have

$$\int_{X_+} \log S(s) ds + \int_{X_-} \log S(s) ds = \int_{X_+} (\log S(s) - \log S(s - 2\pi j)) ds = 2\pi p_k.$$

Since $|S(s)| = |S(s - 2\pi j)|$ we have

$$\log S(s) - \log S(s - 2\pi j) = \arg S(s) - \arg S(s - 2\pi j) = 2\pi$$

and we find that

$$I_3 = 2\pi \sum p_k$$

Letting the small circles go to zero and the large circle go to infinity and adding the contributions from all right half plane poles p_k gives

$$I_1 + I_2 + I_3 = -2i \int_0^R \log |S(j\omega)| d\omega + \sum_k 2\pi p_k = 0.$$

which is Bode's formula (12.15).

12.5 Robust Pole Placement

Many design methods for control systems do not take robustness into account. In such cases it is essential to always investigate the robustness because there are seemingly reasonable designs that give controller with poor robustness. Any design method which does not take robustness explicitly into account can give controllers with poor robustness. We illustrate this by analyzing controllers designed by state feedback and observers. The closed loop poles can be assigned to arbitrary locations if the system is observable and controllable. However if we want to have a robust closed loop system, the poles and zeros of the process impose severe restrictions on the location of the closed loop poles. Some examples are first given; based on analysis of these examples we then obtain design rules for robust pole placement.

Slow Stable Zeros

We will first explore the effects of slow stable zeros, and we begin with a simple example.

Example 12.6 (Vehicle steering). Consider the linearized model for vehicle steering in Example 8.4 which has the transfer function.

$$P(s) = \frac{0.5s + 1}{s^2}.$$

A controller based on an observer and state feedback, where the closed loop poles were given by $\omega_c = 1$, $\zeta_c = 0.707$, $\omega_o = 2$ and $\zeta_o = 0.707$ was designed in Example 7.3. Assume that we want a faster closed loop system and choose $\omega_c = 10$, $\zeta_c = 0.707$, $\omega_o = 20$ and $\zeta_o = 0.707$. A pole assignment design

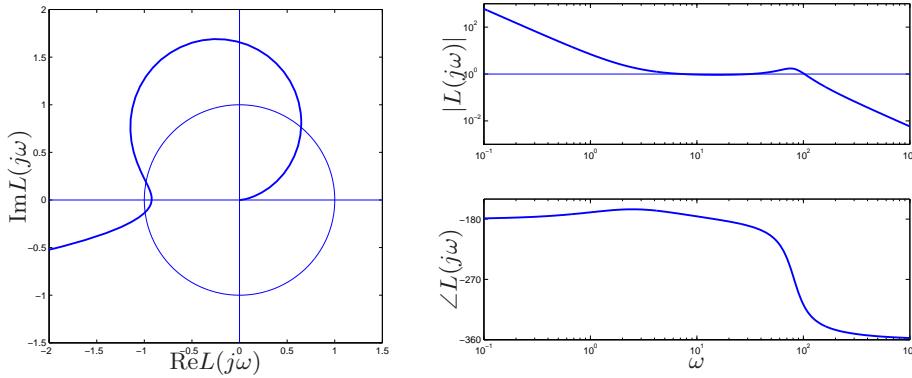


Figure 12.12: Nyquist (left) and Bode (right) plots of the loop transfer function for vehicle steering with a controller based on state feedback and an observer.

gives state feedback gain $k_1 = 100$ and $k_2 = -35.86$ and an observer gains $l_1 = 28.28$ and $l_2 = 400$. The controller transfer function is

$$C(s) = \frac{-11516s + 40000}{s^2 + 42.4s + 6657.9}.$$

Figure 12.12 shows Nyquist and Bode plots of the loop transfer function. The Nyquist plot indicates that the robustness is very poor since the loop transfer function is very close to the critical point -1 . The phase margin is only 7° . This also shows up in the Bode plot where the gain curve hovers around the value 1 and the phase curve is close to 180° for a wide frequency range.

