Universität Hamburg
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SP Signal Processing

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Digital Media Signal Processing

1. Introduction of Basic Concepts

Outline

What is Digital Media Signal Processing I

- **Signal**: any quantity that varies with time, space, or other variables.
  - Audio signals (varies with time)
  - Speech signals (varies with time)
  - Image (varies with space)
  - Video (varies with time and space)
- **Digital Signal**: The signal is presented in machine code. This requires the signal to be discretized in tim (sampling) and amplitude (quantization)
- **Digital Media Signals**: We apply the general and powerful tools specifically to digital media signals such as audio and images.
- **Processing**: Processing of signals includes
  - Resampling, Changing the temporal and spectral content, Compression (lossy and lossless)

Motivation I

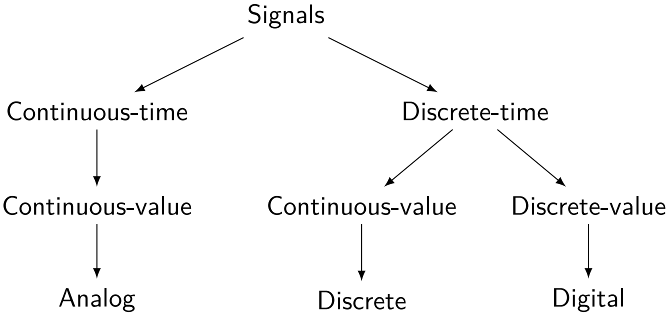
- **Signal**: variable x whose value varies with time (audio: $x(n)$) or space (image $x(n, m)$)
- The value of the signal may represent physical quantities such as
  - The sounds pressure level (audio)
  - The color value (image)
- When the value of the signal is available over a continuum of times, it is referred to as **continuous-time signal**.
- Continuous-time signals whose amplitudes also vary over a continuous range are called **analog signal**.
- If the value of the signal is available only at discrete instants of time, it is called a **discrete-time signal**

- Some signals (e.g. economic data) are discrete in nature. However media signals, like audio, need to be discretized by taking time samples of the analog signal $x_a(t)$, referred to as **sampling**

$$x(n) = x_a(nT), \quad |n| = 0, 1, 2, ...$$

  - With T the sampling period
- When finite precision is used to represent the value of $x(n)$, the sequence of quantized values is called a **digital signal**
- A system or algorithm which processes one digital signal $x(n)$ to produce a digital output signal $y(n)$ is called digital signal processor.

Motivation III



Applications of Digital Signal Processing

- speech and audio enhancement, coding, and transmission
- processing of music, images, and video
- detection of targets (audio, image, video, radar, sonar),
- medical signal processing (EEG, EKG, ultrasound)

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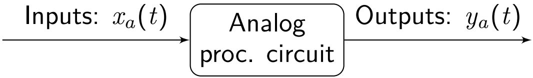
Rapid Development of DSP algorithms

- Digital Signal Processing has developed rapidly over the past 50 years
- The development is a result of significant advances in digital computer technology and integrated-circuit fabrication.
- Algorithms do not require dedicated devices, but run on small portable devices
  - laptops, smartphones, hearing aids
- Along with very-large-scale integration of electronic circuits, the hardware is getting
  - more powerful, smaller, faster, and cheaper

➜ highly sophisticated algorithms are enabled.

