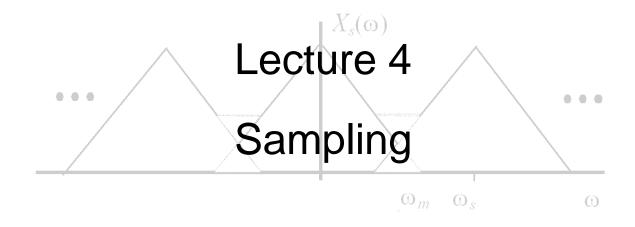
### Digital Filters & Spectral Analysis



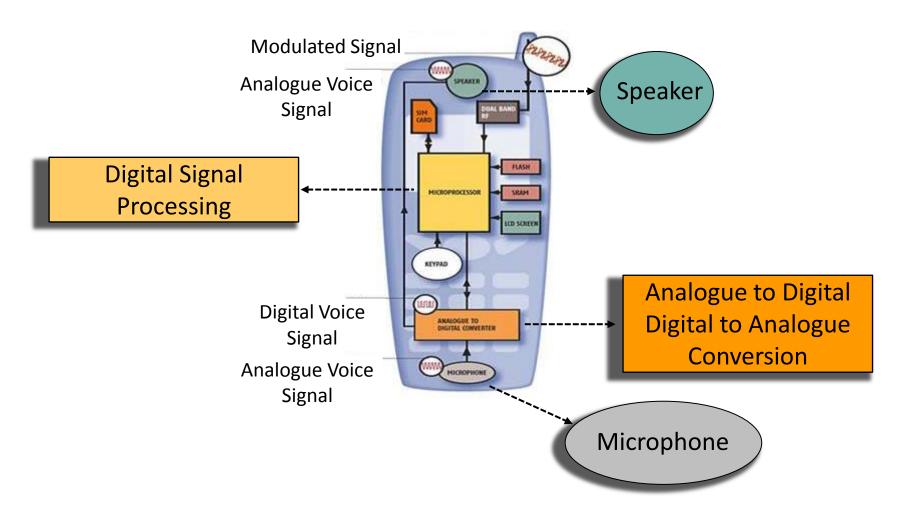


Converting continuous-time signals to discrete-time signals



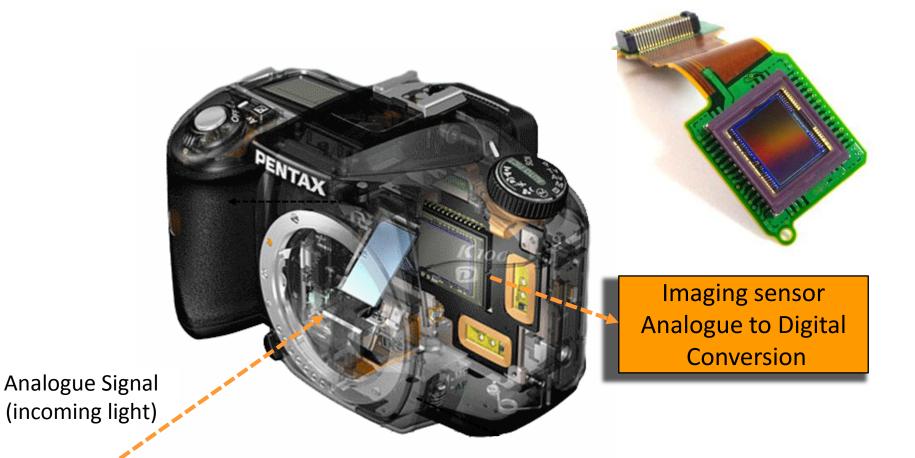
### **Digital Signal Processing**

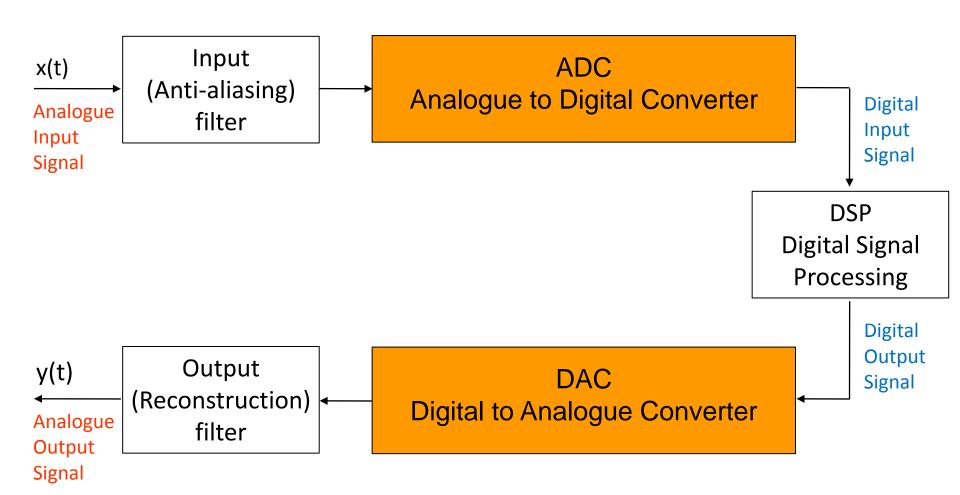
#### 1D Sampling Example (Audio)

