

ESE 531: Digital Signal Processing

Lec 7: February 6, 2020
Sampling and Reconstruction



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Lecture Outline

- Sampling
 - Frequency Response of Sampled Signal
- Reconstruction
- Anti-aliasing Filter

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Video Example

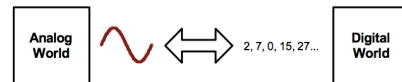


□ <https://www.youtube.com/watch?v=ByTsISFXUoY>

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The Data Conversion Problem

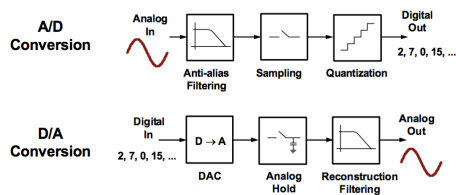


- Real world signals
 - Continuous time, continuous amplitude
- Digital abstraction
 - Discrete time, discrete amplitude
- Two problems
 - How to go discrete in time and amplitude
 - A/D conversion
 - How to "undescretize" in time and amplitude
 - D/A conversion

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Overview

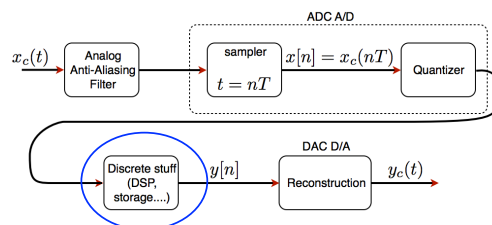


- We'll first look at these building blocks from a functional, "black box" perspective

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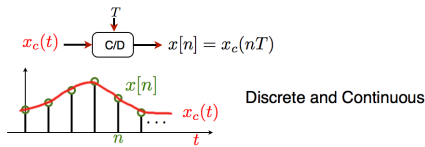
DSP System



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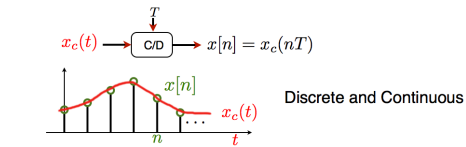
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Ideal Sampling Model

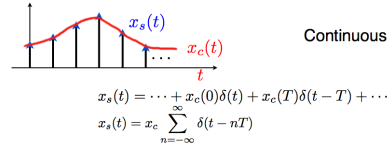


- Ideal continuous-to-discrete time (C/D) converter
 - T is the sampling period
 - $f_s = 1/T$ is the sampling frequency
 - $\Omega_s = 2\pi/T$

Ideal Sampling Model



define impulsive sampling:



Ideal Sampling Model

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

- Dirac delta function, $\delta(t)$
 - Infinitely high and thin, area of 1
 - Not physical—for modeling

$$x[n] \leftrightarrow x_s(t) \leftrightarrow x_c(t)$$

- Three signals. How are they related? In time? In frequency?

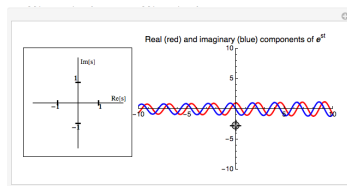
Reminder: Laplace Transform

- The Laplace transform takes a function of time, t, and transforms it to a function of a complex variable, s.
- Because the transform is invertible, no information is lost and it is reasonable to think of a function f(t) and its Laplace transform F(s) as two views of the same phenomenon.
- Each view has its uses and some features of the phenomenon are easier to understand in one view or the other.

S-Plane

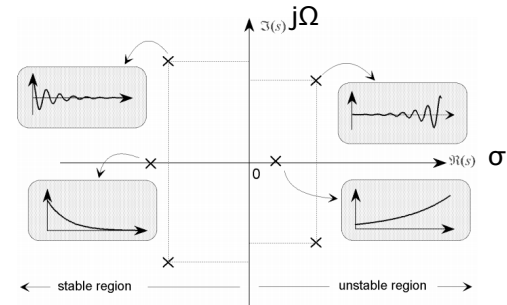
$$s = \sigma + j\Omega$$

- Wolfram Demo

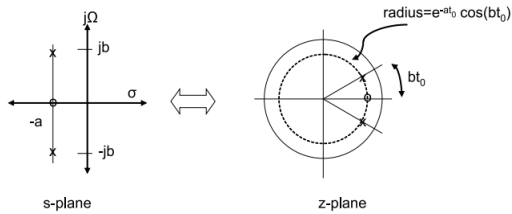


- <http://pilot.cnsxproject.org/content/collection/col10064/latest/module/m10060/latest>

S-plane and stability



S-Plane Mapping to Z-Plane



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Frequency Domain Analysis

How is $x[n]$ related to $x_s(t)$ in frequency domain?