Digital and Analog Processing I

- For many years, almost all signal processing was done in analog circuits



- Advantages
  - extremely low processing latencies can be achieved
  - can be a requirement to process extremely wideband signals

- Today Signal processing is done digitally as

- Three components are needed
  - Analog-to-digital converter
  - Actual processing
  - Digital-to-analog converter
- Advantages
  - Flexible programmable operations
  - Often a higher order of precision

Outline

Signals I

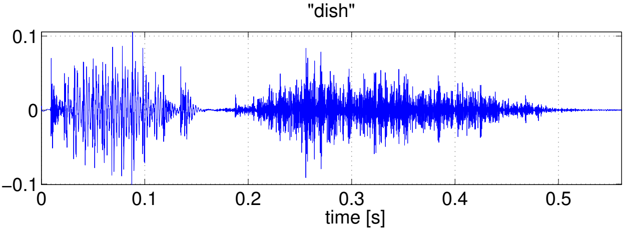
- A *signal* is defined as any physical quantity that varies with time (e.g. audio), space (e.g. image), or any other independent variable(s).
- Mathematically, a signal is a function of these independent variables, e.g.

$$\begin{aligned} s_1(t) &= 5t \\ s_2(t) &= 20t^2 \end{aligned} \tag{1}$$

or

$$s(x, y) = 3x + 2xy + 10y^2 \tag{2}$$

- Many signals, like speech or images cannot be described functionally by an expression as given in (1)



- However, a *segment* of speech can be represented to a high degree of accuracy as a sum of several sinusoids of different amplitudes, frequencies, and phases

$$\sum_{i=1}^{N} A_i(t) \sin[2\pi F_i(t) t + \theta_i] \tag{3}$$

Systems I

- Signal generation is usually associated with a *system*
  - Speech is generated by forcing (vibrating) air through the vocal tract
  - Images are obtained by exposing a photographic sensor/film to a scene or object
- A system may also be defined as a physical device that performs an operation on a signal
  - A room is a system (adds reverberation)
- Also a software realization of operations on a signal is referred to as a system
  - A noise reduction filter is a system
  - An image-blurring filter is a system
- When passing a signal through a system, as in filtering, we say we have *processed* the signal

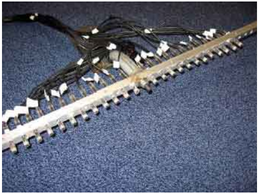
Outline

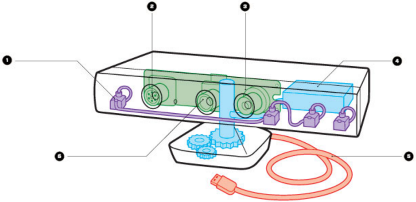
Multichannel and Multidimensional Signals

- The methods chosen for processing and/or analyzing a signal heaviliy depend on the signals characterstics
- Any investigation in signal processing thus starts with a classification of the targeted signals
- Signals can e.g. be
  - real-valued, e.g. $s_1(t) = A\sin(2\pi t)$
  - complex-valued, e.g. $s_2(t) = Ae^{j3\pi t} = A\cos(3\pi t) + jA\sin(3\pi t)$
  - scalar / vector
- Real-world physical signals are always real-valued
- Signals recorded by multiple sources or sensors can be represented by vectors

Classification of Signals

Multichannel Signals





- Vector representation of multichannel signal (3 dimensions)

$$\mathbf{S}_3 = \begin{bmatrix} s_1(t) \\ s_2(t) \\ s_3(t) \end{bmatrix}$$

Multidimensional Signals

- The dimensionality of a signal is determined by the number of independent variables
  - Audio is 1-dimensional in time-domain, e.g. $s(t)$ (but frequently processed in a 2-D time-frequency space)
  - B/W Image is 2-dimensional, e.g. $I(x, y)$
  - B/W Video is 3-dimensional, e.g. $I(x, y, t)$
- A color TV RGB signal is a 3-dimensional and 3-channel signal

$$\mathbf{I}(x, y, t) = \begin{bmatrix} I_r(x, y, t) \\ I_g(x, y, t) \\ I_b(x, y, t) \end{bmatrix}$$