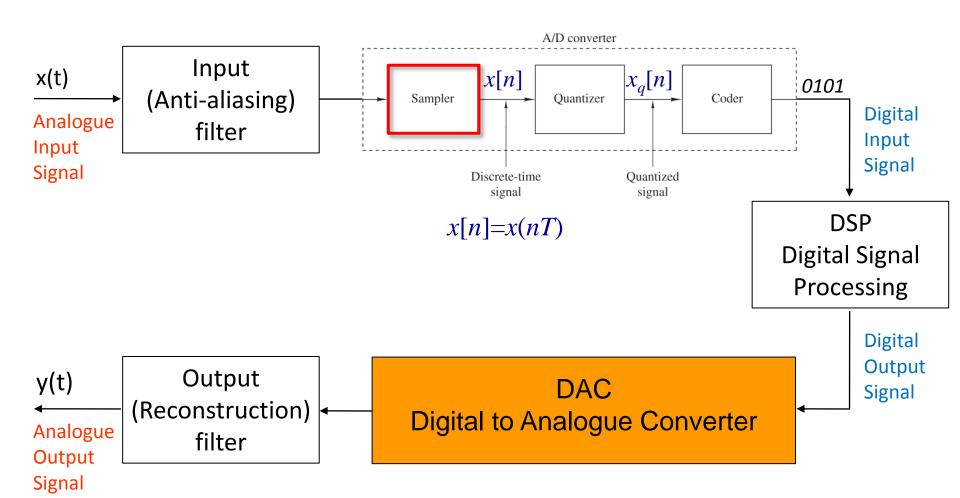


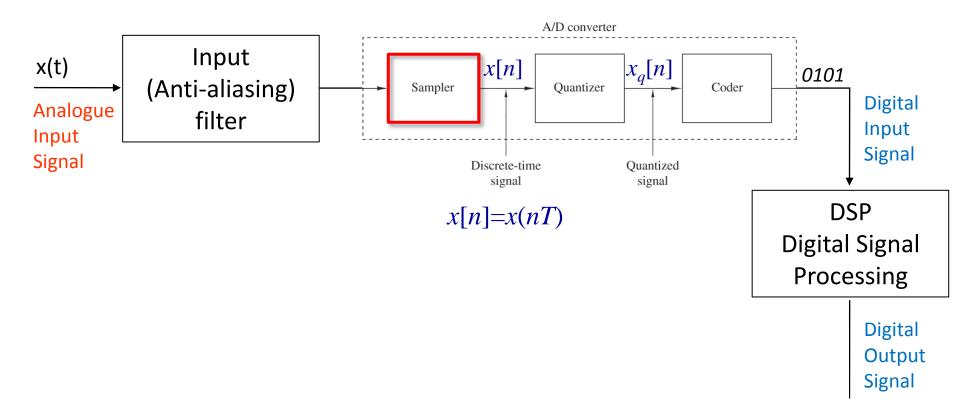
### **Digital Signal Processing**

2D Sampling Example (Image)







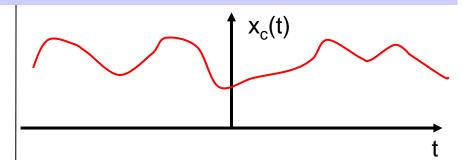


### Periodic Sampling

#### Mathematical Representation of Sampling

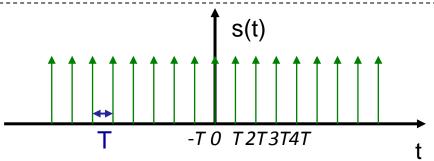
$$x_{c}(t) \longrightarrow \mathbf{X} \longrightarrow x_{s}(t) = x_{c}(t) \times s(t)$$

$$s(t)$$



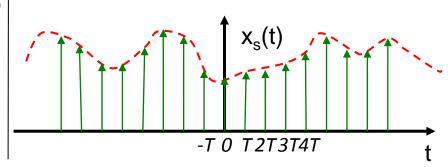
$$s(t) = \sum_{n=-\infty}^{\infty} \delta(t - nT)$$
,  $f_s = \frac{1}{T}$ 

#### Sampling Frequency



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

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



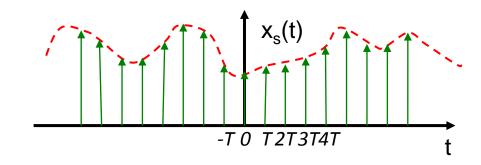


### Periodic Sampling

#### Mathematical Representation of Sampling

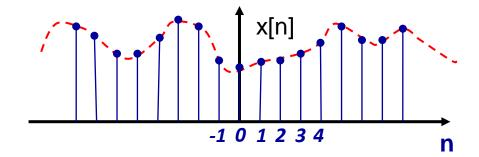
$$x_{s}(t) = \sum_{n=-\infty}^{\infty} x_{c}(nT) \delta(t - nT)$$

Continuous time signal



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

Discrete time signal



- Time is normalised (n contains no explicit information about the sampling period T)
- Normalisation by a factor of T ([n] = (nT))

$$x_s(t) = x_c(t) \times s(t) \implies X_s(\omega) = \frac{1}{2\pi} X_c(\omega) * S(\omega)$$

FT Frequency Convolution:
Multiplication in time

⇔ convolution in frequency

$$s(t) = \sum_{n=-\infty}^{\infty} \delta(t - nT_s) \quad \stackrel{F}{\longleftrightarrow} S(\omega) = \omega_s \sum_{k=-\infty}^{\infty} \delta(\omega - k\omega_s)$$

FT of an Impulse train

$$X_{s}(\omega) = \frac{1}{2\pi} X_{c}(\omega) * S(\omega) = \frac{\omega_{s}}{2\pi} \sum_{k=-\infty}^{\infty} X_{c}(\omega - k\omega_{s})$$

Convolution of a signal with a sifted impulse => shifting of the signal at the location of the impulse

$$X_{s}(\omega) = \frac{1}{T_{s}} \sum_{k=-\infty}^{\infty} X_{c}(\omega - k\omega_{s})$$

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

$$X_{s}(\omega) = \frac{1}{T_{s}} \left\{ \dots + X(\omega + 2\omega_{s}) + X(\omega + \omega_{s}) + X(\omega) \dots \right\}$$

$$+ X(\omega - \omega_{s}) + X(\omega - 2\omega_{s}) + \dots$$

Copies of original spectrum at integer multiples of the sampling frequency

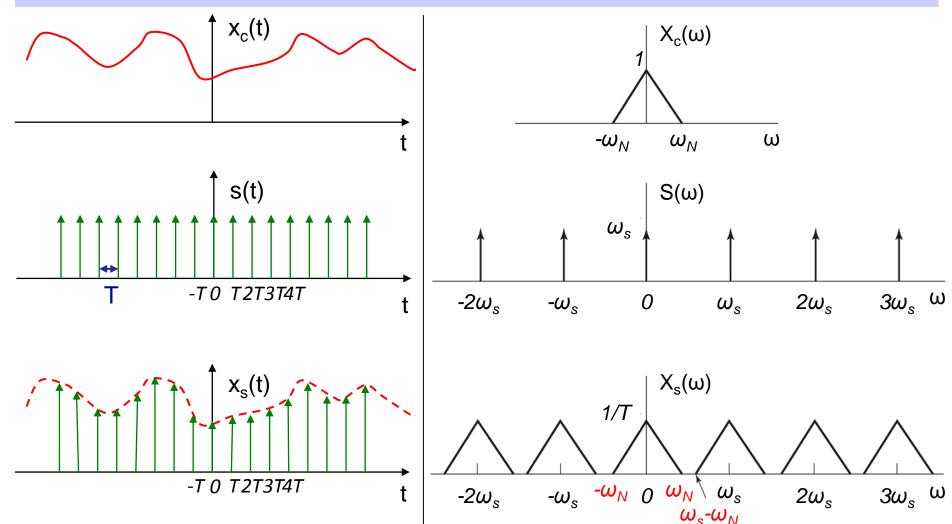
$$X_{s}(\omega + m\omega_{s}) = \frac{1}{T_{s}} \sum_{k=-\infty}^{\infty} X(\omega + m\omega_{s} - k\omega_{s})$$

$$= \frac{1}{T_{s}} \sum_{k-m=-\infty}^{\infty} X(\omega - (k-m)\omega_{s}) = X_{s}(\omega)$$

