

Bioengineering 280A  
Principles of Biomedical Imaging

Fall Quarter 2009  
CT/Fourier Lecture 5

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## Topics

- Sampling Requirements in CT
- Sampling Theory
- Aliasing

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## CT Sampling Requirements

What should the size of the detectors be?

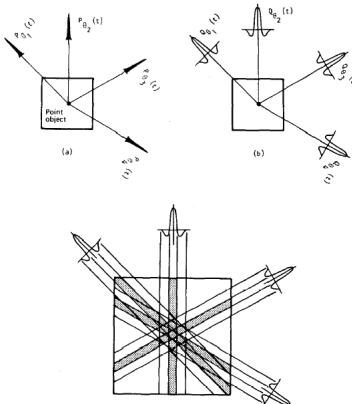
How many detectors do we need?

How many views do we need?

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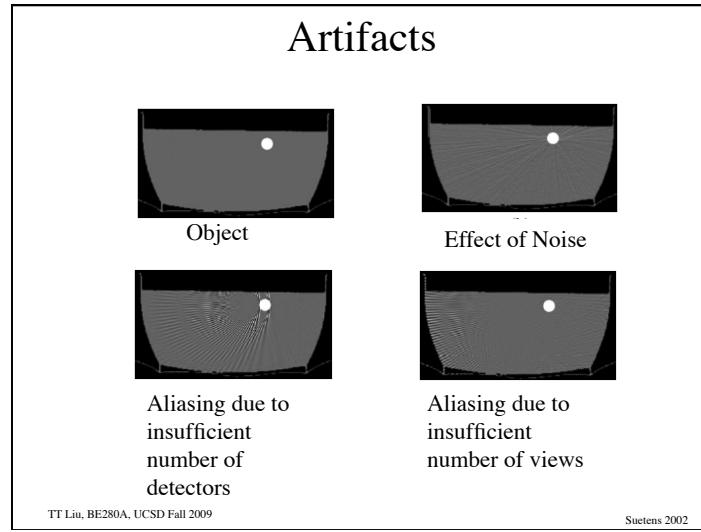
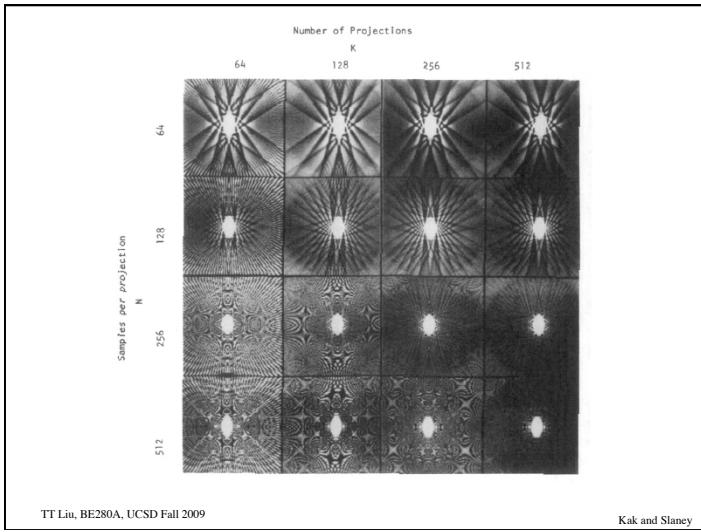
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## View Aliasing