More insight is obtained by analyzing the sensitivity functions. The full lines in Figure 12.13 shows the sensitivity functions. The maximum sensitivities are $M_s = 13$ and $M_t = 12$, which are much too large indicating that the system has very poor robustness. ∇

At first sight it is very surprising that a controller where the nominal system has well damped poles and zeros which are far to the left in the right half plane is so sensitive to process variations. We have an indication that something is unusual because the controller has a zero $s = 3.9$ in the right half plane. To understand what happens we will investigate the reason for the peaks of the sensitivity functions. Let the transfer functions of the process and the controller be

$$P(s) = \frac{n_p(s)}{d_p(s)} \quad C(s) = \frac{n_c(s)}{d_c(s)},$$

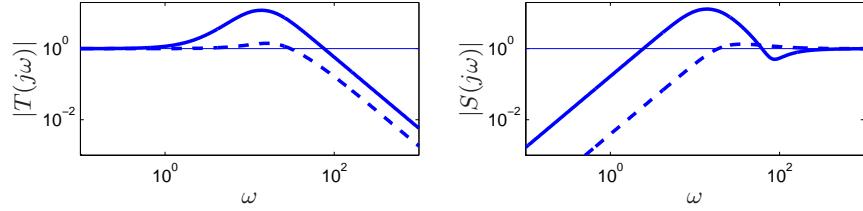


Figure 12.13: Sensitivity function for the system with $\omega_c = 10$, $\zeta_c = 0.707$, $\omega_o = 20$, $\zeta_o = 0.707$ (solid) and with $\omega_c = 10$, $\zeta_c = 2.6$ (dashed).

where $n_p(s)$, $n_c(s)$, $d_p(s)$ and $d_c(s)$ are polynomials.

The complementary sensitivity function is

$$T(s) = \frac{PC}{1+PC} = \frac{n_p(s)n_c(s)}{d_p(s)d_c(s) + n_p(s)d_p(s)}.$$

It is 1 for low frequency and start to increase at its first zero which is the process zero at $s = 2$, it increases further at the controller zero at $s = 3.9$ and it does not start to decrease until the closed loop poles appear at $\omega_c = 10$ and $\omega_o = 20$. We can thus conclude that there will be a peak in the complementary sensitivity function. The magnitude of the peak depends on the ratio of the zeros and the poles of the transfer function.

The peak of the complementary sensitivity function can be avoided by assigning a closed loop zero close to the slow process zero. We can achieve this by choosing $\omega_c = 10$ and $\zeta_c = 2.6$ which gives the closed loop poles at $s = -2$ and $s = -50$. The controller transfer function then becomes

$$C(s) = \frac{3628s + 40000}{s^2 + 80.28s + 156.56} = 3628 \frac{s + 11.02}{(s + 2)(s + 78.28)}$$

The sensitivity functions are shown in dashed lines in Figure 12.13. The controller gives the maximum sensitivities M_s and M_t which give a good robustness. Notice that the controller has a pole at $s = 2$ which cancels the slow process zero. The design can also be done simply by canceling the slow stable process zero and designing the system for the simplified system. One lesson from the example is that it is necessary to choose closed loop poles that are equal to or close to slow stable process zeros. Another lesson is that slow unstable process zeros impose limitations on the achievable bandwidth as was already noted in Section 11.4.

Fast Stable Process Poles

The next example shows the effect of fast stable poles.