Spectrum of sampled signal is periodic

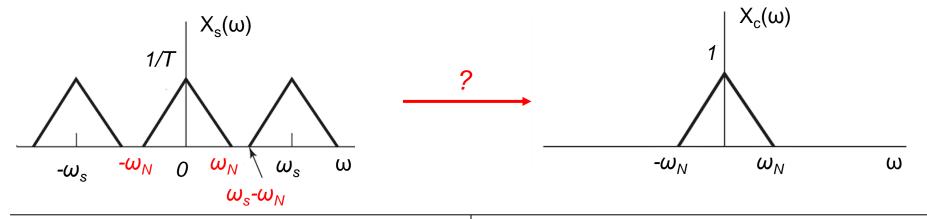
### Frequency Domain Representation of Sampling

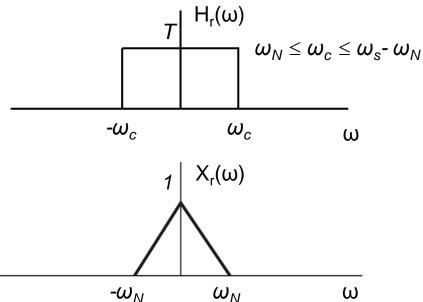
What happens to the spectrum of the sampled signal?



### Frequency Domain Representation of Sampling

Can we recover the original signal (spectrum)?

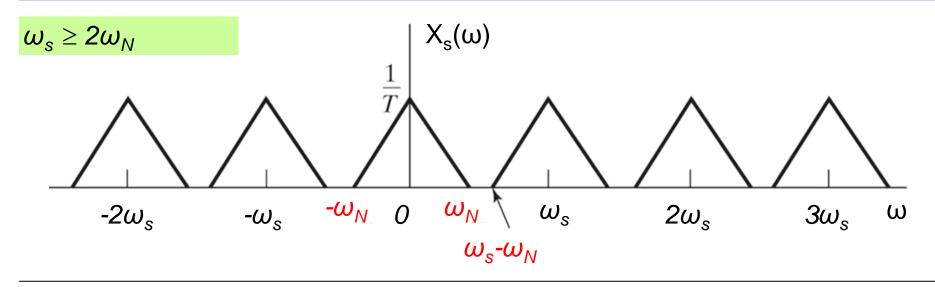


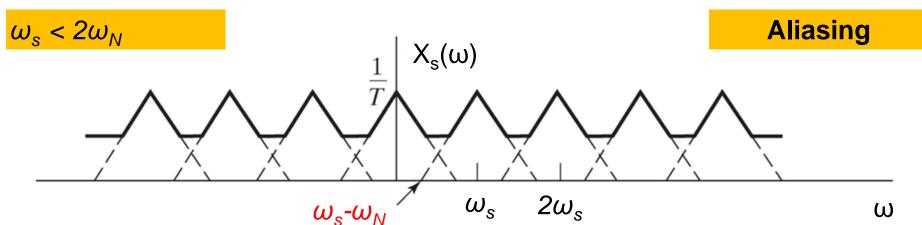


Filter the sampled signal with an ideal low pass filter to recover the original

### Frequency Domain Representation of Sampling

Is the choice of sampling frequency important?







### Aliasing

a) Spectrum of band-limited signal  $x_c(t)$ 

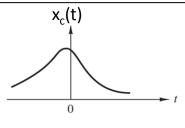
$$X_c(f) = 0, |X(f)| \ge B$$

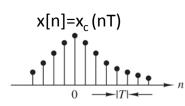
b) Sampling with  $f_s \ge 2B$ 

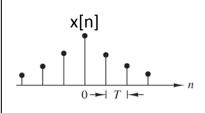
c) Sampling with  $f_s < 2B$ 

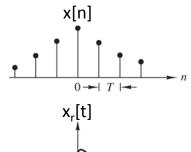
d) Aliasing - overlap of spectral images

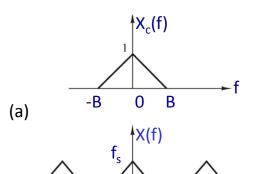
e) Impossible to recover original signal after low pass (reconstruction) filtering (aliasing is irreversible)

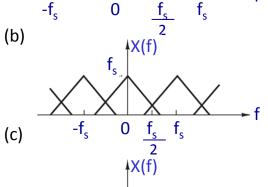


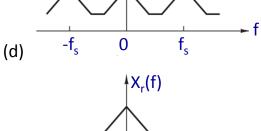


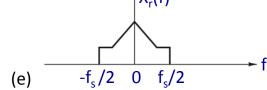






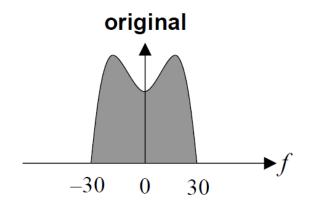


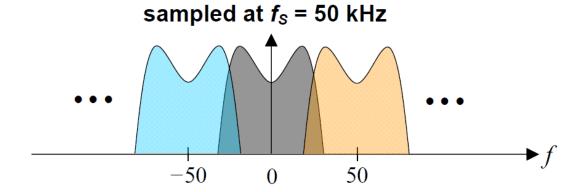




### Aliasing

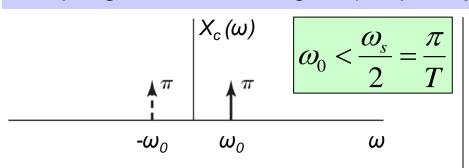
Just to make clear that the spectrum does not always look like a triangle.....