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Kak and Slaney

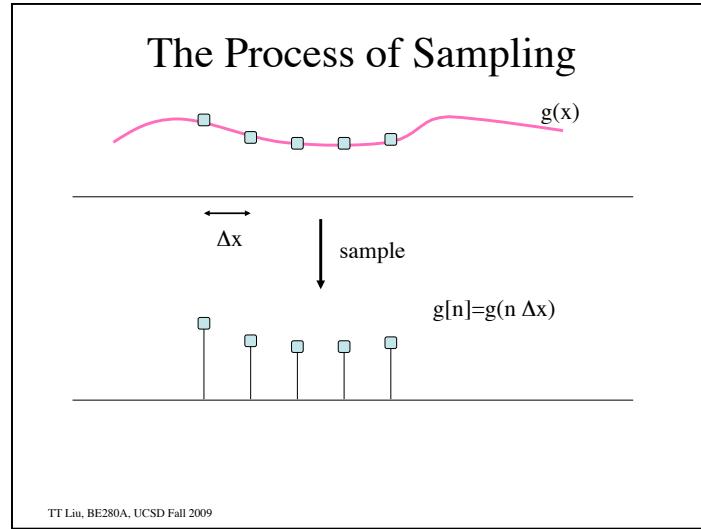


## Analog vs. Digital

**The Analog World:**  
Continuous time/space, continuous valued signals or images, e.g. vinyl records, photographs, x-ray films.

**The Digital World:**  
Discrete time/space, discrete-valued signals or images, e.g. CD-Roms, DVDs, digital photos, digital x-rays, CT, MRI, ultrasound.

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## Questions

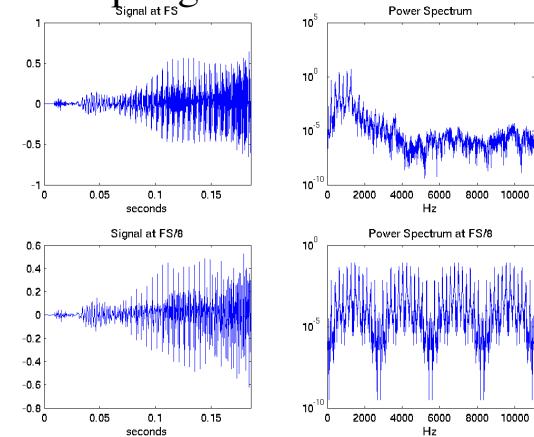
How finely do we need to sample?

What happens if we don't sample finely enough?

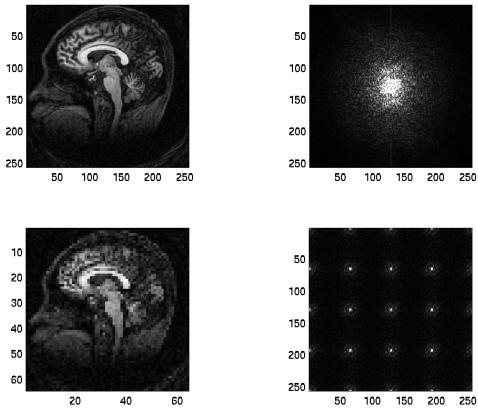
Can we reconstruct the original signal or image from its samples?

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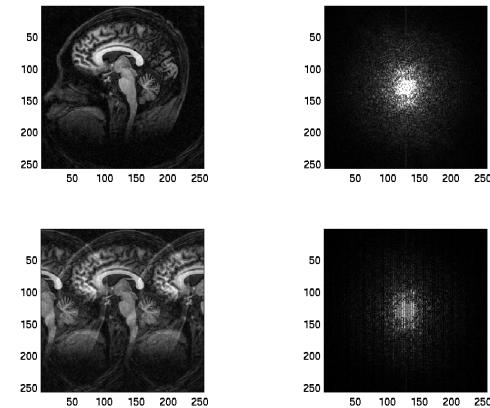
## Sampling in the Time Domain



