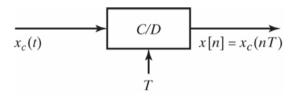
Ideal Sampling of Continuous-Time Signals

#### Periodic Sampling

Continous-time signals are usually sampled periodically every T seconds:

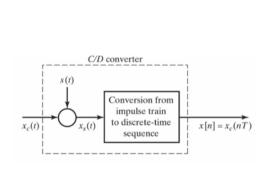
$$x[n] = x_c(nT) \qquad -\infty < n < \infty$$

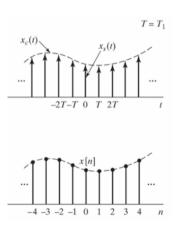


Since T is the sampling period, its reciprocal  $F_s = \frac{1}{T}$  (samples/sec) is the sampling frequency, or in radians per second:  $\Omega_s = \frac{2\pi}{T}$ .

#### Sampling With a Periodic Impulse Train

$$x_s(t) = x_c(t) \sum_{n = -\infty}^{\infty} \delta(t - nT) = \sum_{n = -\infty}^{\infty} x_c(nT)\delta(t - nT)$$





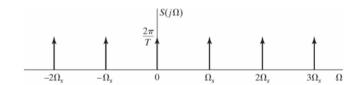
#### Frequency-Domain Perspective of Sampling

The impulse train that we used in the model of the sampling process,

$$s(t) = \sum_{n=0}^{\infty} \delta(t - nT)$$

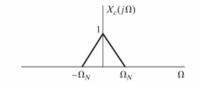
has a Fourier transform

$$S(j\Omega) = \frac{2\pi}{T} \sum_{k=-\infty}^{\infty} \delta(\Omega - k\Omega_s)$$



#### Frequency-Domain Perspective of Sampling (Continued)

The continuous-time signal,  $x_c(t)$ , has a Fourier-transform represented by this arbitrary spectrum:



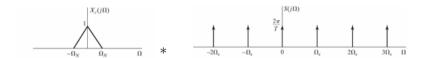
Notice this spectrum is bandlimited:

$$X_c(j\Omega) = 0$$
 for  $|\Omega| \ge \Omega_N$ 

#### Frequency-Domain Perspective of Sampling (Continued)

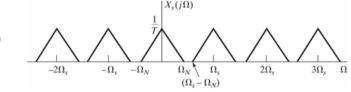
In the sampling process, we multiply the impulse train, s(t), the continuous-time signal,  $x_c(t)$ , which is equivalent to convolving their spectra:

$$X_s(j\Omega) = \frac{1}{2\pi} X_c(j\Omega) * S(j\Omega)$$



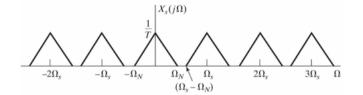
Spectrum of sampled signal:

$$X_s(j\Omega) = \frac{1}{T} \sum_{c}^{\infty} X_c \left( j \left( \Omega - k\Omega_S \right) \right)$$

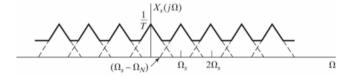


#### Sampling Rate to Avoid Aliasing Distortion

 $\Omega_s - \Omega_N \ge \Omega_N$ , or  $\Omega_s \ge 2\Omega_N$ , Fourier transform of sampled signal:



 $\Omega_s < 2\Omega_N$ , causes aliasing:



#### Nyquist-Shannon Sampling Theorem

Let  $x_c(t)$  be a bandlimited signal with

$$X_c(j\Omega) = 0$$
 for  $|\Omega| \ge \Omega_N$ .

Then  $x_c(t)$  is uniquely determined by its samples  $x[n] = x_c(nT), n = 0, \pm 1, \pm 2, ...,$  if

$$\Omega_s = \frac{2\pi}{T} \ge 2\Omega_N.$$

 $\Omega_N$  is the Nyquist frequency.

 $2\Omega_N$  is the Nyquist rate.