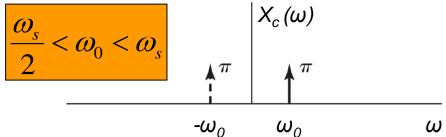


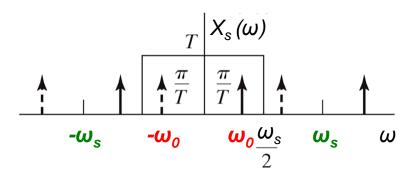


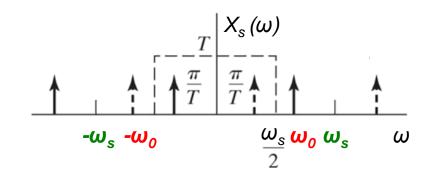
### Aliasing

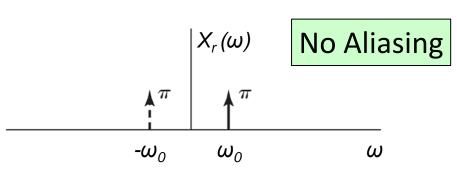
#### Sampling a sinusoidal signal (frequency domain representation)

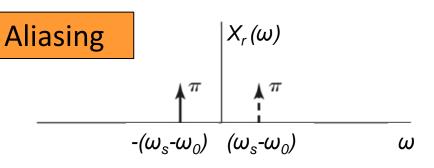














### Aliasing

#### Sampling a sinusoidal signal (time & frequency domain representation)

#### Aliasing in the time domain

$$x_r(t) = \cos(2\pi f t)$$

$$T = 3s$$

$$f = 1/T = 0.333 Hz$$

#### Aliasing in the frequency domain

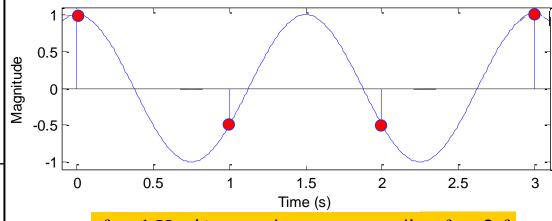
$$X_{s}(f) = \frac{1}{T_{s}} \sum_{k=-\infty}^{\infty} X(f - kf_{s})$$

$$k = 0 \Rightarrow \begin{cases} \delta(f) = \delta(0.666Hz) \\ \delta(-f) = \delta(-0.666Hz) \end{cases}$$

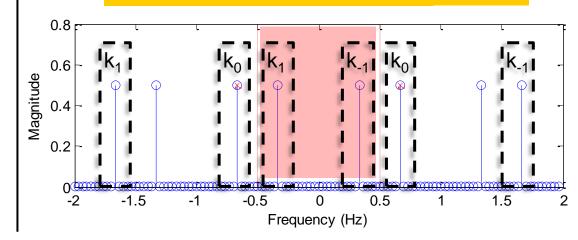
$$k = 1 \Rightarrow \begin{cases} \delta(f-1) = \delta(-0.333Hz) \\ \delta(-f-1) = \delta(-1.666Hz) \end{cases}$$

$$k = -1 \Rightarrow \begin{cases} \delta(f+1) = \delta(1.666Hz) \\ \delta(-f+1) = \delta(0.333Hz) \end{cases}$$

$$x(t) = \cos(2\pi f t), f = 0.666Hz(T = 3/2s)$$



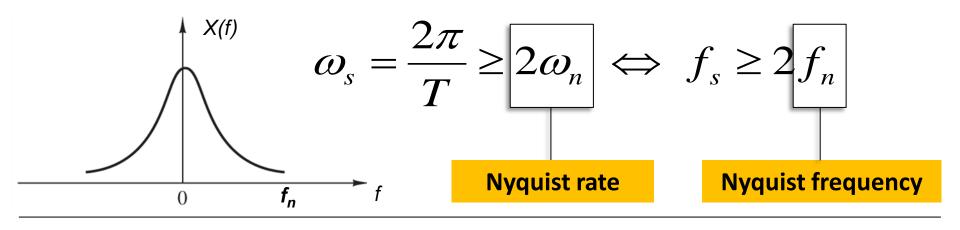
 $f_s = 1Hz$  (1 sample per second),  $f_s < 2f$ 

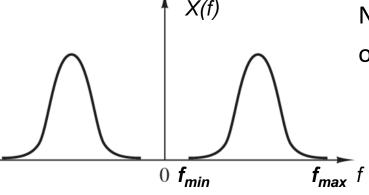


### **Avoiding Aliasing**

#### Nyquist - Shannon Sampling Theorem

If a signal, x(t), is band-limited with  $X(\omega) = 0$ ,  $\forall |\omega| > \omega_n$  then x(t) is uniquely determined by its samples, x[n] = x(nT), provided that:





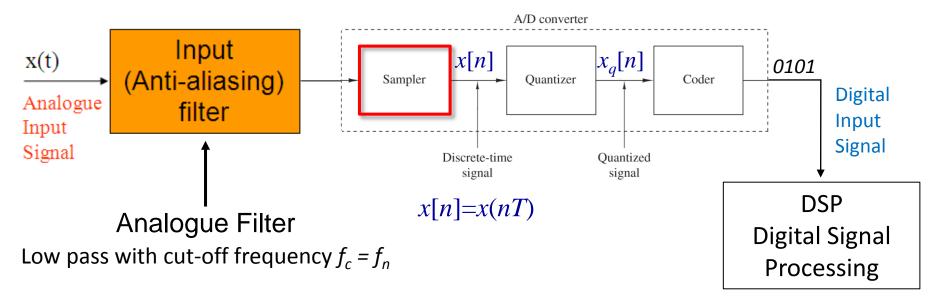
Not all signals are low pass signals. For other types of signals we talk about bandwidth

$$|f_s| \ge 2B$$
,  $B = f_{\text{max}} - f_{\text{min}}$ 

### **Avoiding Aliasing**

#### Anti-aliasing Filter

If the sampling rate is fixed then the input continuous time signal x(t) will have to be band-limited if we want to avoid aliasing

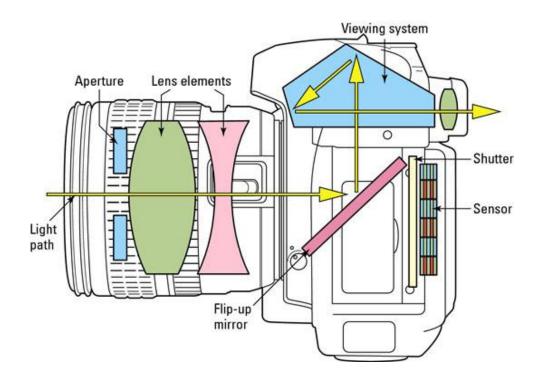


Apply low-pass filtering prior to sampling in order to ensure that the input CT signal is band-limited below the Nyquist frequency i.e. X(f) = 0,  $\forall |f| > f_n$ ,  $f_n = f_s/2$ 