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

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Frequency Domain Analysis

How is $x[n]$ related to $x_s(t)$ in frequency domain?

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

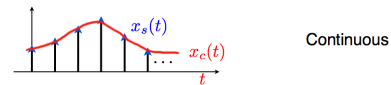
$$\begin{aligned} x_s(t) &: \text{C.T.} & X_s(j\Omega) &= \sum_n x_c(nT) e^{-j\Omega nT} \\ x[n] &: \text{D.T.} & X(e^{j\omega}) &= \sum_n x[n] e^{-j\omega n} \end{aligned} \quad \omega = \Omega T$$

$$X(e^{j\omega}) = X_s(j\Omega)|_{\Omega=\omega/T} \quad X_s(j\Omega) = X(e^{j\omega})|_{\omega=\Omega T}$$

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Frequency Domain Analysis

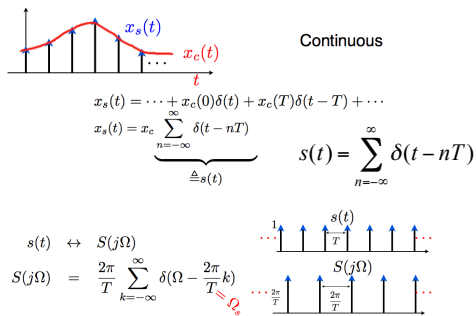


$$\begin{aligned} x_s(t) &= \dots + x_c(0)\delta(t) + x_c(T)\delta(t-T) + \dots \\ x_s(t) &= x_c \sum_{n=-\infty}^{\infty} \delta(t - nT) \\ &\triangleq s(t) \end{aligned} \quad s(t) = \sum_{n=-\infty}^{\infty} \delta(t - nT)$$

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Frequency Domain Analysis



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Frequency Domain Analysis

$$x_s(t) = s(t) \cdot x_c(t)$$

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Frequency Domain Analysis

$$x_s(t) = s(t) \cdot x_c(t)$$

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

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Frequency Domain Analysis

$$x_s(t) = s(t) \cdot x_c(t)$$

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

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

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Frequency Domain Analysis

$$x_s(t) = s(t) \cdot x_c(t)$$

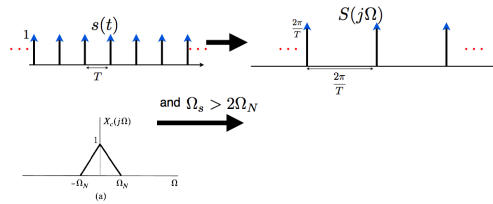
$$X_s(j\Omega) = \frac{1}{2\pi} X_c(j\Omega) * S(j\Omega) = \frac{1}{T} \sum_{k=-\infty}^{\infty} X_c(j(\Omega - k\Omega_s)) \quad | \quad \Omega_s = \frac{2\pi}{T}$$

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

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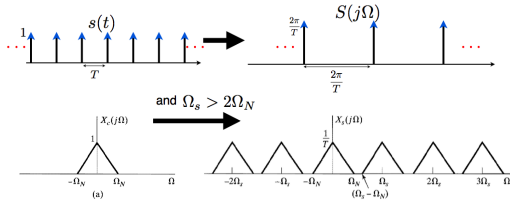
Frequency Domain Analysis



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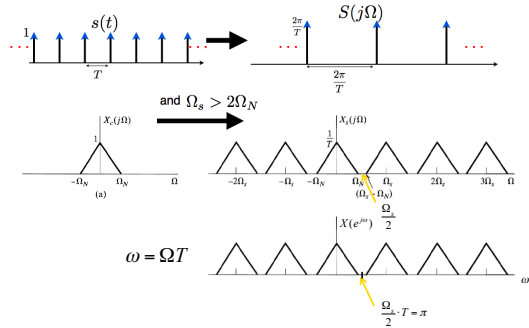
Frequency Domain Analysis