Frequency Variables with Periodic Sampling

Relationship Between Continuous-Time and Discrete-Time

#### Discrete-Time Sinusoidal Signals

$$x[n] = A\cos(\omega n + \theta) = A\cos(2\pi f n + \theta)$$
 where n is an integer

- ▶ A discrete-time sinusoid is periodic only if its frequency f is a rational number:  $f = \frac{k}{N}$ , where k and N are integers (common factors cancelled, N is period)
- ▶ Discrete-time sinusoids whose frequencies are separated by an integer multiples of  $2\pi$  are identical:  $\cos[(\omega + 2\pi)n + \theta] = \cos(\omega n + 2\pi n + \theta) = \cos(\omega n + \theta)$ .
- The highest rate of oscillation in a discrete-time sinusoid is when frequency  $w = \pm \pi$  (or  $f = \pm 1/2$ ); fundamental range:  $-\pi \le \omega \le \pi$   $(-\frac{1}{2} \le f \le \frac{1}{2})$

#### Relative or Normalized Frequency

Periodic sampling creates relationship between time variables t and n:

$$t = nT = \frac{n}{F_o}$$

This leads to a relationship between the continuous-time frequency F (or  $\Omega$ ) and the discrete-time frequency f (or  $\omega$ ), assuming the signal is sampled at  $F_s = 1/T$  samples per second.

$$x_c(t) = A\cos(2\pi F t + \theta)$$

$$x[n] = x_c(nT) = A\cos(2\pi F nT + \theta) = A\cos\left(\frac{2\pi nF}{F_s} + \theta\right)$$

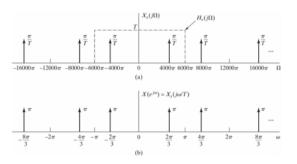
$$f = \frac{F}{F_s}$$
 or,  $\omega = \Omega T$ 

#### Example: Sampled Sinusoidal Signal

If we sample  $x_c(t) = \cos(4000\pi t)$  with a sampling period of T = 1/6000 we obtain:

$$x[n] = x_c(nT) = \cos(4000\pi T n) = \cos(\frac{2\pi}{3}n)$$

The sample rate is  $\Omega_s = 2\pi/T = 12000\pi$  rad/sec which is more than twice the frequency of the original signal so there is no aliasing.



The DTFT is a function of the normalized frequency:  $\omega = \Omega T$ 

#### Example: Sampling Two Analog Signals

Determine the discrete-time signals from sampling analog signals at  $f_s = 40$  Hz:

$$x_1(t) = \cos(2\pi 10t)$$
$$x_2(t) = \cos(2\pi 50t)$$

replace  $t = nT = \frac{n}{t_c} = \frac{n}{40}$ :

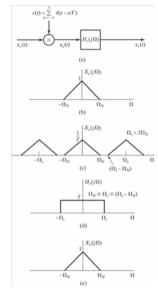
$$x_1[n] = \cos\left(2\pi \frac{10}{40}n\right) = \cos\left(\frac{\pi}{2}n\right)$$
  
 $x_2[n] = \cos\left(2\pi \frac{50}{40}n\right) = \cos\left(\frac{5\pi}{2}n\right)$ 

However, 
$$\cos\left(\frac{5\pi}{2}n\right) = \cos\cos\left(\frac{5\pi}{2}n - 2\pi n\right) = \cos\left(\frac{\pi}{2}n\right)$$
 so  $x_2[n] = x_1[n]$ .