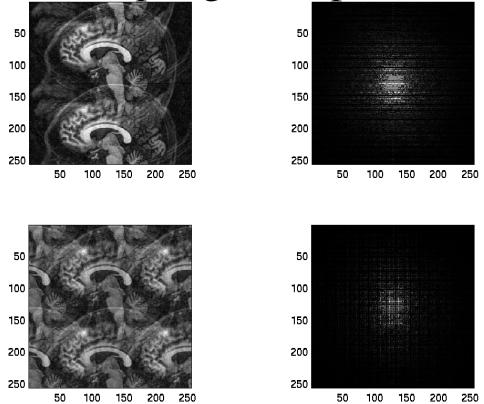
## Sampling in Image Space



## Sampling in k-space



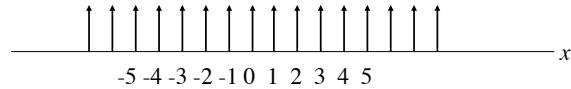
## Sampling in k-space



1

## Comb Function

$$comb(x) = \sum_{n=-\infty}^{\infty} \delta(x - n)$$

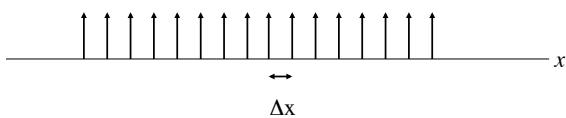


Other names: Impulse train, bed of nails, shah function.

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## Scaled Comb Function

$$\begin{aligned} comb\left(\frac{x}{\Delta x}\right) &= \sum_{n=-\infty}^{\infty} \delta\left(\frac{x}{\Delta x} - n\right) \\ &= \sum_{n=-\infty}^{\infty} \delta\left(\frac{x - n\Delta x}{\Delta x}\right) \\ &= \Delta x \sum_{n=-\infty}^{\infty} \delta(x - n\Delta x) \end{aligned}$$



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## 1D spatial sampling

$$\begin{aligned} g_s(x) &= g(x) \frac{1}{\Delta x} comb\left(\frac{x}{\Delta x}\right) \\ &= g(x) \sum_{n=-\infty}^{\infty} \delta(x - n\Delta x) \\ &= \sum_{n=-\infty}^{\infty} g(n\Delta x) \delta(x - n\Delta x) \end{aligned}$$

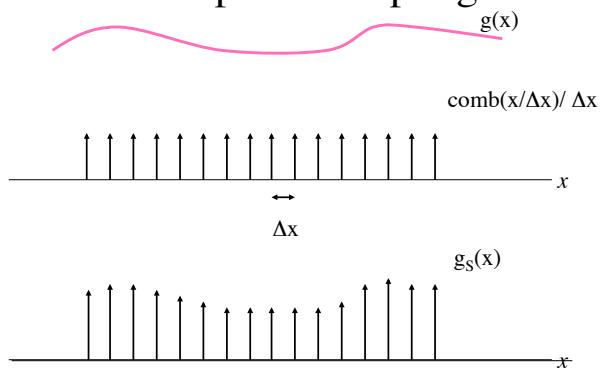
Recall the sifting property  $\int_{-\infty}^{\infty} g(x)\delta(x - a) dx = g(a)$

But we can also write  $\int_{-\infty}^{\infty} g(a)\delta(x - a) dx = g(a) \int_{-\infty}^{\infty} \delta(x - a) dx = g(a)$

So,  $g(x)\delta(x - a) = g(a)\delta(x - a)$

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## 1D spatial sampling



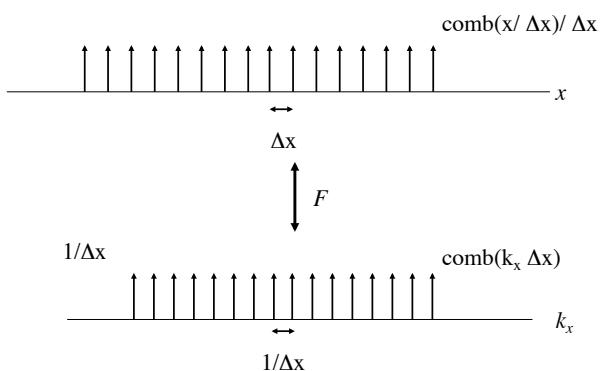
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## Fourier Transform of $\text{comb}(x)$