### **Avoiding Aliasing**

#### Anti-aliasing Filter Example – Digital camera

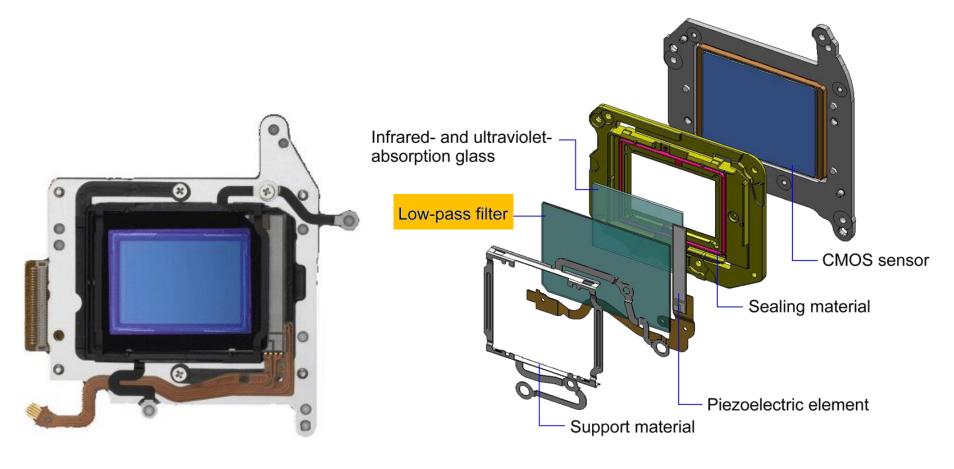
The resolution and hence the sampling frequency of the imaging sensor is fixed. The bandwidth of the input analogue signal (the real world scene seen through the lens) can vary.



### **Avoiding Aliasing**

#### Anti-aliasing Filter Example – Digital camera

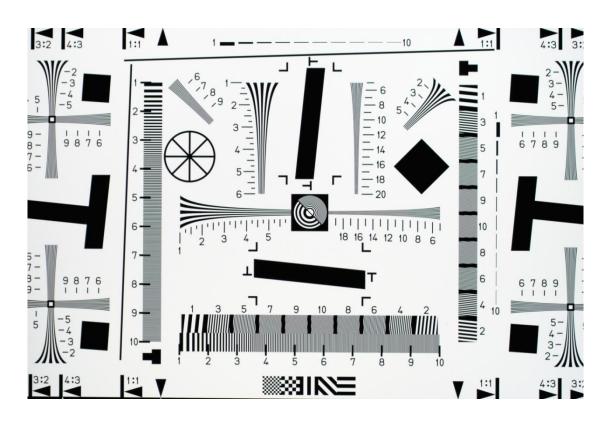
In most digital cameras an optical low pass filter is used for band-limiting the input analogue signal (the imaged scene) below the Nyquist frequency (half the sensor's sampling frequency)



### **Avoiding Aliasing**

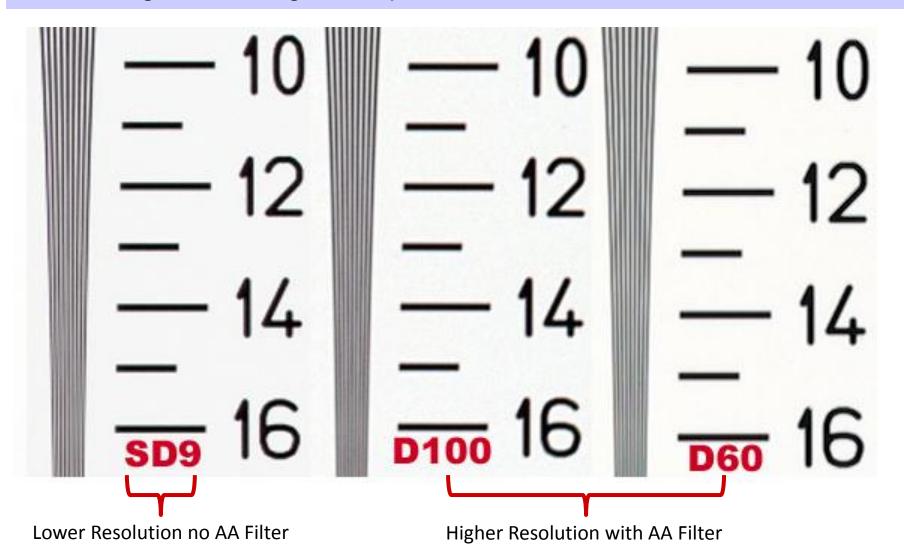
#### Anti-aliasing Filter Example – Digital camera

The "sharpness" of the camera will depend largely on the lens (which acts as a filter) and the sampling process performed at the sensor (which depends on the resolution and the antialiasing filter used). To test the sharpness the ISO 12233 Test Chart shown below is often used