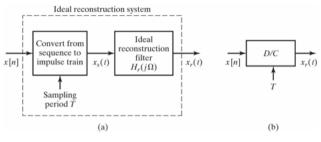
50 Hz is an alias of 10 Hz when the sampling frequency is 40 Hz

Reconstruction of a Signal From Its Samples

#### Recovery of Signal From Its Samples: Frequency Domain



#### Recovery of Signal From Its Samples: Time Domain



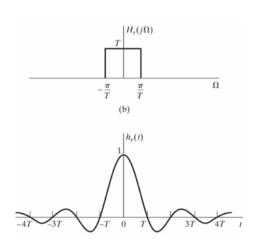
Sampled signal represented by impulse train of successive values:

$$x_s(t) = \sum_{n=\infty}^{\infty} x[n]\delta(t - nT)$$

Reconstructed signal is output of ideal lowpass filter, with impulse response,  $h_r(t)$ :

$$x_r(t) = x_s(t) * h_r(t) = \dots = \sum_{s=0}^{\infty} x[n]h_r(t - nT)$$

#### Impulse Responses of Ideal Reconstruction Filter



#### Cutoff frequency:

$$\Omega_c = \Omega_s/2 = \pi/T$$

Impulse response:

$$h_r(t) = \frac{\sin(\pi t/T)}{\pi t/T}$$
$$= \operatorname{sinc}(t/T)$$

Using normalized sinc function:

$$\operatorname{sinc}(x) = \frac{\sin(\pi x)}{\pi x}$$

### Reconstruction of the Original Signal

#### Output of reconstruction filter:

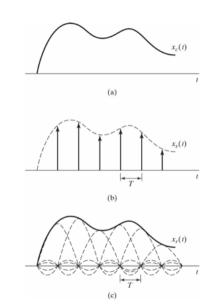
$$x_r(t) = \sum_{n=-\infty}^{\infty} x[n]h_r(t - nT)$$

where impulse response is

$$h_r(t) = \operatorname{sinc}(t/T)$$

#### Output:

$$x_r(t) = \sum_{n=-\infty}^{\infty} x[n] \operatorname{sinc}((t - nT)/T)$$



Discrete-Time Processing of Continuous-Time Signals

#### Summary of Mathematical Representations

$$x_c(nT)$$

$$x[n] = x_c(nT)$$

$$X[n] \equiv X_c(nT)$$

$$X(e^{j\omega}) = \frac{1}{T} \sum_{c}^{\infty} X_c \left[ j \left( \frac{\omega}{T} - \frac{2\pi k}{T} \right) \right]$$

$$(T)$$
 $\infty$ 

 $y_r(t) = \sum_{n=0}^{\infty} y[n] \operatorname{sinc} [(t - nT)/T]$ 

 $Y_r(j\Omega) = H_r(j\Omega)Y(e^{j\Omega T}) = \begin{cases} TY(e^{j\Omega T}), & |\Omega| < \pi/T \\ 0, & \text{otherwise} \end{cases}$ 



#### Overall Frequency Response



For the LTI discrete-time system:

$$Y(e^{j\omega}) = H(e^{j\omega})X(e^{j\omega})$$

The Fourier-transform of the output of entire system is:

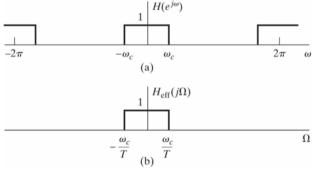
$$Y_r(j\Omega) = H_{\text{eff}}(j\Omega)X_c(j\Omega)$$

where

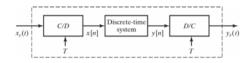
$$H_{\text{eff}}(j\Omega) = \begin{cases} H(e^{j\Omega T}), & |\Omega| < \pi/T \\ 0, & |\Omega| \ge \pi/T \end{cases}$$

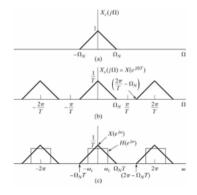
#### Example: Ideal Lowpass Filter

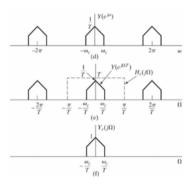
$$H(e^{j\omega}) = \begin{cases} 1, & |\omega| < \omega_c \\ 0, & \omega_c < |\omega| \le \pi \end{cases} \qquad H_{\text{eff}}(j\Omega) = \begin{cases} 1, & |\Omega T| < \omega_c \text{ or } |\Omega| < \omega_c/T \\ 0, & |\Omega T| \ge \omega_c \text{ or } |\Omega| \ge \omega_c/T \end{cases}$$