$$\begin{aligned} F[\text{comb}(x)] &= \text{comb}(k_x) \\ &= \sum_{n=-\infty}^{\infty} \delta(k_x - n) \\ F\left[\frac{1}{\Delta x} \text{comb}\left(\frac{x}{\Delta x}\right)\right] &= \frac{1}{\Delta x} \Delta x \text{comb}(k_x \Delta x) \\ &= \sum_{n=-\infty}^{\infty} \delta(k_x \Delta x - n) \\ &= \frac{1}{\Delta x} \sum_{n=-\infty}^{\infty} \delta(k_x - \frac{n}{\Delta x}) \end{aligned}$$

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## Fourier Transform of $\text{comb}(x/\Delta x)$



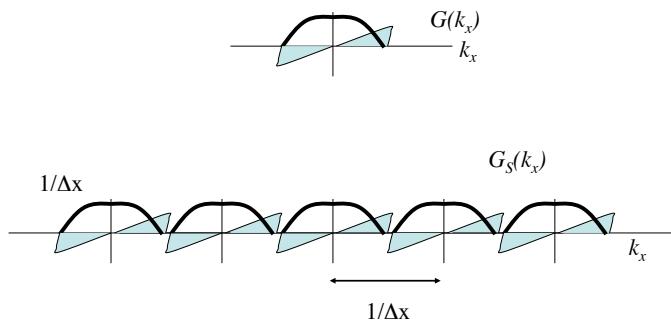
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## Fourier Transform of $g_s(x)$

$$\begin{aligned} F[g_s(x)] &= F\left[g(x) \frac{1}{\Delta x} \text{comb}\left(\frac{x}{\Delta x}\right)\right] \\ &= G(k_x) * F\left[\frac{1}{\Delta x} \text{comb}\left(\frac{x}{\Delta x}\right)\right] \\ &= G(k_x) * \frac{1}{\Delta x} \sum_{n=-\infty}^{\infty} \delta\left(k_x - \frac{n}{\Delta x}\right) \\ &= \frac{1}{\Delta x} \sum_{n=-\infty}^{\infty} G(k_x) * \delta\left(k_x - \frac{n}{\Delta x}\right) \\ &= \frac{1}{\Delta x} \sum_{n=-\infty}^{\infty} G\left(k_x - \frac{n}{\Delta x}\right) \end{aligned}$$

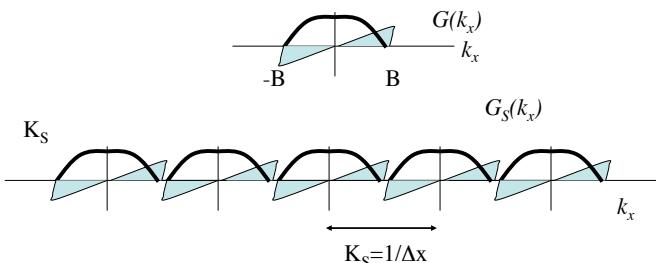
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## Fourier Transform of $g_s(x)$



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## Nyquist Condition



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## Example

Assume that the highest spatial frequency in an object is  $B = 2 \text{ cm}^{-1}$ .

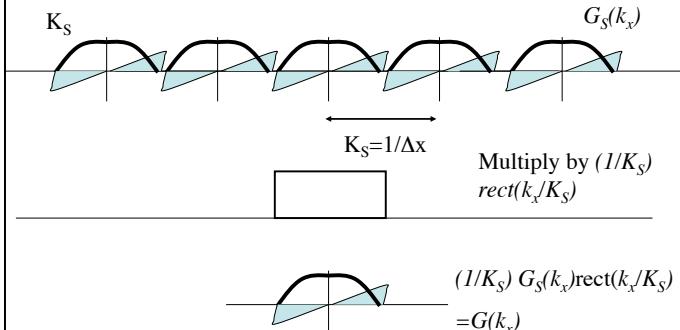
Thus, smallest spatial period is  $0.5 \text{ cm}$ .