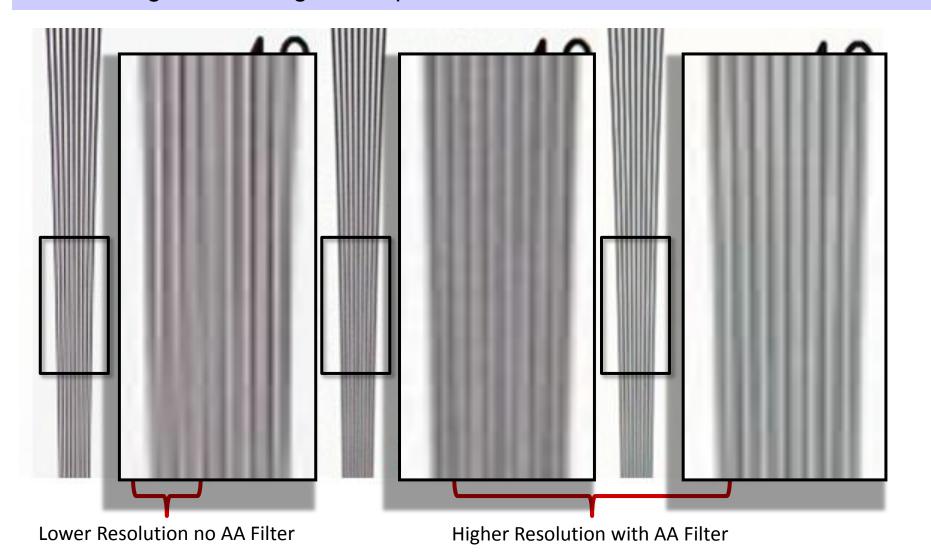
### **Avoiding Aliasing**

#### Anti-aliasing filter – Image example



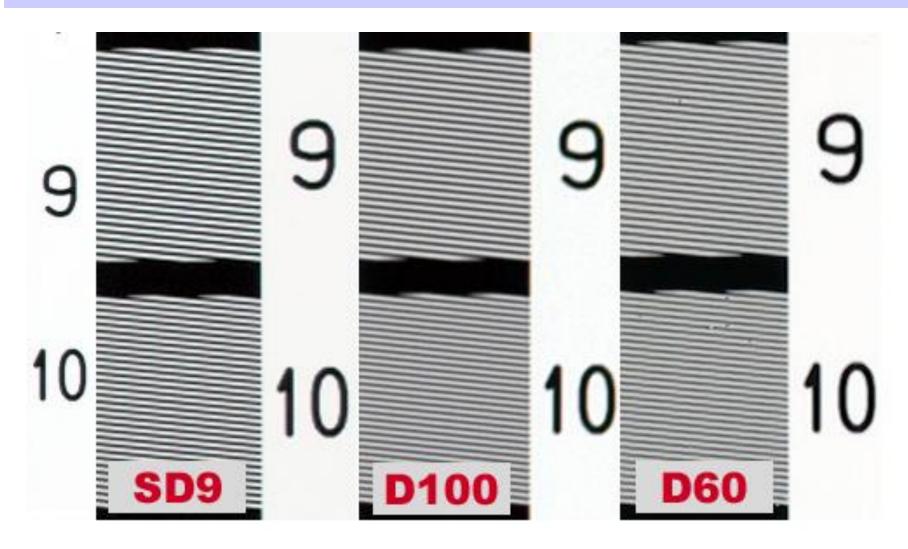
### **Avoiding Aliasing**

#### Anti-aliasing filter – Image example



### **Avoiding Aliasing**

Anti-aliasing filter – Image example



### **Avoiding Aliasing**

Anti-aliasing Filter Example – Digital camera with (left) & without filter (right)



### **Avoiding Aliasing**

Anti-aliasing filter – Image example

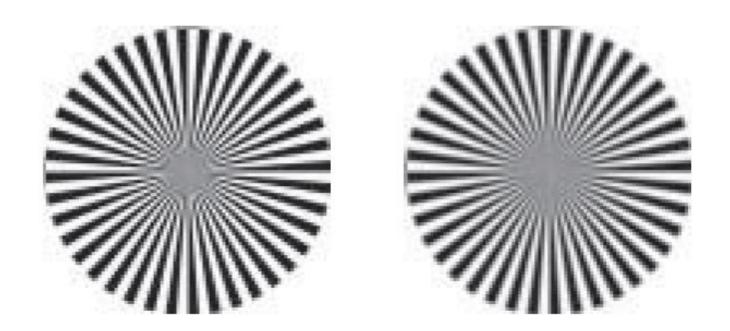


Image acquisition without anti alias filter (left) and with filter (right)

### Sampled Signal Frequency

Relationship between continuous time and discrete time signal frequency

$$x[n] = \cos(2\pi f n T_s)$$

$$t = nT_s, T_s = \frac{1}{f_s}$$

$$x[n] = \cos(2\pi n \frac{f}{f_s})$$

$$x(t) = \cos(2\pi f t)$$

$$F = \frac{f}{f_s} \Leftrightarrow \Omega = \omega T_s$$

The normalised (or digital) frequency  $\mathbf{F}$  is related to the analogue frequency  $\mathbf{f}$  through the sampling frequency  $\mathbf{f}_s$ :

$$F = \frac{f}{f_s} \Leftrightarrow \Omega = \omega T_s \Leftrightarrow f = F \times f_s$$

### Sampled Signal Frequency

Relationship between continuous time and discrete time signal frequency

The frequency f of a continuous time sinusoid when sampled at a rate  $f_s$  falls within

$$-\frac{f_s}{2} < f < \frac{f_s}{2}$$

the range  $-\frac{f_s}{2} < f < \frac{f_s}{2}$  (Fundamental Frequency Range). Anything outside this

range is an alias.

$$-\frac{f_s}{2} < f < \frac{f_s}{2}$$

$$f = F \times f_s$$

$$-\frac{1}{2} < F < \frac{1}{2}$$

$$\Omega = 2\pi F$$

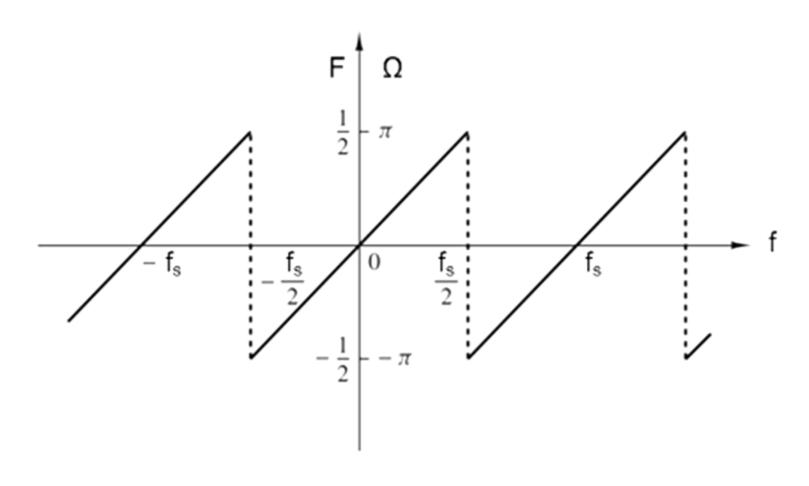
$$-\pi < \Omega < \pi$$

The **highest rate of oscillation** of a discrete time sinusoid is attained when  $\Omega = \pi$ (or equivalently **F=1/2**)