#### Example: Ideal Lowpass Filter (Continued)



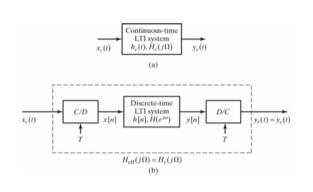




# System in Discrete-Time

Impulse Invariance for Implementing Continuous-Time

#### Impulse Invariance (Given a Desired Continuous-Time System)



Desired:  $h_c(t)$ ,  $H_c(j\Omega)$ 

Choose:

$$H(e^{j\omega}) = H_c(j\omega/T), \ |\omega| < \pi$$

Select T such that:

$$H_c(j\Omega) = 0, \ |\Omega| \ge \pi/T$$

Then the *impulse-invariant* version of  $h_c(t)$  is:

$$h[n] = Th_c(nT)$$

#### Example: Lowpass Filter Using Impulse Invariance

Use the impulse invariance technique to find an ideal lowpass discrete-time filter with cutoff frequency  $\omega_c < \pi$ , given this continuous-time ideal lowpass filter:

$$H_c(j\Omega) = \begin{cases} 1, & |\Omega| < \Omega_c \\ 0, & |\Omega| \ge \Omega_c \end{cases}$$
 where  $\Omega_c = \omega_c/T < \pi/T$ 

The inverse Fourier transform is the impulse response of this system:

$$h_c(t) = \frac{\sin(\Omega_c t)}{\pi t} = \frac{\Omega_c}{\pi} \operatorname{sinc}\left(\frac{\Omega_c t}{\pi}\right)$$

Finding the impulse-invariant system  $h[n] = Th_c(nT)$ :

$$h[n] = Th_c(nT) = T\frac{\sin(\Omega_c nT)}{\pi nT} = \frac{\sin(\omega_c n)}{\pi n} \iff H(e^{j\omega}) = \begin{cases} 1, & |\omega| < \omega_c \\ 0, & \omega_c \le |\omega| \le \pi \end{cases}$$

#### Example: Rational System Function Using Impulse Invariance

Use the impulse invariance technique to find discrete-time system to implement:

$$h_c(t) = Ae^{s_0t}u(t)$$

Applying the impulse invariance method:  $h[n] = Th_c(nT) = ATe^{s_0Tn}u[n]$ 

Finding z-transform:

$$H(z) = \frac{AT}{1 - e^{s_0 T z^{-1}}} \quad |z| > |e^{s_0 T}|$$

Gives frequency response, assuming  $Re(s_0) < 0$ :

$$H(e^{j\omega}) = \frac{AT}{1 - e^{s_0 T} e^{-j\omega}} \qquad \neq \qquad H_c(j\frac{\omega}{T}) = \frac{A}{j\frac{\omega}{T} - s_0}$$

(original continuous-time system did not have bandlimited frequency response)

Sample Rate Conversion: Downsampling

### Sample Rate Reduction: Downsampling

$$x[n] \qquad \downarrow M \qquad x_d[n] = x[nM]$$
Sampling period  $T$  Sampling period  $T_d = MT$ 

$$x_d[n] = x[nM] = x_c(nMT)$$

- ightharpoonup Reduce sample rate by integer factor M
- ▶ Same as sampling  $x_c(t)$  if  $T_d = MT$ ,
- Assume  $X_c(j\Omega) = 0$  for  $|\Omega| \ge \Omega_N$
- Using mapping  $\Omega = \omega/T$ : No aliasing if  $\pi/T_d = \pi/(MT) \ge \Omega_N$
- ightharpoonup Can reduce sampling rate by factor of M without aliasing if original sample rate is at least M times Nyquist rate (or bandwidth reduced by factor of M)