Deterministic Versus Random Signals

- A *Signal Model* is used to describe a signal mathematically
- Any signal that can be uniquely described by an explicit mathematical expression, a table of data, or a well-defined rule is called **deterministic**
  - ➡ all past, present, and future values are known precisely, i.e. without any uncertainty
- In practice the most interesting signals (i.e. those that carry information) are per se not fully predictable and cannot be fully described by explicit mathematical formulas. These signals are referred to as **random** signals.
  - ➡ Mathematical framework: theory of probability and stochastic processes.
- In practice both a deterministic signal model and a random signal model can be reasonable to solve a specific DSP problem

Outline

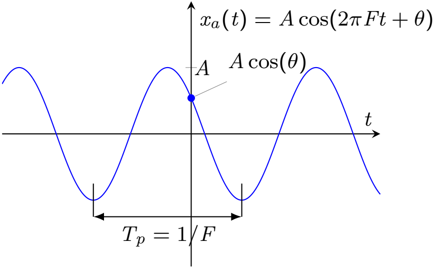
Continuous-Time Sinusoidal Signals I

- Frequency is related to periodic motion and has the physical dimension $[1/\mathrm{s}] = [\mathrm{Hz}]$
- A simple harmonic oscillation is mathematically described by a sinusoidal signal

$$x_a(t) = A\cos(\Omega t + \theta)\,, \quad -\infty < t < \infty \tag{4}$$

- completely characterized by three parameters
  - A: the signal *amplitude*
  - Ω: the *angular frequency* in radians per second $[\mathrm{rad/s}]$
  - θ: is the *phase* in radians
- Instead of the angular frequency Ω, we often use the frequency F in cycles per second or hertz $[1/\mathrm{s}] = [\mathrm{Hz}]$, where

$$\Omega = 2\pi F$$



- This signal $x_a(t)$ in (4) has the following properties
  - For a fixed frequency F, $x_a(t)$ is periodic, i.e. $x_a(t + T_p) = x_a(t)$, with $T_p = 1/F$, the *fundamental period*
  - Increasing the frequency F increases the rate of oscillation of the signal, i.e. more periods are included in a given time interval.
  - there is no principal limit to $F = 1/T_p$

Continuous-Time Complex Exponentials I

- These relations carry over to the class of complex exponential signals given by

$$x_a(t) = Ae^{j(\Omega t+\theta)}$$

- This can be seen by using Euler's equation

$$e^{\pm j\phi} = \cos\phi \pm j\sin\phi \tag{5}$$

- By definition, frequency is inherently positive quantity, namely the number of cycles per unit time in a periodic signal
- Negative frequencies are used for mathematical convenience. A real-valued cosine can be represented using (5) as

$$x_a(t) = A\cos(\Omega t+\theta) = \frac{A}{2}e^{j(\Omega t+\theta)} + \frac{A}{2}e^{-j(\Omega t+\theta)}$$

Continuous-Time Complex Exponentials II

$$x_a(t) = A\cos(\Omega t + \theta) = \frac{A}{2}e^{j(\Omega t+\theta)} + \frac{A}{2}e^{-j(\Omega t+\theta)}$$

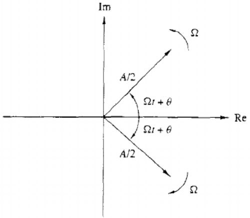


Fig: Representation of a cosine function by a pair of complex-conjugate exponentials (phasors)

Discrete-Time Sinusoidal Signals I

- A discrete-time sinusoidal signal may be expressed as

$$x(n) = A\cos(\omega n + \theta)\,, \quad -\infty < n < \infty$$

  - n: integer variable, called *sample number*
  - A: *Amplitude*
  - ω: *angular frequency* in radians per sample
- instead of the angular frequency ω we use the frequency variable f, as

$$\omega = 2\pi f$$

  - f has unit cycles per sample

Discrete-Time Sinusoidal Signals II

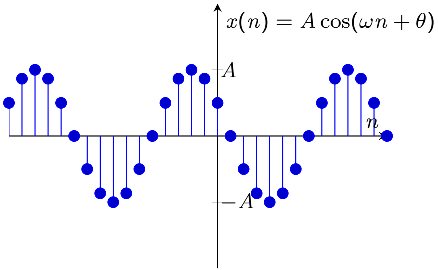


Fig: Example of a discrete-time sinusoidal signal ($\omega = \pi/6$, $f = 1/12$ and $\theta = \pi/3$)