Nyquist theorem says we need to sample with  $\Delta x < 1/2B = 0.25 \text{ cm}$

This corresponds to 2 samples per spatial period.

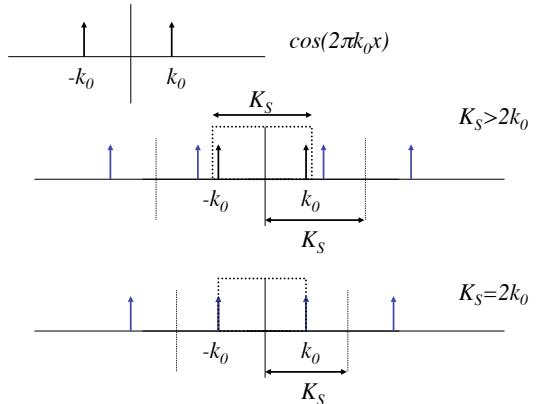
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## Reconstruction from Samples



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## Example Cosine Reconstruction



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## Reconstruction from Samples

If the Nyquist condition is met, then

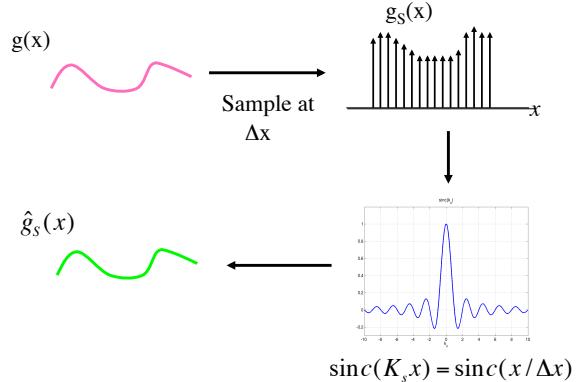
$$\hat{G}_s(k_x) = \frac{1}{K_s} G_s(k_x) \text{rect}(k_x/K_s) = G(k_x)$$

And the signal can be reconstructed by convolving the sample with a sinc function

$$\begin{aligned}\hat{g}_s(x) &= g_s(x) * \text{sinc}(K_s x) \\ &= \left( \sum_{n=-\infty}^{\infty} g(n\Delta X) \delta(x - n\Delta X) \right) * \text{sinc}(K_s x) \\ &= \sum_{n=-\infty}^{\infty} g(n\Delta X) \text{sinc}(K_s(x - n\Delta X))\end{aligned}$$

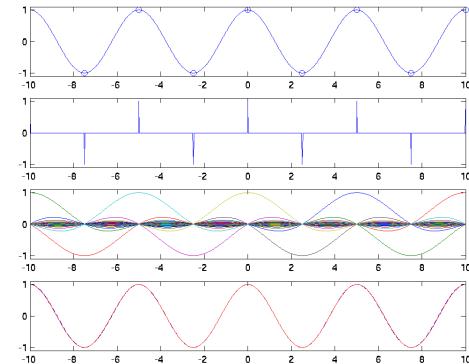
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## Reconstruction from Samples



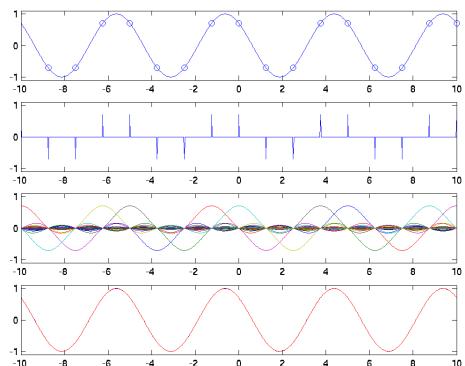
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## Cosine Example with $K_s=2k_0$