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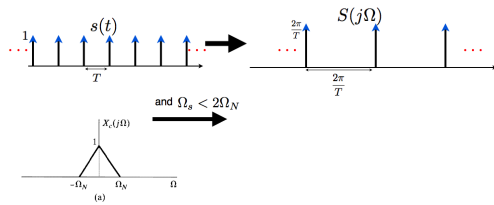
Frequency Domain Analysis



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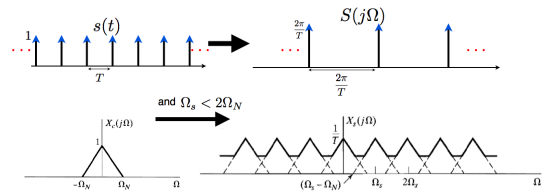
Frequency Domain Analysis w/ Aliasing



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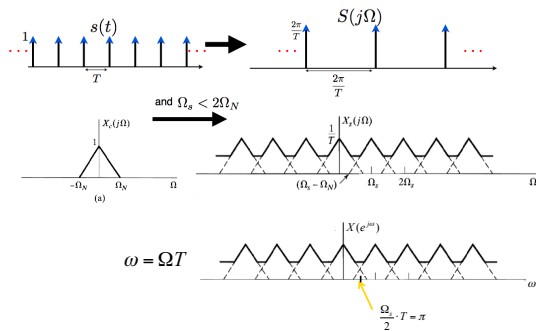
Frequency Domain Analysis w/ Aliasing



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Frequency Domain Analysis w/ Aliasing



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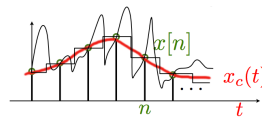
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Reconstruction of Bandlimited Signals

- Nyquist Sampling Theorem: Suppose $x_c(t)$ is bandlimited. I.e.

$$X_c(j\Omega) = 0 \quad \forall \quad |\Omega| \geq \Omega_N$$

- If $\Omega_s \geq 2\Omega_N$, then $x_c(t)$ can be uniquely determined from its samples $x[n] = x_c(nT)$
- Bandlimitedness is the key to uniqueness

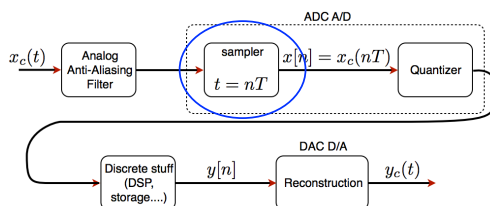


Multiple signals go through the samples, but only one is bandlimited within our sampling band

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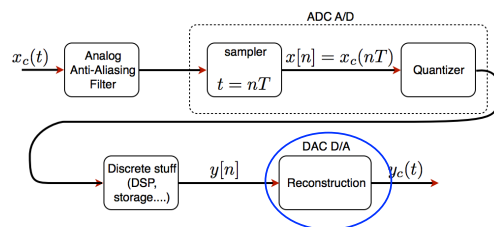
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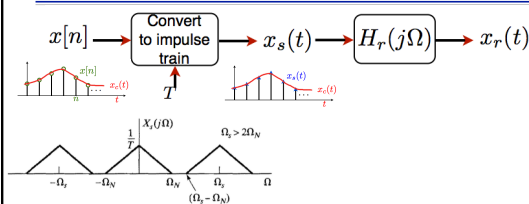
DSP System



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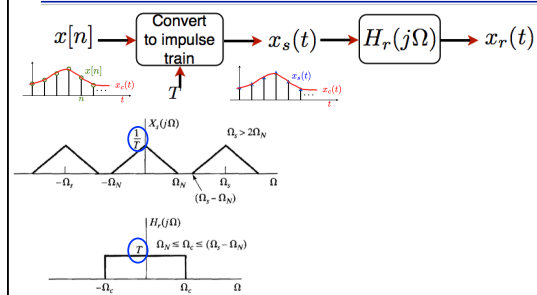
Reconstruction in Frequency Domain



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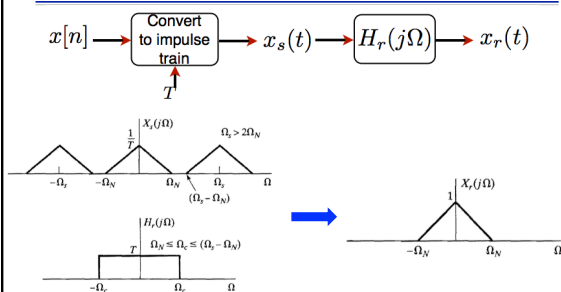
Reconstruction in Frequency Domain