- $f = 1/12$, means 12 samples per cycle

Discrete-Time Sinusoidal Signals III

It holds that

1. *Discrete-time sinusoids are periodic with period N only if their frequency f is a rational number (only then we have an integer number of samples per cycle), and*

$$x(n+N) = x(n)$$

2. *Discrete-time sinusoids whose frequencies are separated by an integer multiple of 2π are identical*

$$\cos[(\omega_0 + 2k\pi)n + \theta] = \cos(\omega_0 n + \theta)$$
$$\cos[2\pi(f_0 + k)n + \theta] = \cos(2\pi f_0 n + \theta)$$

- Any sequence with a frequency $|\omega| > \pi$ or $|f| > \frac{1}{2}$ is identical to a sequence obtained from a sinusoidal signal with frequency $|\omega| < \pi$

➡ Frequencies in the range $-\pi \leq \omega \leq \pi$ or $-\frac{1}{2} \leq f \leq \frac{1}{2}$ are unique

➡ Frequencies in the range $|\omega| > \pi$ or $|f| > \frac{1}{2}$ are **aliases**

Discrete-Time Sinusoidal Signals IV

3. *The highest rate of oscillation in a discrete-time sinusoid is attained when* $|\omega| = \pi$ *or* $|f| = \frac{1}{2}$*)*

➡ Usually we choose the *fundamental range* $0 \leq \omega \leq 2\pi$ $(0 \leq f \leq 1)$ or $-\pi \leq \omega \leq \pi$ $(-\frac{1}{2} \leq f \leq \frac{1}{2})$, as these ranges constitute all existing sinusoids.

Continuous-time Exponentials

- **Continuous-time Exponentials** with harmonically related frequencies

$$s_k(t) = e^{jk2\pi F_0 t}, \quad k = 0, \pm 1, \pm 2, \ldots \tag{6}$$

  - $F_0 = 1/T_p$ is the fundamental frequency
- from (6) a linear combination of harmonically related complex coefficients can be obtained

$$x_a(t) = \sum_{k=-\infty}^{\infty} c_k s_k(t) = \sum_{k=-\infty}^{\infty} c_k e^{jk2\pi F_0 t} \tag{7}$$

  - c_k are arbitrary complex constants
- The signal $x_a(t)$ is periodic with fundamental period $T_p = 1/F_0$
- (7) is called the **Fourier series expansion of** $x_a(t)$, with
  - Fourier coefficients c_k and
  - harmonics $s_k(t)$

- **Discrete-time Exponentials** with harmonically related frequencies

$$s_k(n) = e^{jk2\pi f_0 n} = e^{j2\pi k \frac{n}{N}}, \quad k = 0, \pm 1m, \pm 2, \ldots \tag{8}$$

  - $N = 1/F_0$ is the number of samples per period
- In contrast to continuous-time, we note that

$$s_{k+N}(n) = e^{j2\pi(k+N)\frac{n}{N}} = s_k(n)e^{j2\pi n} = s_k(n) \tag{9}$$

  ➡ There are only N distinct periodic complex exponentials
  ➡ typically we choose $k = 0, 1, 2, \ldots, N-1$

Harmonically Related Exponentials II

Discrete-time Exponentials

- Similar to the continuous case, we have

$$x(n) = \sum_{k=-\infty}^{\infty} c_k s_k(n) = \sum_{k=-\infty}^{\infty} c_k e^{j2\pi k \frac{n}{N}} \tag{10}$$