Example 12.7 (Fast system poles). Consider PI control of a first order system, where the process and the controller have the transfer functions

$$P(s) = \frac{b}{s+a} \quad C(s) = k + \frac{k_i}{s}.$$

The loop transfer function is

$$L(s) = \frac{b(ks + k_i)}{s(s + a)}$$

The closed loop characteristic polynomial is

$$s(s + a) + b(ks + k_i) = s^2 + (a + bk)s + k_i$$

Let the desired closed loop characteristic polynomial be

$$(s + p_1)(s + p_2),$$

we find that the controller parameters are given by

$$k = \frac{p_1 + p_2 - a}{b} \quad k_i = \frac{p_1 p_2}{b}.$$

The sensitivity functions are then

$$S(s) = \frac{s(s + a)}{(s + p_1)(s + p_2)} \quad T(s) = \frac{(p_1 + p_2 - a)s + p_1 p_2}{(s + p_1)(s + p_2)}.$$

Assume that the process pole a is much larger than the closed loop poles p_1 and p_2 , say $a > p_2 > p_1$. Notice that the proportional gain is negative and that the controller has a zero in the left half plane if $a > p_1 + p_2$, an indication that the system has bad properties..

Next consider the sensitivity function, which is 1 for high frequencies. Moving from high to low frequencies we find that the sensitivity increases at the process pole $s = a$. The sensitivity does not decrease until the closed loop poles are reached resulting in a large sensitivity peak which is approximately a/p_2 . The magnitude of the sensitivity function is shown in Figure 12.14 for $a = b = 1$, $p_1 = 0.05$, $p_2 = 0.2$. Notice the high sensitivity peak. For comparison we have also shown the gain curve for the when the process pole is slower than the process pole ($a = b = a$, $p_1 = 5$, $p_2 = 200$) The problem

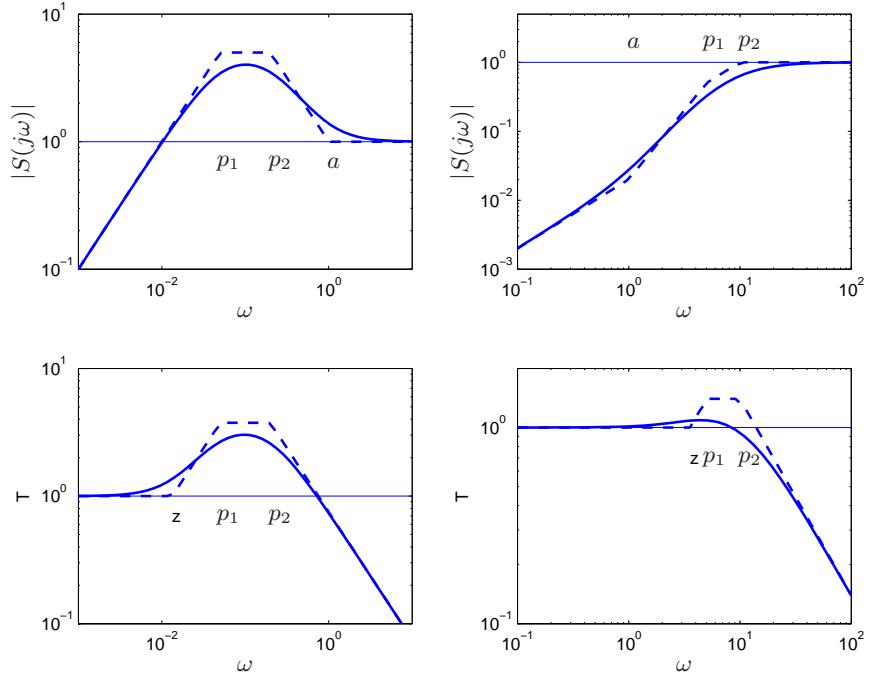


Figure 12.14: Gain curves for Bode plots of the sensitivity function S for designs with $p_1 < p_2 < a$ (left) and $a < p_1 < p_2$ (right). The full lines are the true sensitivities and the dashed lines are the asymptotes

with the poor robustness can be avoided by choosing one closed loop pole equal to the process pole, i.e. $p_2 = a$. The controller gains then becomes

$$k = \frac{p_1}{b} \quad k_i = \frac{ap_1}{l},$$

which means that the fast process pole is canceled by a controller zero. The loop transfer function and the sensitivity functions are

$$L(s) = \frac{bk}{s} \quad S(s) = \frac{s}{s + bk} \quad T(s) = \frac{bk}{s + bk}.$$