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Reconstruction in Frequency Domain



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Example: Cosine Input

- Sample and reconstruct the continuous-time signal $x_c(t) = \cos(4000\pi t)$ with sampling period $T = 1/6000$ s ($f_s = 6\text{kHz}$)

$$\begin{aligned} X_s(j\Omega) &= \frac{1}{2\pi} X_c(j\Omega) * S(j\Omega) \\ &= \frac{1}{T} \sum_{k=-\infty}^{\infty} X_c(j(\Omega - k\Omega_s)) \quad \Omega_s = \frac{2\pi}{T} \end{aligned}$$

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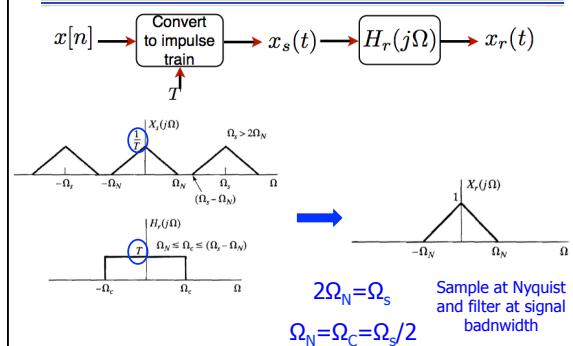
Example: Cosine Input

- Sample and reconstruct the continuous-time signal $x_c(t) = \cos(16000\pi t)$ with sampling period $T = 1/6000$ s ($f_s = 6\text{kHz}$)

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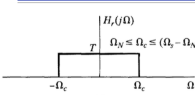
Reconstruction in Frequency Domain



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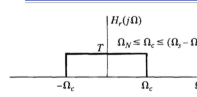
Reconstruction in Time Domain $\Omega_N = \Omega_C = \Omega_s/2$

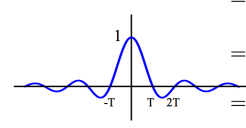


$$h_r(t) = \frac{1}{2\pi} \int_{-\Omega_s/2}^{\Omega_s/2} T e^{j\Omega t} d\Omega$$

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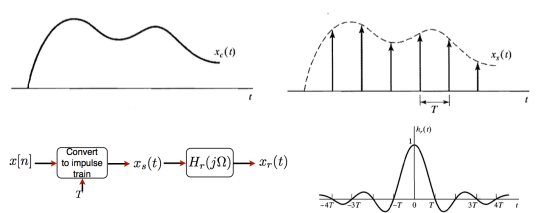
Reconstruction in Time Domain $\Omega_N = \Omega_C = \Omega_s/2$



$$\begin{aligned} h_r(t) &= \frac{1}{2\pi} \int_{-\Omega_s/2}^{\Omega_s/2} T e^{j\Omega t} d\Omega \\ &= \frac{T}{2\pi} \frac{1}{jt} \left[e^{j\Omega t} \right]_{-\Omega_s/2}^{\Omega_s/2} \\ &= \frac{T}{\pi t} \frac{e^{j\frac{\Omega_s}{2}t} - e^{-j\frac{\Omega_s}{2}t}}{2j} \\ &= \frac{T}{\pi t} \sin\left(\frac{\Omega_s}{2}t\right) = \frac{T}{\pi t} \sin\left(\frac{\pi}{T}t\right) \\ &= \text{sinc}\left(\frac{t}{T}\right) \end{aligned}$$


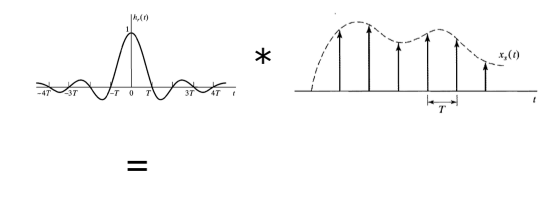
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Reconstruction in Time Domain

$$\begin{aligned} x_r(t) &= x_s(t) * h_r(t) = \left(\sum_n x[n] \delta(t - nT) \right) * h_r(t) \\ &= \sum_n x[n] h_r(t - nT) \end{aligned}$$


