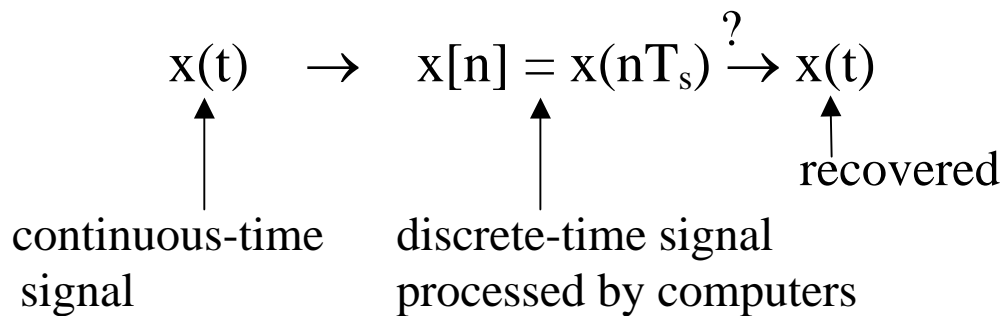


1.3 Sampling Theorem —Replacing Continuous-time Signals by Sequences of Data

Question: Under What Kind of Conditions Can Signal Waveforms Uniquely Recovered from Its Samples?



T_s : sampling period

$\omega_s = \frac{2\pi}{T_s}$: sampling frequency

- In general there can be infinite numbers of continuous-time signals having the same samples

See Fig. 7.1, p. 515 of Oppenheim

Considerations from Single Frequency Components

- $x(t) = A \cos(\omega_0 t)$

$$y(t) = b \cos[(\omega_0 + \omega_s) t], \omega_s : \text{sampling frequency}$$

$$z(t) = x(t) + y(t)$$

- $x(nT_s) = A \cos(\omega_0 nT_s)$

$$y(nT_s) = b \cos[(\omega_0 + \omega_s) nT_s] = b \cos(\omega_0 nT_s)$$

$$\omega_s = \frac{2\pi}{T_s}$$

$$z(nT_s) = (A + b) \cos(\omega_0 nT_s)$$

- Any two frequency components ω_1, ω_2 become indistinguishable if $|\omega_1 - \omega_2| = m \cdot \omega_s$, m : integer, when sampled at frequency ω_s
- Aliasing effect
- For discrete-time signal $x[n]$ at sampling frequency ω_s , only the frequency range $[0, \omega_s]$ (or an equivalent) makes sense. Other frequency ranges are simply repetitive

Considerations for a Continuous Spectrum

- $X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt$

assume $X(\omega)$ has a bandwidth W ,

$$|X(\omega)| = 0, \quad |\omega| > W$$

$x(t)$ sampled at ω_s , $x[n] = x(nT_s)$

- if $\omega_s < 2W$

aliasing effect occurs

frequency components mixed, can't be recovered

- if $\omega_s > 2W$

No aliasing effect

Spectra do not overlap

Original signal can be recovered by taking only those frequencies below W , or low pass filtering

Sampling Theorem

- if $\omega_s > 2 W$
the original signal can be uniquely recovered by
low pass filtering
- if $\omega_s < 2 W$
the original signal can't be recovered

See Fig. 7.3, 7.4, pp. 518-519 of Oppenheim

• **Mathematical formulation**

$$p(t) = \sum_{k=-\infty}^{\infty} \delta(t-nT_s)$$

$$x_p(t) = x(t)p(t) = \sum_{k=-\infty}^{\infty} x(nT_s)\delta(t-nT_s)$$

See Fig. 7.2, p. 516 of Oppenheim

- It can be shown the Fourier transform of $x_p(t)$ is

$$X_p(\omega) = \sum_{n=-\infty}^{\infty} X(\omega - n\omega_s)$$

See Fig. 7.3, p.518 of Oppenheim

• **An Example for Aliasing Effect**

See Fig. 7.15, 7.16, pp. 529-531 of Oppenheim

Practical Considerations

- Over-sampling
- Pre-filtering

Ref. 7.0, 7.1.1, 7.3 of Oppenheim

1.4 Pulse-coded Modulation (PCM) – Digital Representation of Continuous-time Signals

$$x(t) \rightarrow x[n] = x(nT_s) \rightarrow 1010110110$$

binary representation of a
real number

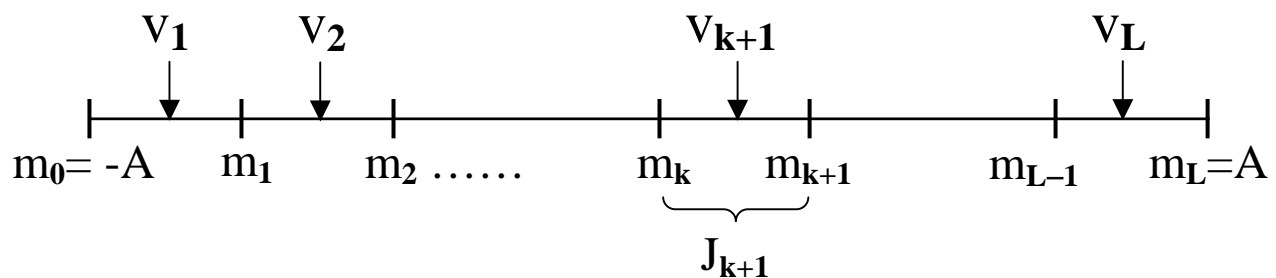
$$\left(\begin{array}{c} \text{number of bits} \\ \text{per sample} \end{array} \right) \longleftrightarrow \left(\begin{array}{c} \text{truncation} \\ \text{error} \end{array} \right)$$

tradeoff

↑
transmission/storage
condition

↑
perceptual
acceptability
condition

Quantization (Scalar Quantization)