  - c_k are arbitrary complex constants
- The signal $x(n)$ is periodic with fundamental period $N = 1/f_0$
- (10) is called the **Fourier series expansion of** $x(n)$, with
  - Fourier coefficients c_k and
  - harmonics $s_k(n)$

Outline

Analog-to-Digital Conversion

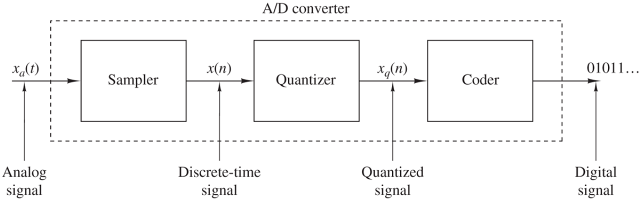


Figure 1.4.1 Basic parts of an analog-to-digital (A/D) converter.

1. **Sampling:** Continuous-time $\rightarrow$ discrete-time
   - $x_a(nT) \equiv x(n)$, where T is the *sampling interval*
2. **Quantization:** continuous-valued signal $\rightarrow$ discrete-value signal
   - introduces quantization error $x(n) - x_q(n)$
3. **Coding:** each discrete value x_q is represented by a b-bit binary sequence

Digital-to-Analog Conversion

- To be able to reproduce an analog signal, e.g. for audio-playback, the discrete samples must be interpolated
- This could be a zeroth-order interpolation, a linear (first order) interpolation, quadratic interpolation, ...

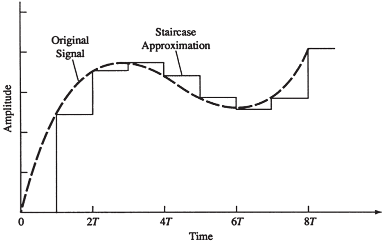


Figure 1.4.2 Zero-order hold digital-to-analog (D/A) conversion.

- Is there an optimal interpolator?
  - For bandlimited signals (i.e. limited frequency content) the sampling theorem yields the optimum form of interpolation

Sampling of Analog Signals I

- We limit ourselves to periodic uniform sampling

$$x(n) = x_a(nT), \quad -\infty < n < \infty$$

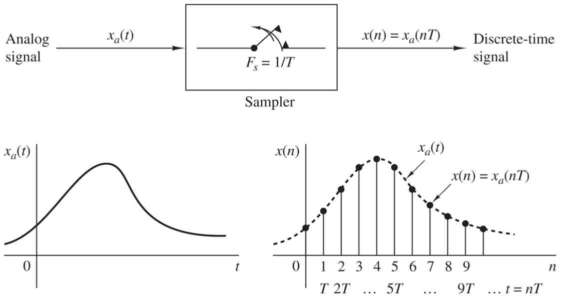


Figure 1.4.3 Periodic sampling of an analog signal.

- T is the time interval between samples
- $F_S = 1/T$ is the sampling rate [samples per second]

Sampling of Analog Signals II

- continuous time and discrete time are related, as $t = nT = \frac{n}{F_\mathrm{S}}$

➜ Also the frequencies F, Ω of analog signals and f, ω of discrete signals are related!

  - $f = \frac{F}{F_\mathrm{S}} = FT \rightarrow$ aka. normalized frequency $\qquad \omega = \Omega T$

- However, recall that
  - $-\infty < F < \infty, \qquad -\infty < \Omega < \infty$
  - $-\frac{1}{2} \leq f \leq \frac{1}{2}, \qquad -\pi \leq \omega \leq \pi$

- Combining these equations reveals that the frequency of an analog sinusoid sampled at F_S must fall in
  - $-\frac{F_\mathrm{S}}{2} \leq F \leq \frac{F_\mathrm{S}}{2} \qquad -\pi F_\mathrm{S} \leq \Omega \leq \pi F_\mathrm{S}$