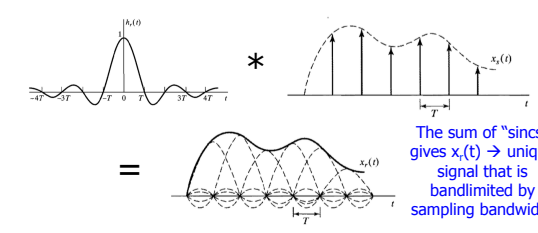
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Reconstruction in Time Domain

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Reconstruction in Time Domain

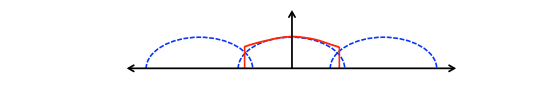
$$\begin{aligned} x_r(t) &= x_s(t) * h_r(t) = \left(\sum_n x[n] \delta(t - nT) \right) * h_r(t) \\ &= \sum_n x[n] h_r(t - nT) \end{aligned}$$


The sum of "sincs" gives $x_c(t)$ → unique signal that is bandlimited by sampling bandwidth

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Aliasing

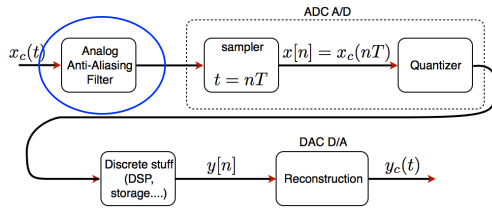
□ If $\Omega_N > \Omega_s/2$, $x_r(t)$ an aliased version of $x_c(t)$



$$X_r(j\Omega) = \begin{cases} TX_s(j\Omega) & \text{if } |\Omega| \leq \Omega_s/2 \\ 0 & \text{otherwise} \end{cases}$$

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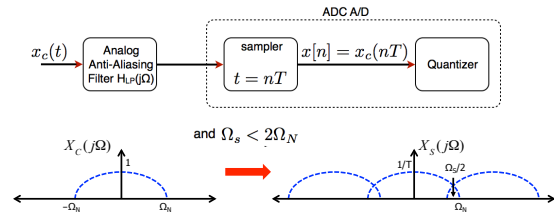
DSP System



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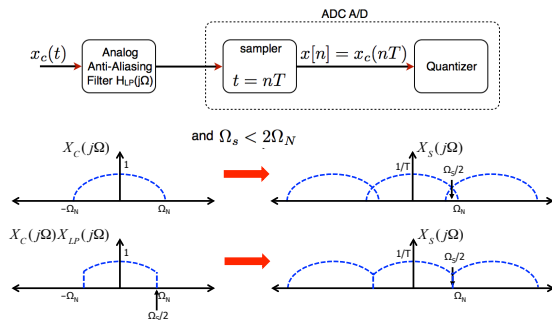
Anti-Aliasing Filter



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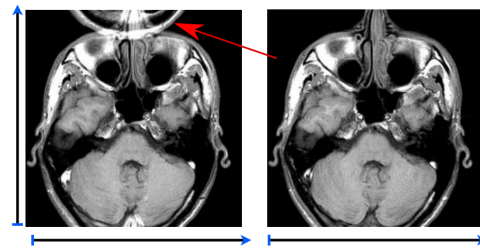
Anti-Aliasing Filter



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MRI aliasing example



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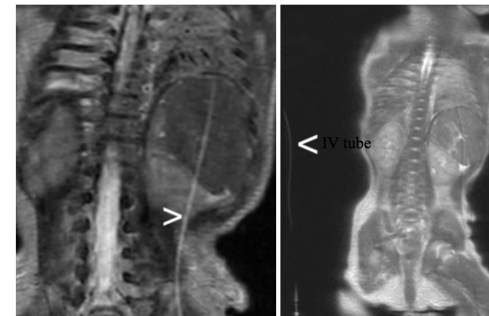
MRI anti-aliasing example



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MRI anti-aliasing example



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Big Ideas

- ❑ Sampling
 - Ideal sampling modeled as impulsive sampling
 - Sample at Nyquist rate for recovery of unique bandlimited signal (i.e. avoid aliasing)
- ❑ Frequency Response of Sampled Signal
 - Sampled signal is period replicated input CT signal
- ❑ Reconstruction
 - Low pass/reconstruction filter results in sum of sines
- ❑ Anti-aliasing filtering
 - Force input signal to be bandlimited

Admin

- ❑ HW 2 due Sunday at midnight
- ❑ HW 3 posted Sunday
- ❑ Check your submission!