The maximum sensitivities are less than 1 for all frequencies. ∇

Design Rules for Pole-Placement

Based on the insight gained from the examples it is now possible to obtain design rules the give designs with good robustness. Consider the expres-

sion (12.5) for the complementary sensitivity function. Let w_{gc} be the desired gain crossover frequency. Assume that the process has zeros which are slower than ω_{gc} . The complementary sensitivity function is one for low frequencies and it increases for frequencies close to the process zeros unless there is a closed loop pole in the neighborhood. To avoid large values of the complementary sensitivity function we find that the closed loop system should have poles close to or equal to the slow stable zeros. This means that slow stable zeros should be canceled by controller poles. Since unstable zeros cannot be canceled slow stable zeros the presence of slow unstable zeros means that achievable gain crossover frequency must be smaller than the slowest unstable process zero, (see Section 11.3).

Now consider process poles that are faster than the desired gain crossover frequency. Consider the expression (12.5) for the sensitivity function. The sensitivity function is 1 for high frequencies. Moving from high to low frequencies the sensitivity function increases at the fast process poles. Large peaks can be obtained unless there are closed loop poles close to the fast process poles. To avoid large peaks in the sensitivity the closed loop system should have poles close that matches the fast process poles. This means that the controller should cancel the fast process poles by controller zeros. Since unstable modes cannot be canceled, the presence of a fast unstable pole implies that the gain crossover frequency must be sufficiently large, (see Section 11.3).

To summarize, we obtain the following simple design rule: slow stable process zeros should be matched slow closed loop poles and fast stable process poles should be matched by fast process poles. Slow unstable process zeros and fast unstable process poles impose severe limitations.

12.6 Design for Robust Performance

Control design is a rich problem where many factors have to be taken into account. Typical requirements are that load disturbances should be attenuated, the controller should only inject a moderate amount of measurement noise, the output should follow variations in the command signal well and the closed loop system should be insensitive to process variations. For the system in Figure 12.9 these requirements can be captured by specifications on the sensitivity functions S and T and the transfer functions G_{yd} , G_{un} , G_{yr} and G_{ur} . Notice that it is necessary to consider at least six transfer functions, as discussed Section 11.1. The requirements are mutually conflicting and it is necessary to make trade-offs. Attenuation of load disturbances will

be improved if the bandwidth is increased but so will the noise injection.

It is highly desirable to have design methods that can guarantee robust performance. Such design methods did not appear until the late 1980. There are many issues to consider in control design. It is interesting that many design methods result in controllers having the same structure as the controller based on state feedback and an observer.

Linear Quadratic Control LQG

One way to make the trade-off between attenuation of load disturbances and injection of measurement noise is to design a controller which minimizes the loss function

$$J = \frac{1}{T} \int_0^T (y^2(t) + \rho u^2(t)) dt,$$

where ρ is a weighting parameters as discussed in Section 6.5. This loss function gives a compromise between load disturbance attenuation and disturbance injection because it balances control actions against deviations in the output. If all state variables are measured, the controller is a state feedback

$$u = K(x_m - x).$$

The controller has the same form as the controller obtained by pole assignment in Section 6.2. The controller gain is, however, obtained by solving the optimization problem. It has been shown that this controller is very robust. It has a phase margin of at least 60° and an infinite gain margin. The controller is called a *linear quadratic control* or *LQ control* because the process model is linear and the criterion is quadratic.

When all state variables are not measured, the state can be reconstructed using an observer as discussed in Section 7.3. It is also possible to introduce process disturbances and measurement noise explicitly in the model and to reconstruct the states using a Kalman filter. The Kalman filter has the same structure as the observer designed by pole assignment in Section 7.3, but the observer gains L are now obtained by solving an optimization problem. The control law obtained by combining linear quadratic control with a Kalman filter is called *linear quadratic Gaussian control* or *LQG Control*. The Kalman filter is optimal when the models for load disturbances and measurement noise are Gaussian.