Relations Among Frequency Variables

TABLE 1.1 RELATIONS AMONG FREQUENCY VARIABLES

Continuous-time signals		Discrete-time signals
$\Omega = 2\pi F$ $\frac{\text{radians}}{\text{sec}}$ Hz		$\omega = 2\pi f$ $\frac{\text{radians}}{\text{sample}}$ $\frac{\text{cycles}}{\text{sample}}$
	$\xrightarrow{\omega = \Omega T,\ f = F/F_s}$	$-\pi \leq \omega \leq \pi$ $-\frac{1}{2} \leq f \leq \frac{1}{2}$
	$\xleftarrow{\Omega = \omega/T,\ F = f \cdot F_s}$	
$-\infty < \Omega < \infty$ $-\infty < F < \infty$		$-\pi/T \leq \Omega \leq \pi/T$ $-F_s/2 \leq F \leq F_s/2$

- The fundamental difference between continuous and discrete time is the range of frequency variables
- Periodic sampling with F_{S} implies a mapping of the infinite frequency range into a finite range with limit $F_{\max} = F_{\mathrm{S}}/2$

Example 1.4.1

- Consider the sampling of the following two signals sampled at $F_\mathrm{S} = 40\,\mathrm{Hz}$

$$\begin{aligned} x_1(t) &= \cos(2\pi\ 10\,\mathrm{Hz}\ t) \\ x_2(t) &= \cos(2\pi\ 50\,\mathrm{Hz}\ t) \end{aligned}$$

Example 1.4.1

- Consider the sampling of the following two signals sampled at $F_\mathrm{S} = 40\,\mathrm{Hz}$

$$\begin{aligned} x_1(t) &= \cos(2\pi\ 10\,\mathrm{Hz}\ t) \\ x_2(t) &= \cos(2\pi\ 50\,\mathrm{Hz}\ t) \end{aligned}$$

- Substitute $t = nT = n/F_\mathrm{S}$

$$\begin{aligned} x_1(n) &= \cos\left(2\pi\ \frac{10\,\mathrm{Hz}}{40\,\mathrm{Hz}}\ n\right) = \cos\frac{\pi}{2}n \\ x_2(n) &= \cos\left(2\pi\ \frac{50\,\mathrm{Hz}}{40\,\mathrm{Hz}}\ n\right) = \cos\frac{5\pi}{2}n = \cos\frac{\pi}{2}n \end{aligned}$$

➜ The two sampled cosines are identical and thus indistinguishable

- $F_2 = 50\,\mathrm{Hz}$ is an **alias** of the frequency $F_1 = 10\,\mathrm{Hz}$ at the sampling rate $F_\mathrm{S} = 40\,\mathrm{Hz}$

Aliasing

- Sampling is unique iff $x_a(t)$ contains frequencies $\leq F_{\mathrm{S}}/2$
- Frequencies $F_k = F_0 + kF_{\mathrm{S}}$ are indistinguishable from F_0 after sampling. We say, they are *aliased* to F_0
- Given a discrete signal $x(n)$ an ambiguity exists to which continuous-time signal $x_a(t)$ it represents

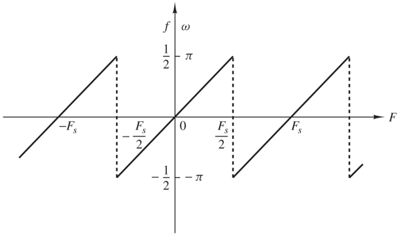


Figure 1.4.4 Relationship between the continuous-time and discrete-time frequency variables in the case of periodic sampling.

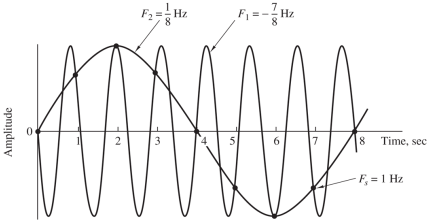


Figure 1.4.5 Illustration of aliasing.