- Assume $|x[n]| \leq A$

divide the range $[-A, A]$ into L quantization levels

$$\{ J_1, J_2, \dots, J_k, \dots, J_L \}$$

$$J_k : [m_{k-1}, m_k]$$

$$L = 2^R$$

each quantization level J_k is represented by a value v_k

$$S = \bigcup_{k=1}^L J_k, V = \{ v_1, v_2, \dots, v_k, \dots, v_L \}$$

- Quantization is a mapping relation

$$Q : S \rightarrow V$$

$$Q[x[n]] = v_k \quad \text{if} \quad x[n] \in J_k$$

each v_k is represented by an R -bit pattern

after transmission/storage the sample $x[n]$ has only L values, $\{ v_1, v_2, \dots, v_L \}$

- Question: how to design the quantizer characteristic (codebook) represented by $\{ J_1, J_2, \dots, J_L \}$ and $\{ v_1, v_2, \dots, v_L \}$ so as to achieve a good tradeoff between the transmission/storage condition and the perceptual acceptability condition?

Quantization Error

$$x_Q[n] = x[n] + e[n]$$

- **Assume simplest case –uniform quantization**

$$\begin{aligned} m_k - m_{k-1} &= \Delta_k = \text{step size for } k\text{-th level} \\ &= \Delta, \quad \text{same for all } k \end{aligned}$$

$$\Delta = \frac{2A}{L}$$

See Fig. 3.11, p. 195 of Haykin

$$|e[n]| < \frac{\Delta}{2}$$

assume $e[n]$ is uniformly distributed (this is reasonable if L is large enough or Δ is small enough)

$$f_e(e) = \begin{cases} \frac{1}{\Delta}, & |e[n]| < \frac{\Delta}{2} \\ 0, & \text{else} \end{cases}$$

- **Mean square error**

$$\sigma_e^2 = E[(e[n])^2] = \int_{-\Delta/2}^{\Delta/2} e^2 f_e(e) de = \frac{1}{12} \Delta^2$$

for a quantization level

- for all possible values $x[n]$

$$\sigma_e^2 = \sum_{k=1}^L P_k \left(\frac{1}{12} \Delta_k^2 \right) = \frac{1}{12} \Delta^2$$

$$P_k = \text{Prob}[x[n] \in J_k]$$

$$\Delta = \frac{2A}{L} = \frac{2A}{2^R}$$

$$\sigma_e^2 = \frac{1}{3} A^2 2^{-2R} (\propto 2^{-2R})$$

Quantization Error

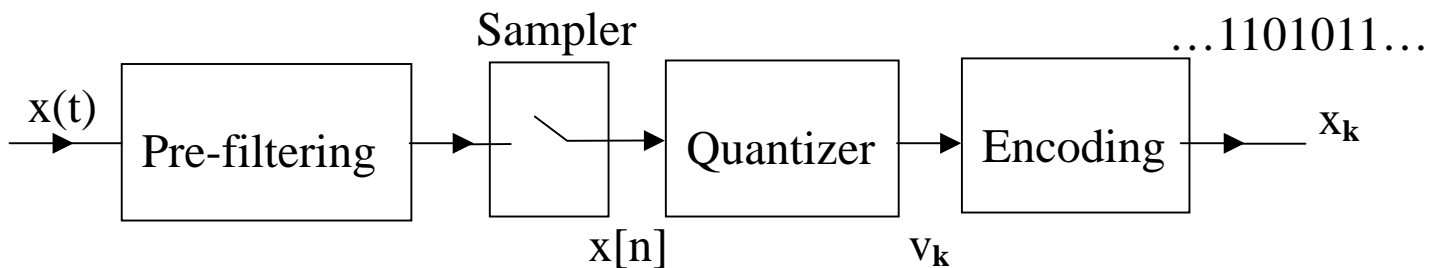
- **Signal-to-noise Ratio**

$$\sigma_x^2 = E[(x[n])^2]$$

$$\text{SNR}_Q = \frac{\sigma_x^2}{\sigma_e^2} = \frac{3\sigma_x^2}{A^2} 2^{2R} (\propto 2^{2R} = L^2)$$

- 6 dB reduction of σ_e^2 every extra bit per sample
- Quantization error can be arbitrarily suppressed by using more bits per sample

PCM Processes



for digital transmission,
storage or processing

Ref: 3.6 of Hankin