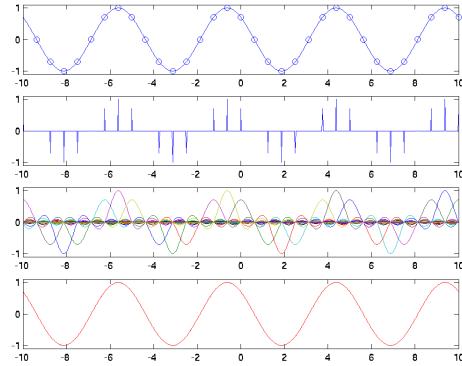
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### Example with $K_s=4k_0$



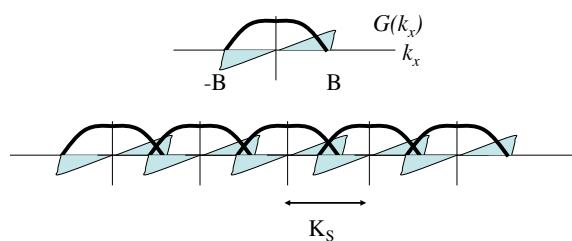
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### Example with $K_s=8k_0$



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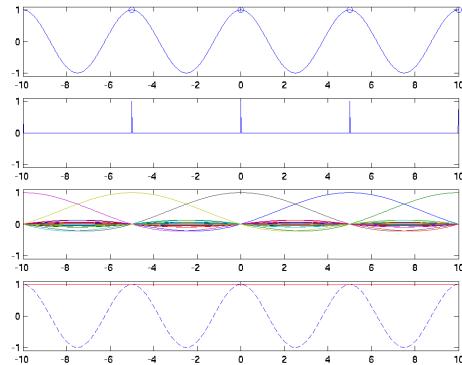
### Aliasing



Aliasing occurs when the Nyquist condition is not satisfied.  
This occurs for  $K_s \leq 2B$

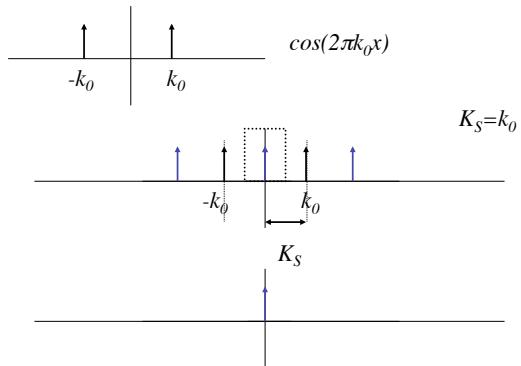
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### Aliasing Example



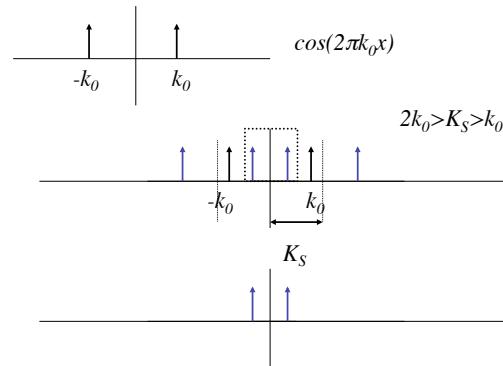
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## Aliasing Example



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## Aliasing Example



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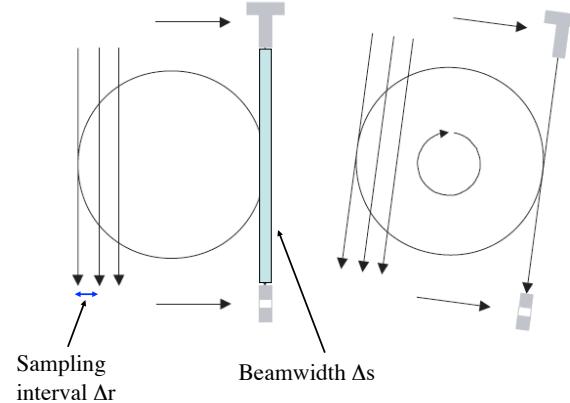
## Example

- Consider the function  $g(x) = \cos^2(2\pi k_0 x)$ . Sketch this function. You sample this signal in the spatial domain with a sampling rate  $K_s = 1/\Delta x$  (e.g. samples spaced at intervals of  $\Delta x$ ). What is the minimum sampling rate that you can use without aliasing? Give an intuitive explanation for your answer.