It is interesting that the solution to the optimization problem leads to a controller having the structure of a state feedback and an observer. The state-feedback gains depend on the parameter ρ and the filter gains depend

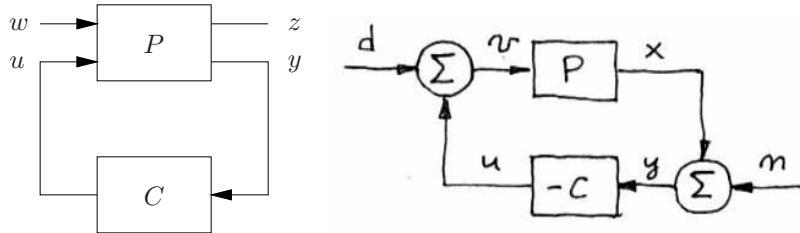


Figure 12.15: The left figure shows a general representation of a control problem used in robust control. The input u represents the control signal, the input w represents the external influences on the system, the output z is the generalized error and the output y is the measured signal. The right figure shows the special case of the system in Figure 12.9 where the reference signal is zero. In this case we have $w = (-n, d)$ and $z = (x, v)$.

on the parameters in the model that characterize process noise and measurement noise, see Section 7.4. There are efficient programs to compute the feedback and observer gains.

The nice robustness properties of state feedback are unfortunately lost when the observer is added. It is possible to choose parameters which give closed loop systems with very poor robustness similar. We can thus conclude that it is a fundamental difference between using sensors for all states and reconstructing the states using an observer.

H_∞ Control



Robust control design is called H_∞ for reasons that will be explained shortly. The basic ideas are simple but the details are complicated and we will therefore just give the flavor of the results. A key idea is illustrated in Figure 12.15 where the closed loop system is represented by two blocks, the process P and the controller C . The process P has two inputs, the control signal u which can be manipulated by the controller, and the generalized disturbance w , which represents all external influences, for example command signals and disturbances. The process has two outputs, the generalized error z which is a vector of error signals representing the deviation of signals from their desired values and the measured signal y which can be used by the controller to compute u . For a linear system and a linear controller the closed loop system can be represented by the linear system

$$z = H(P(s), C(s))w \quad (12.16)$$

which tells how the generalized error w depends on the generalized disturbances w . The control design problem is to find a controller C such that the gain of the transfer function H is small even when the process has uncertainties. There are many different ways to specify uncertainty and gain, giving rise to different designs. The names H_2 and H_∞ control corresponds to the corresponding norms $\|H\|_2$ and $\|H\|_\infty$.

To illustrate the ideas we will consider a regulation problem for the system in Figure 12.9. The reference signal is assumed to be zero and the external signals are the load disturbance d and the measurement noise n . The generalized input is $w = (-n, d)$. (The negative sign of n is not essential, it is chosen taken to get somewhat nicer equations.) The generalized error is chosen as $z = (x, v)$, where x is the process output, and v which the part of the load disturbance that is not compensated by the controller Figure 12.9. The closed loop system is thus modeled by

$$z = \begin{pmatrix} x \\ v \end{pmatrix} = H(P, C) \begin{pmatrix} -n \\ d \end{pmatrix} = \begin{pmatrix} 1 & P \\ \frac{C}{1+PC} & \frac{PC}{1+PC} \end{pmatrix} \begin{pmatrix} -n \\ d \end{pmatrix}, \quad (12.17)$$

which is the same as equation (12.16). A straight forward calculation shows that

$$\|H(P, C)\|_\infty = \sup_{\omega} \frac{\sqrt{(1 + |P(j\omega)|^2)(1 + |C(j\omega)|^2)}}{|1 + P(j\omega)C(j\omega)|}. \quad (12.18)$$

There are efficient numerical methods to find a controller such that $\|H(P, T)\|_\infty < \gamma$, if such a controller exist. The best controller can then be found by iterating on γ . The calculations can be made by solving *algebraic Riccati* equations for example by using the command `hinfsyn` in MATLAB. The controller has the same order as the process, and the same structure as the controller based on state feedback and an observer, see Figure 7.5 and Equation (7.17).