Example 1.4.2

- Consider the analog signal

$$x_a(t) = 3\cos(100\,\mathrm{Hz}\ \pi\ t)$$

(a) Determine the minimum sampling rate required to avoid aliasing
(b) Suppose that the signal is sampled at the rate $F_\mathrm{S} = 200\,\mathrm{Hz}$. What is the discrete-time signal obtained after sampling?
(c) Suppose that the signal is sampled at the rate $F_\mathrm{S} = 75\,\mathrm{Hz}$. What is the discrete-time signal obtained after sampling?
(d) What is the frequency $0 < F < F_\mathrm{S}/2$ of a sinusoid that yields samples identical to those obtained in part (c)?

The Sampling Theorem

- Given an analog signal, how should be set the sampling period T?
- depends on the frequency content
  - Speech has most important content up to 4kHz (fricatives up to 8kHz)
  - Musik has content up to 20kHz
  - analog TV signals up to 5MHz
- alias frequencies are avoided if

$$F_{\mathrm{S}} > 2F_{\max}$$

→ if no alias frequencies exist, the analog signal can be reconstructed perfectly from the sampled signal

The Sampling Theorem

Sampling Theorem

- If the highest frequency contained in an analog signal $x_a(t)$ is $F_{\text{max}} = B$ and the signal is sampled at a rate

$$F_{\text{S}} > 2F_{\text{max}} \equiv 2B$$

then $x_a(t)$ can be **perfectly reconstructed** from its sample values.
- The sampling rate $F_{\text{N}} = 2B = 2F_{\text{max}}$ is called the **Nyquist rate**

Perfect reconstruction is then obtained using the interpolation function

$$g(t) = \frac{\sin(2\pi Bt)}{2\pi Bt}$$

as

$$x_a(t) = \sum_{-\infty}^{\infty} x(n) g\left(t - \frac{n}{F_{\text{S}}}\right)$$

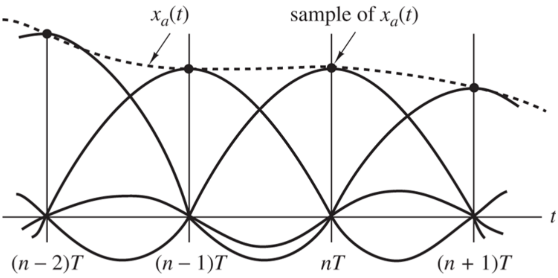


Figure 1.4.6 Ideal D/A conversion (interpolation).

- The ideal reconstruction

$$x_a(t) = \sum_{-\infty}^{\infty} x(n) g\left(t - \frac{n}{F_\mathrm{S}}\right)$$

  involves an infinite sum

➡ In practice, approximations are used

Example 1.4.3

- Consider the analog signal

$$x_a(t) = 3\cos(50\,\mathrm{Hz}\;\pi\;\;t) + 10\sin(300\,\mathrm{Hz}\;\pi\;\;t) - \cos(100\,\mathrm{Hz}\;\pi\;\;t)$$

- What is the Nyquist rate for this signal?

Example 1.4.3

- Consider the analog signal

$$x_a(t) = 3\cos(50\,\mathrm{Hz}\ \pi\ \ t) + 10\sin(300\,\mathrm{Hz}\ \pi\ \ t) - \cos(100\,\mathrm{Hz}\ \pi\ \ t)$$

- What is the Nyquist rate for this signal?