## Downsampling: Frequency Domain Perspective

DTFT of 
$$x[n]$$
, the original sampled signal:

$$X(e^{j\omega}) = \frac{1}{T} \sum_{k=-\infty}^{\infty} X_c \left[ j \left( \frac{\omega}{T} - \frac{2\pi k}{T} \right) \right]$$

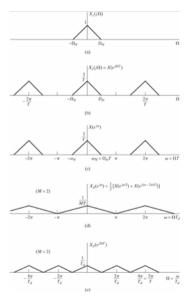
DTFT of  $x_d[n] = x[nM]$ , in terms of  $X_c(i\Omega)$ :

$$X_d(e^{j\omega})=rac{1}{MT}\sum_{r=-\infty}^{\infty}X_c\left[j\left(rac{\omega}{MT}-rac{2\pi r}{MT}
ight)
ight]$$

or DTFT of 
$$x_d[n] = x[nM]$$
, in terms of the spectrum of  $x[n]$ 

or DTFT of 
$$x_d[n]=x[nM]$$
, in terms of the spectrum of  $x[n]$  
$$X_d(e^{j\omega})=\frac{1}{M}\sum^{M-1}X\left(e^{j(\omega/M-2\pi i/M)}\right)$$

#### Example: Downsampling, M = 2, With No Aliasing



To avoid aliasing, ensure  $X(e^{j\omega})$  is bandlimited:

$$X(e^{j\omega}) = 0, \quad \omega_N \le |\omega| \le \pi$$

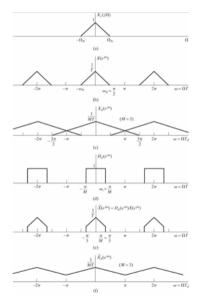
and  $2\pi/M$  is above the Nyquist rate:

$$2\pi/M \ge 2\omega_N$$

or

$$\pi/M \ge \omega_N$$

#### Example: Downsampling, M = 3, With Aliasing and Prefilter



Highest frequency:

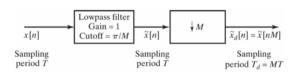
$$\omega_N = \Omega_N T$$

To avoid aliasing:

$$\omega_M \le \pi$$
 or  $\omega_N \le \pi/M$ 

In this example:  $M\omega_N = 3\pi/2 \nleq \pi$ 

Decimation: Lowpass filtering followed by compression



Sample Rate Conversion: Upsampling and Changing Sample Rate by a Rational Factor

#### Sample Rate Reduction: Upsampling

Goal is to obtain:  $x_i[n] = x_c(nT_i)$ 

where  $T_i = T/L$ , from original sequence:  $x[n] = x_c(nT)$ 

$$x_e[n] = \begin{cases} x[n/L], & n = 0, \pm L, \pm 2L, \dots \\ 0, & \text{otherwise} \end{cases} \quad \text{or} \quad x_e[n] = \sum_{k=-\infty}^{\infty} x[k]\delta[n-kL]$$

#### Upsampling: A frequency Domain Perspective

After upsampling:

$$x_e[n] = \sum_{k=0}^{\infty} x[k]\delta[n-kL]$$

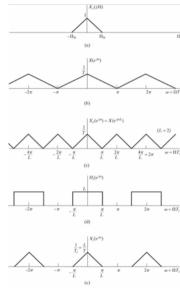
Fourier transform of upsampled sequence:

$$X_{e}(e^{j\omega}) = \sum_{n=-\infty}^{\infty} \left( \sum_{k=-\infty}^{\infty} x[k]\delta[n-kL] \right) e^{-j\omega n}$$
$$= \sum_{k=-\infty}^{\infty} x[k]e^{-j\omega Lk} = X(e^{j\omega L})$$

DTFT is frequency scaled version of input:

$$\omega \to \omega L$$
 so that  $\omega L = \Omega T$  and  $\omega = \Omega(T/L) = \Omega T_i$ 