Notice that if we minimize $\|H(P, T)\|_\infty$ we make sure that the transfer functions $G_{yd} = P/(1 + PC)$, that represent transmission of load disturbances to the output, and $G_{un} = -C/(1 + PC)$, that represent how measurement noise is transmitted to the control signal, are small. Since the sensitivity and the complementary sensitivity functions are also elements of $H(P, C)$ we have also guarantees that the sensitivities are also less than γ . The design methods thus balances performance and robustness.

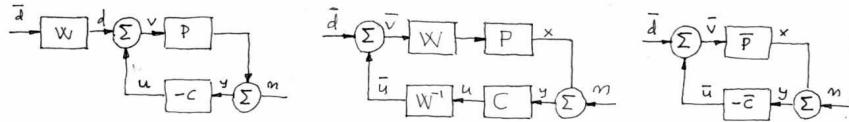


Figure 12.16: Block diagrams of a system with disturbance weighting.

Disturbance Weighting

Minimizing the gain $\|H(P, C)\|_\infty$ means that gains of all individual signal transmissions from disturbances to outputs are less than γ for all frequencies of the input signals. The assumption that the disturbances are equally important and that all frequencies are also equally important is not very realistic, recall that load disturbances typically have low frequencies and measurement noise is typically dominated by high frequencies. It is straight forward to modify the problem so that disturbances of different frequencies are given different emphasis, by introducing a weighting filter on the load disturbance as shown in Figure 12.15. For example low frequency load disturbances will be enhanced by choosing W_d as a low pass filter because the actual load disturbance is $W_d \bar{d}$. By using block diagram manipulation as shown in Figure 12.16 we find that the system with frequency weighting is equivalent to the system with no frequency weighting in Figure 12.16 and the signals are related through

$$z_w = \begin{pmatrix} x \\ \bar{v} \end{pmatrix} \begin{pmatrix} \frac{1}{1 + P_w C_w} & \frac{P_w}{1 + P_w C_w} \\ \frac{C_w}{1 + P_w C_w} & \frac{P_w C_w}{1 + P_w C_w} \end{pmatrix} \begin{pmatrix} -n \\ \bar{d} \end{pmatrix} = H(P_w, C_w) w_w \quad (12.19)$$

where $P_w = PW_d$ and $C_w = W_d^{-1}C$. The problem of finding a controller C_w which minimizes the gain of $H(P_w, C_w)$ is thus equivalent to the problem without disturbance weighting, having obtained C_w the controller for the original system is then $C = W_d C_w$. Notice that if we introduce the frequency weighting $W_d = k/s$ we will automatically get a controller with integral action.

Robustness

There are strong robustness results associated with the H_∞ controller. We can understand this intuitively by comparing Equations (12.1) and (12.18). We can then conclude that

$$\|H(P, C)\|_\infty = \frac{1}{d(P, -1/C)} \quad (12.20)$$

The inverse of $\|H(P, C)\|_\infty$ is thus equal to chordal distance between P and $1/C$. If we find a controller C with $\|H(P, C)\|_\infty < \gamma$ this controller will then stabilize any process P_* such that $d(P, P_*) < \gamma$.

Limits of Robust Design

There is a limit to what can be achieved by robust design. In spite of the nice properties of feedback there are situations where the process variations are so large that it is not possible to find a linear controller which gives a robust system with good performance. It is then necessary to use other controllers. In some cases it is possible to measure a variable that is well correlated with the process variations. Controllers for different parameters values can then be designed and the corresponding controller can be chosen based on the measured signal. This type of controller is called *gain scheduling*. The cruise controller is a typical example where the measured signal could be gear position and velocity. Gain scheduling is the common solution for high performance aircraft where scheduling is done based on Mach number and dynamic pressure. When using gain scheduling it is important to make sure that switches between the controllers do not create undesirable transients.