### Sampled Signal Frequency

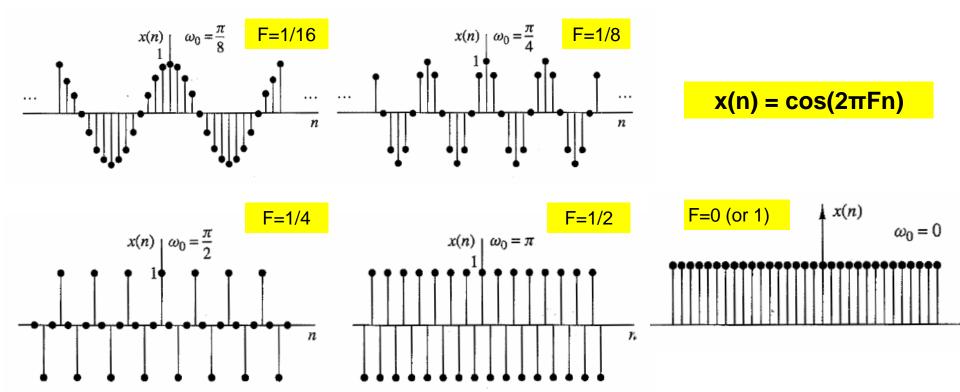
Relationship between continuous time and discrete time signal frequency

Digital Frequency (F) vs. Analogue Frequency (f)

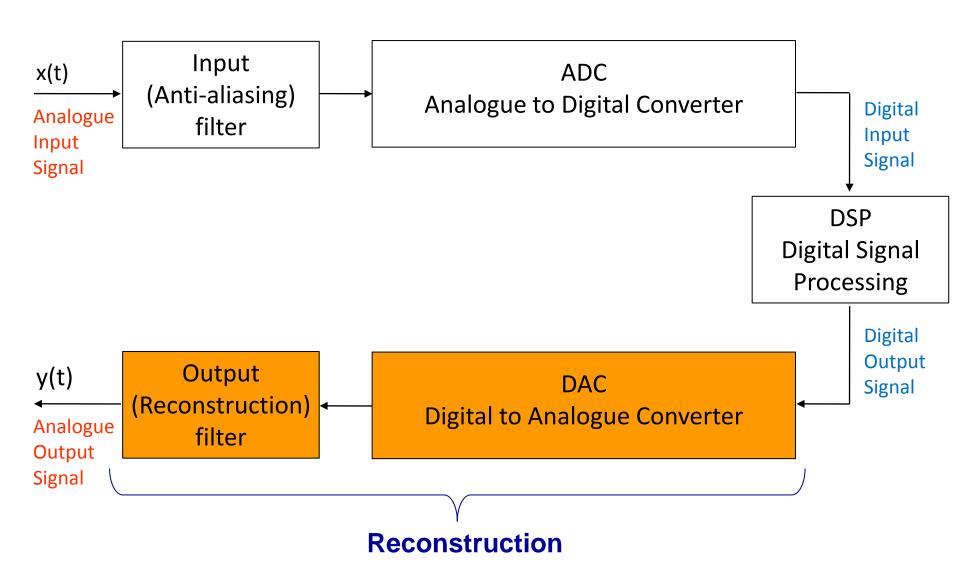


### Sampled Signal Frequency

Relationship between continuous time and discrete time signal frequency



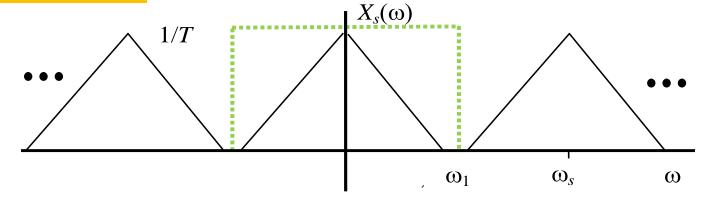
With a sampled signal we measure the **frequency in cycles per sample**. With a continuous time signal we measure it in cycles per second (Hz)

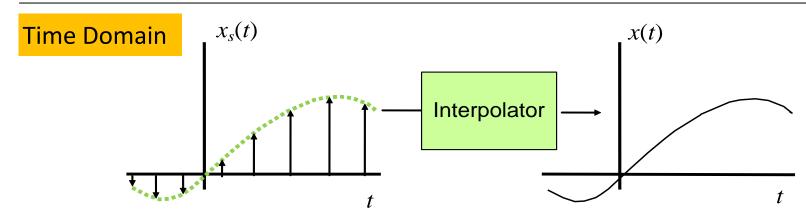


### Reconstruction

#### Ideal reconstruction

#### **Frequency Domain**

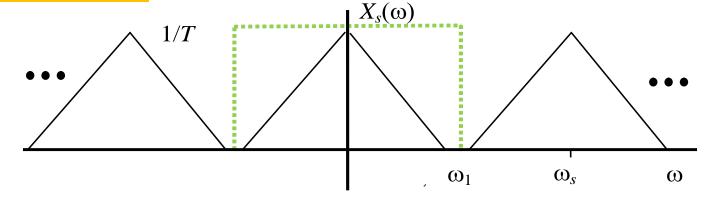




#### Reconstruction

#### Ideal reconstruction filter

#### **Frequency Domain**



#### **Time Domain**

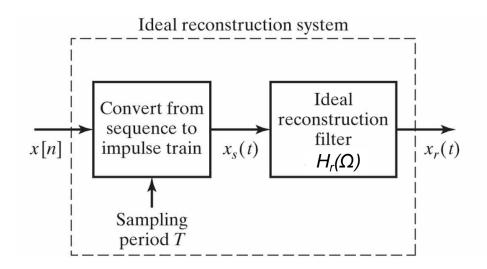
$$h(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} H(\omega) e^{j\omega t} d\omega$$

$$H(\omega) = \begin{cases} 1 & \omega_1 \le \omega \le \omega_1 \\ 0 & \text{Elsewhere} \end{cases} \Rightarrow h(t) = \frac{1}{2\pi} \int_{-\omega_1}^{\omega_1} e^{j\omega t} d\omega = \frac{\omega_1}{\pi} \left( \frac{\sin(\omega_1 t)}{\omega_1 t} \right) = \frac{\omega_1}{\pi} \operatorname{sinc}(\omega_1 t)$$

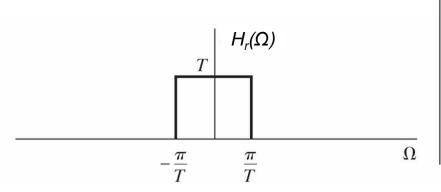
#### Reconstruction

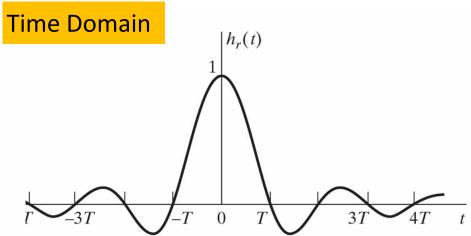
#### Ideal reconstruction filter

- In the frequency domain we multiply the spectrum of the ideal reconstruction filter with the spectrum of the sampled sign
- In the time domain this multiplication becomes a convolution between a sinc function and a train of impulses (the sampled signal)