- Solution:
  - The frequencies in this signal are $F_1 = 25\,\mathrm{Hz}, F_2 = 150\,\mathrm{Hz}, F_3 = 50\,\mathrm{Hz}$
  - $F_{\mathrm{max}} = 150\,\mathrm{Hz}$
  - $F_{\mathrm{S}} > 2F_{\mathrm{max}} = 300\,\mathrm{Hz}$
  - Nyquist rate: $F_{\mathrm{N}} = 2F_{\mathrm{max}} = 300\,\mathrm{Hz}$

Example 1.4.3

- Consider the analog signal

$$x_a(t) = 3\cos(50\,\mathrm{Hz}\ \pi\ t) + 10\sin(300\,\mathrm{Hz}\ \pi\ t) - \cos(100\,\mathrm{Hz}\ \pi\ t)$$

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- Solution:
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  - $F_{\mathrm{max}} = 150\,\mathrm{Hz}$
  - $F_{\mathrm{S}} > 2F_{\mathrm{max}} = 300\,\mathrm{Hz}$
  - Nyquist rate: $F_{\mathrm{N}} = 2F_{\mathrm{max}} = 300\,\mathrm{Hz}$

➜ Observe that sampling at the Nyquist rate results in sampling only zeros from the sinusoid above. Solution: sample slightly higher than at Nyquist rate

Example 1.4.4

- Consider the analog signal

$$x_a(t) = 3\cos(2000\,\mathrm{Hz}\ \pi\ \ t) + 5\sin(6000\,\mathrm{Hz}\ \pi\ \ t) - 10\cos(12000\,\mathrm{Hz}\ \pi\ \ t)$$

(a) What is the Nyquist rate for this signal?
(b) Assume now that we sample this signal using a sampling rate $F_\mathrm{S} = 5000\,\mathrm{Hz}$. What is the discrete-time signal obtained after sampling
(c) What is the analog signal $y_a(t)$ that we can reconstruct frim the samples if we use ideal interpolation?

Quantization of Continuous-Amplitude Signals

- A **digital signal** is a discrete-time signal where each sample is represented by a finite number of digits
- The process of converting a discrete-time continuous amplitude signal into a digital signal is called **quantization**
- As opposed to sampling, quantization always introduces an error also referred as **quantization noise**
- We denote the process of quantization as

$$x_q(n) = Q[x(n)]$$

- The quantization noise denotes the introduced quantization error

$$e_q(n) = x_q(n) - x(n)$$

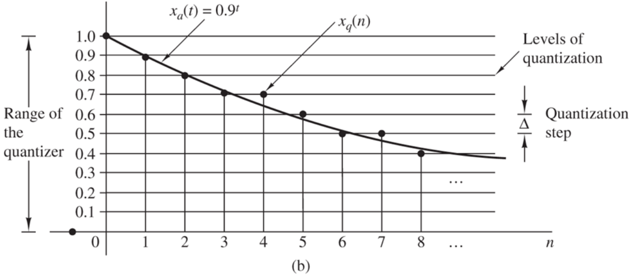

Figure 1.4.7 Illustration of quantization.

- Important parameters of a quantization scheme are
  - Quantization levels (here: $0.1, 0.2, 0.3, ...$)
  - Quantization step-size Δ (distance between two levels)
  - Range of the quantizer should match range of signal amplitudes
  - Quantization can be achieved by
    - rounding (take the closer line), e.g. $0.86 \to 0.9$
    - truncation (take the next lower line), e.g. $0.86 \to 0.8$

Quantification of Quantization noise

- The power of the quantization noise is dominated by the step size Δ, and given by

$$P_q = \frac{\Delta^2}{12}$$

- The signal-to-noise (SNR) level is proportional to the number of bits b spent

$$\mathrm{SNR[dB]} \propto 6\mathrm{dB} \cdot b$$

Coding of Quantized Samples

- If we need L quantization levels, we need at least L different binary numbers
- With a word length of b bits we can create 2^b different numbers
- Hence we need $b \geq \log_2 L$ bit.
- Examples
  - ISDN telephone speech: $b = 8$ bit (non-uniformly quantized)
  - Audio CD: $b = 16$ bit (uniformly)
  - Audio recordings: $b = 24$ bit (uniformly)
- Q: why does it make sense to use a higher bitrate for audio recordings?
- Q: Would it be reasonable to also use higher sampling rates?