### Example: Upsampling (Interpolation)



## Upsampling: Interpolation Formula

Output of expander and input to lowpass filter:

$$x_e[n] = \sum_{k=0}^{\infty} x[k]\delta[n - kL]$$

Impulse response of lowpass filter:

$$h_i[n] = \frac{\sin(\pi n/L)}{\pi n/L}$$
 note:  $h_i[0] = 1$  and  $h_i[n] = 0$ ,  $n = 0, \pm L, \pm 2L, ...$ 

Output of lowpass filter:

$$x_i[n] = \sum_{k=-\infty}^{\infty} x[k] \frac{\sin(\pi(n-kL)/L)}{\pi(n-kL)/L}$$

With this ideal filter:  $x_i[n] = x[n/L] = x_c(nT/L) = x_c(nT_i), n = 0, \pm L, \pm 2L, ...$ 

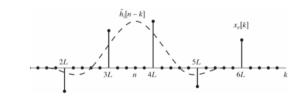
## Simple and Practical Interpolation Filters

Linear Interpolation:

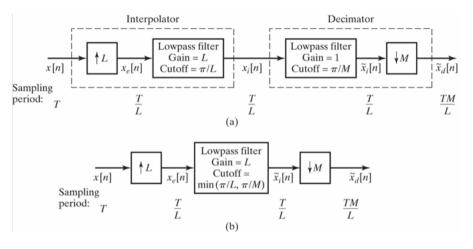
$$h_{\text{lin}}[n] = \begin{cases} 1 - |n|L, & |n| \le L \\ 0, & \text{otherwise} \end{cases}$$

FIR Filter for interpolation, where  $\tilde{h}_i[n] = 0$  for  $|n| \geq KL$ :

$$\tilde{x}_i[n] = \sum_{k=n-KL+1}^{n+KL-1} x_e[k]\tilde{h}_i[n-k]$$



## Changing Sample Rate by Rational Factor

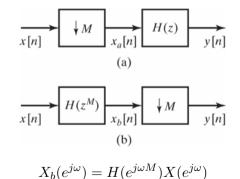


If M > L: increase in sample period (decrease sampling rate).

## Multirate Signal Processing

## Interchange of Lowpass Filter with Compressor

These two systems are equivalent:



From downsampling, output of second system:

$$Y(e^{j\omega}) = \frac{1}{M} \sum_{i=0}^{M-1} X_b(e^{j(\omega/M - 2\pi i/M)})$$
$$= \frac{1}{M} \sum_{i=0}^{M-1} X(e^{j(\omega/M - 2\pi i/M)}) H(e^{j(\omega - 2\pi i)})$$

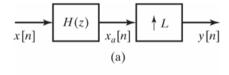
Since  $H(e^{j(\omega-2\pi i)}) = H(e^{j\omega})$ :

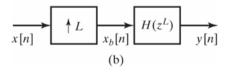
$$Y(e^{j\omega}) = H(e^{j\omega}) \frac{1}{M} \sum_{i=0}^{M-1} X(e^{j(\omega/M - 2\pi i/M)})$$
$$= H(e^{j\omega}) X_a(e^{j\omega})$$

## Interchange of Lowpass Filter with Expander

These two systems are equivalent:

(Linear filter modified)





Spectrum at expander output (2nd system):

$$X_b(e^{j\omega}) = X(e^{j\omega L})$$

Spectrum at output (1st system):

$$Y(e^{j\omega}) = X_a(e^{j\omega L})$$

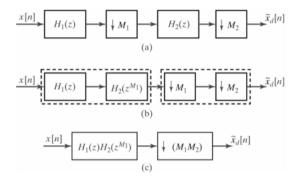
$$= X(e^{j\omega L})H(e^{j\omega L})$$

$$= H(e^{j\omega L})X_b(e^{j\omega})$$

(which corresponds to output of second system)