If it is not possible to measure variables related to the parameters, it is possible to use *automatic tuning* and *adaptive control*. In automatic tuning process dynamics is measured by perturbing the system and a controller is then designed automatically. Automatic tuning requires that parameters remain constant, it has been widely applied for PID control, it is a reasonable guess that, in the future, many controllers will have features for automatic tuning. If parameters are changing it is possible to use adaptive methods where process dynamics is measured on-line.

12.7 Further Reading

Robustness was a central issue in classical control, see [Bod45]. It was deemphasized in the euphoria of the development of design methods based

on optimization. The strong robustness of LQ control based on state feedback shown by Anderson and Moore [?] contributed to the optimism. The poor robustness of output feedback based on LQG was pointed out by Rosenbrock [RM71], Horowitz [Hor75] and Doyle [Doy78] resulted in a renewed interest in robustness. A major step forward was the development of design methods where robustness was explicitly taken into account. Seminal work by Zames [Zam81] was a major step forward. Robust control was originally developed using powerful results from the theory of complex variables which unfortunately gave controllers of very high order. A major breakthrough was given by Doyle, Glover, Khargonekar, and Francis [DGKF89] who showed that the solution could be obtained using Riccati equations and that a controller of low order could be found. This paper led to an extensive treatment of the so-called H_∞ control [Fra87, MG90, DFT92, GL95, ZDG96, SP96, Vin01]. A major advantage of the theory is that it combines much of the intuition from servomechanism theory with sound numerical algorithms based on numerical linear algebra and optimization. The results have been extended to nonlinear systems by treating the design problem as a game where the disturbances are generated by an adversary as described in [BB91]. Auto-tuning and adaptive control are treated in [ÅW95] and automatic tuning is dealt with in depth in [ÅH05].

12.8 Exercises

1. Show that an additive disturbance δ_{add} , show that it can create RHP zeros, but not RHP poles, and that a feedback disturbance δ_{fbk} can create RHP poles but not RHP zeros. Also give constructive examples.
2. Compute the distance between the systems

$$P_1(s) = \frac{k}{s+1}, \text{ and } P_2(s) = \frac{k}{s-11}.$$

for $k = 1, 2$ and 5 .

3. The distance measure is closely related to closed loop systems with unit feedback. Show how the measure can be modified to applied to an arbitrary feedback.
4. Consider the Nyquist curve in Figure 12.12. Explain why part of the curve is approximately a circle. Derive a formula for the center and the radius and compare with the actual Nyquist curve.

5. Consider the transfer functions in examples 12.2 and 12.3. Compute the distance measure $\delta(P_1, P_1)$ in both cases. Repeat the calculations when the controller is $C = 0.1$.
6. (Ideal Delay Compensator) Consider a process whose dynamics is a pure time delay, the transfer function is $P(s) = e^{-s}$. The ideal delay compensator is a controller with the transfer function $C(s) = 1/(1 - e^{-s})$. Show that the sensitivity functions are $T(s) = e^{-s}$ and $S(s) = 1 - e^{-s}$ and that the closed loop system will be unstable for arbitrary small changes in the delay.
7. Let P and C be matrices whose entries are complex numbers, show that the singular values of the matrix

$$H(P, C) = \begin{pmatrix} 1 & P \\ \frac{1+PC}{C} & \frac{1+PC}{PC} \\ \frac{1+PC}{1+PC} & \frac{1+PC}{1+PC} \end{pmatrix}$$

are $\sigma_1 = 0$ and $\sigma_2 = \sup_{\omega} \frac{\sqrt{(1 + |P(j\omega)|^2)(1 + |C(j\omega)|^2)}}{|1 + P(j\omega)C(j\omega)|}$.

8. Show that

$$\sup_w \frac{|1 + P(j\omega)C(j\omega)|}{\sqrt{(1 + |P(j\omega)|^2)(1 + |C(j\omega)|^2)}} = d(P, -1/C)$$

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