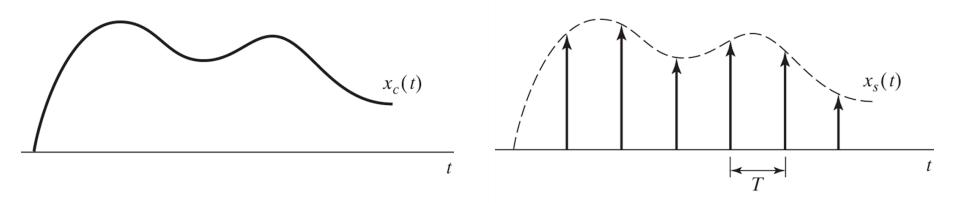
#### **Frequency Domain**



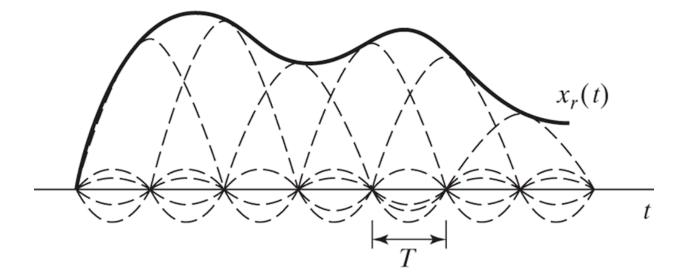


### Reconstruction

#### Ideal reconstruction filter

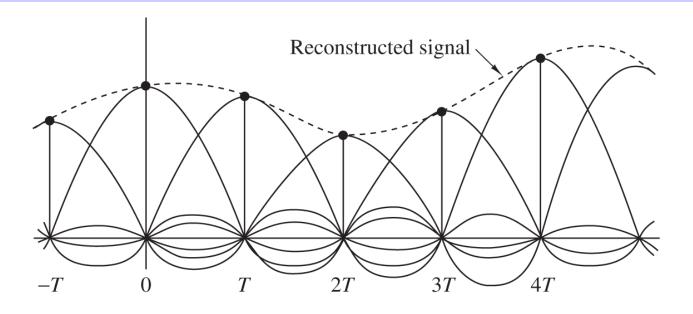


Result of convolution of ideal reconstruction filter (sinc) with sampled signal (train of impulses)



#### Reconstruction

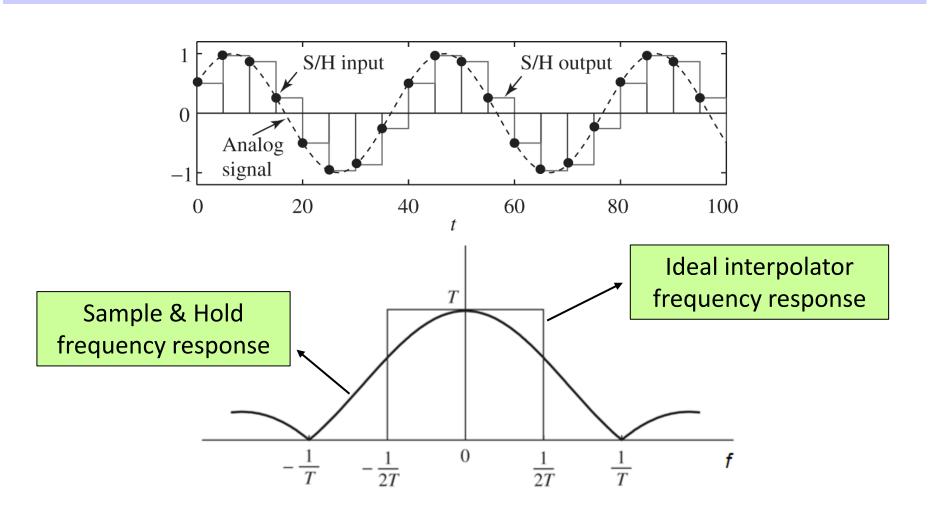
#### Ideal reconstruction filter



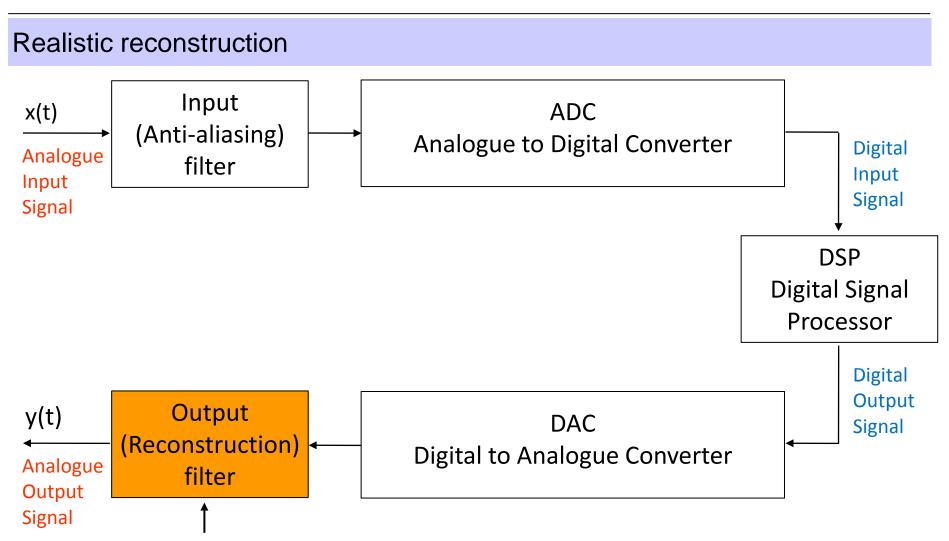
$$x_r(t) = \frac{\omega_1}{\pi} \sum_{n=-\infty}^{\infty} x_s(nT_s) \operatorname{sinc}\left(\omega_1(t - nT_s)\right)$$

#### Reconstruction

#### Realistic reconstruction



#### Reconstruction



Low pass filter: Smoothens edges of sample & hold operation in time domain Attenuates high frequencies let through by sample & hold filter in frequency domain