## Multistage Decimation To Reduce Computation

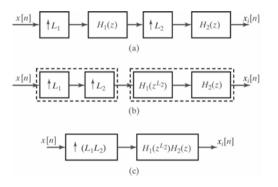
Two-stage decimation system with overall rate reduction  $M = M_1 M_2$ :



Equivalent single-stage lowpass filter:  $H(z) = H_1(z)H_2(z^{M_1})$ Single-stage required lowpass cutoff frequency:  $\pi/(M_1M_2)$ Two-stage required lowpass cutoff frequencies:  $\pi/M_1$  and  $\pi/M_2$ 

## Multistage Interpolation To Reduce Computation

Two-stage interpolation system with overall sample rate increase  $L = L_1 L_2$ :

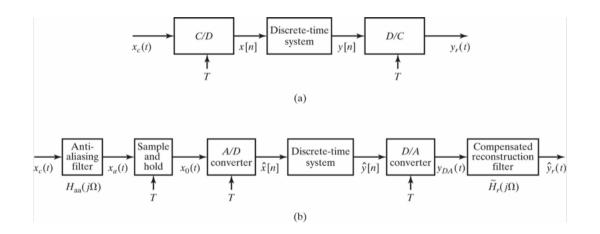


Equivalent single-stage lowpass filter:

$$H(z) = H_1(z^{L_2})H_2(z)$$

## Prefiltering to Avoid Aliasing

## Digital Processing of Analog Signals



## Anti-Aliasing Filter to Avoid Aliasing

Remember frequency scaling:  $\omega = \Omega T$ 

Anti-aliasing filter:

$$H_{aa}(j\Omega) = \begin{cases} 1, & |\Omega| < \Omega_c \le \pi/T \\ 0, & |\Omega| \ge \Omega_c \end{cases}$$

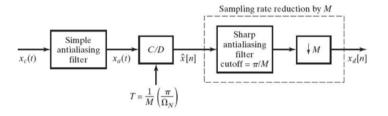
From  $x_a(t)$  to  $y_r(t)$ :

$$H_{\mathrm{eff}}(j\Omega) = egin{cases} H(e^{j\Omega T}), & |\Omega| < \Omega_c \ 0, & |\Omega| \geq \Omega_c \end{cases}$$

Since  $H_{aa}(j\Omega)$  can't be ideally bandlimited, the overall frequency response is:

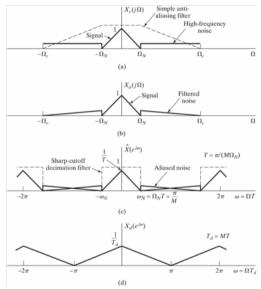
$$H_{\rm eff}(j\Omega) \approx H_{\rm aa}(j\Omega)H(e^{j\Omega T})$$

## Oversampling to Simplify Anti-Aliasing Filter



- ▶ Simple anti-aliasing filter with gradual cutoff at  $\Omega_N$
- ▶ Significant attenuation at  $M\Omega_N$
- ▶ Sample at rate higher than  $2\Omega_N$  (sample at  $2M\Omega_N$ )
- ► Implement sharp antialiasing filter in discrete-time domain when downsampling by factor of M
- ▶ Subsequent discrete-time processing completed at lower sampling rate

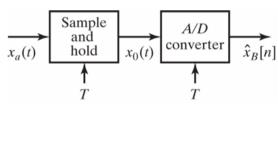
## Spectrum of Oversampling Followed by Decimation