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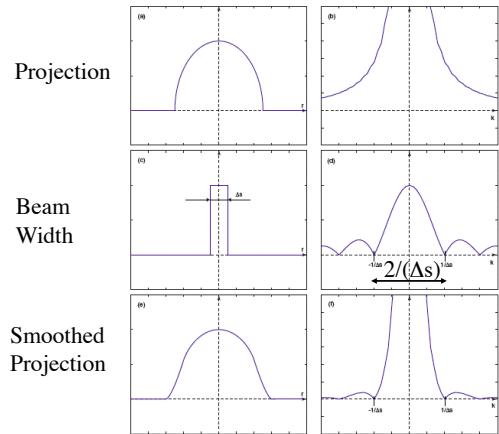
## Detector Sampling Requirements



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## Smoothing of Projection



## Smoothing of Projection

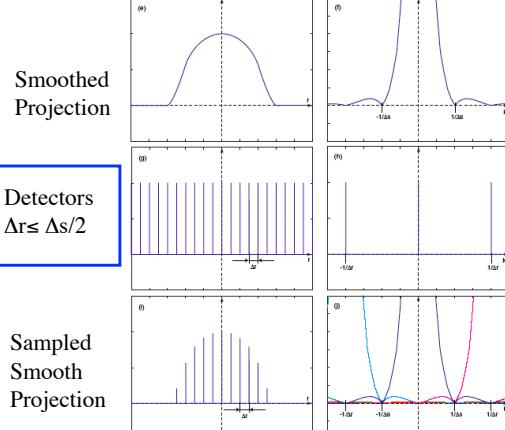
$$g_s(l, \theta) = \text{rect}(l/\Delta s) * g(l, \theta)$$

$$G_s(k_x, \theta) = \Delta s \sin c(k_x \Delta s) G(k_x, \theta)$$

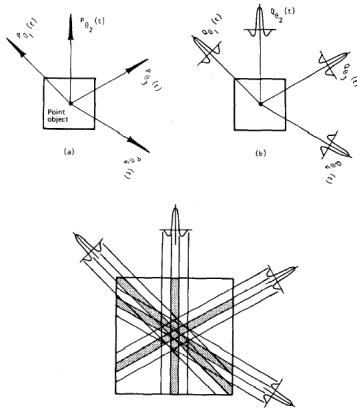
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## Sampling Requirements



## View Aliasing



## View Sampling Requirements

View Sampling -- how many views?

Basic idea is that to make the maximum angular sampling the same as the projection sampling.

$$\frac{\pi FOV}{N_{views}} = \Delta r$$

$$N_{views,360} = \frac{\pi FOV}{\Delta r} = \pi N_{proj} \text{ (for 360 degrees)}$$

$$N_{views,180} = \frac{\pi N_{proj}}{2} \text{ (for 180 degrees)}$$

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## Example

beamwidth  $\Delta s = 1 \text{ mm}$

Field of View (FOV) = 50 cm

$\Delta r = \Delta s / 2 = 0.5 \text{ mm}$

$500 \text{ mm} / 0.5 \text{ mm} = N = 1000 \text{ detector samples}$

$\pi * N = 3146 \text{ views per } 360 \text{ degrees}$

$\approx 1500 \text{ views per } 180 \text{ degrees}$

CT "Rule of Thumb"

$N_{view} = N_{detectors} = N_{pixels}$

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