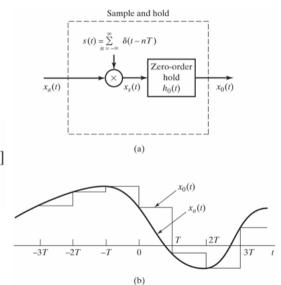


# Analog-to-Digital Conversion

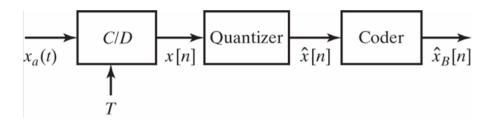
## Ideal Sample-and-Hold

### Analog-to-digital conversion:





## Analog-to-Digital Conversion System

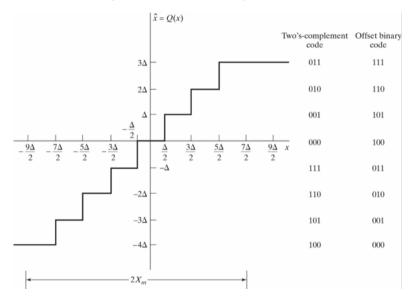


Quantizer maps input sample to finite set of values:

$$\hat{x}[n] = Q(x[n])$$

Coder will label each quantization level with binary code of (B+1)-bits.

## Quantizer for A/D Conversion (8 Levels with B+1 bits, B=2)

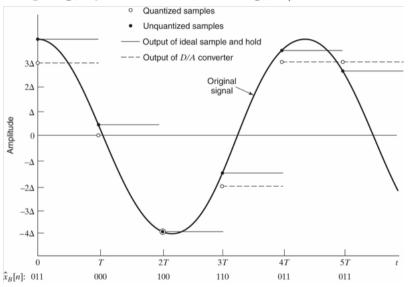


size:  $2X_m - X_n$ 

Quantizer step

$$\Delta = \frac{2X_m}{2^{B+1}} = \frac{X_m}{2^B}$$

## Example: Sampling, Quantization, Coding, D/A Conversion (3-bits)



Analysis of Quantization Errors

## Quantization Error

Quantization error is difference between quantized sample and true sample value:

$$e[n] = \hat{x}[n] - x[n]$$

If  $\Delta$  is the step-size and the input samples stay within the full range of

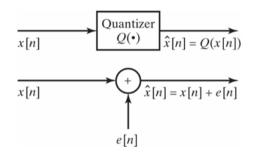
$$(-X_m - \Delta/2) < x[n] \le (X_m - \Delta/2)$$

then the quantization error will be between:

$$-\Delta/2 \le e[n] < \Delta/2$$

otherwise, then  $|e[n]| > \Delta/2$  and samples are *clipped* (quantizer is *overloaded*)

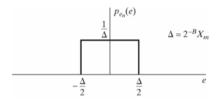
## Model of Quantizer



- e[n] is sample sequence of stationary random process
- ightharpoonup e[n] is uncorrelated with x[n]
- ightharpoonup e[n] is a white noise process
- uniform distribution over the range of quantization error

## Statistical Model for Quantization Noise

Probability density function of e[n], the quantization error using (B+1) bits:



Variance (and quantization noise power):

$$\sigma_e^2 = \int_{\Delta/2}^{\Delta/2} e^2 \frac{1}{\Delta} de = \frac{\Delta^2}{12} = \frac{2^{-2B} X_m^2}{12}$$
 since  $\Delta = \frac{X_m}{2^B}$ 

Since autocorrelation is  $\phi_{ee}[m] = \sigma_e^2 \delta[m]$ , the power spectral density is:

$$P_{ee}(e^{j\omega}) = \sigma_e^2 = \frac{2^{-2B}X_m^2}{12} \quad |\omega| \le \pi$$

## Signal-to-Quantization-Noise Ratio (SNR)

SNR for (B+1)-bit uniform quantizer is

$$SNR_Q = 10 \log_{10} \left( \frac{\sigma_x^2}{\sigma_e^2} \right) = 10 \log_{10} \left( \frac{12 \cdot 2^{2B} \sigma_x^2}{X_m^2} \right)$$
$$= 6.02B + 10.8 - 20 \log_{10} \left( \frac{X_m}{\sigma_x} \right)$$

- ► SNR increases about 6 dB for each bit added (doubling of quantization levels)
- $\blacktriangleright$  To prevent last term from becoming large and negative, signal amplitude should be matched to full-scale amplitude of A/D