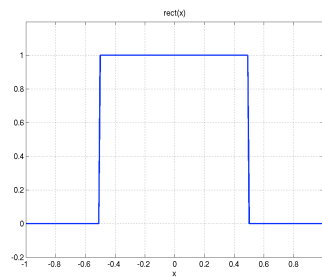


Bioengineering 280A Principles of Biomedical Imaging

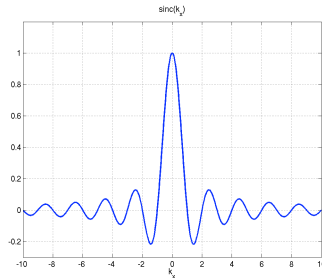
Fall Quarter 2005
Linear Systems Lecture 3

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Fourier Sampling

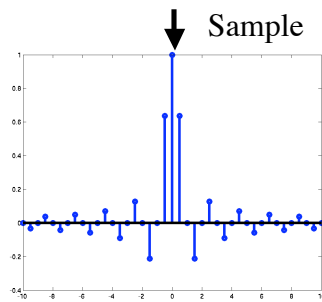


→
F



Instead of sampling the
signal, we sample its Fourier
Transform

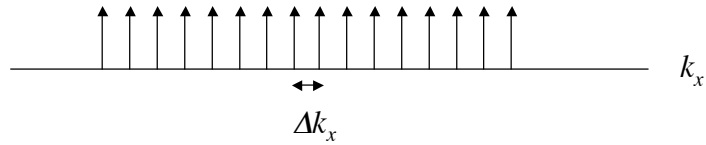
←
???
F⁻¹



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Fourier Sampling

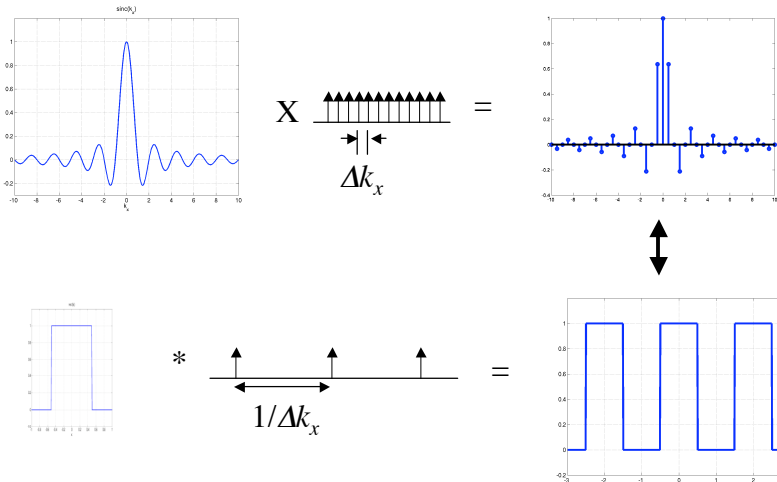
$$(1/\Delta k_x) \text{comb}(k_x/\Delta k_x)$$



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

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Fourier Sampling -- Inverse Transform



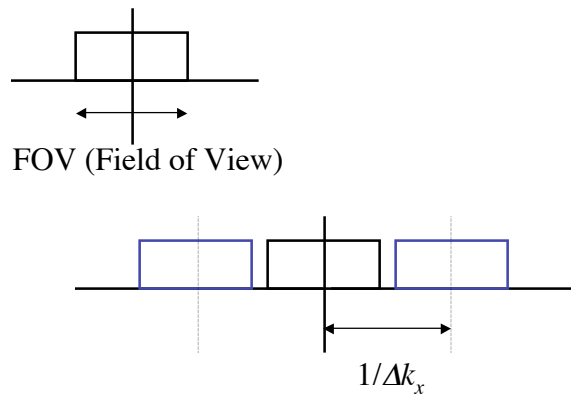
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Fourier Sampling -- Inverse Transform

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

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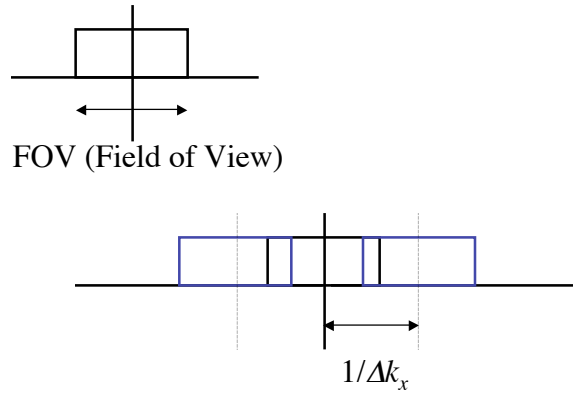
Nyquist Condition



To avoid overlap, $1/\Delta k_x > \text{FOV}$, or equivalently, $\Delta k_x < 1/\text{FOV}$

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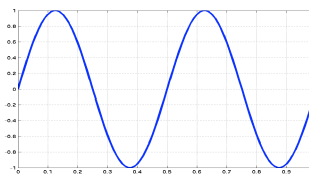
Aliasing



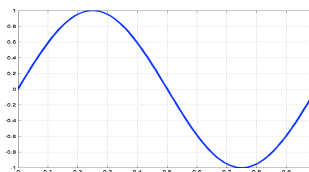
Aliasing occurs when $1/\Delta k_x < \text{FOV}$

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Intuitive view of Aliasing



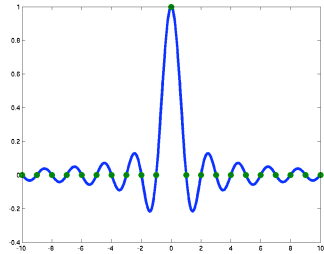
$$k_x = 2/\text{FOV}$$



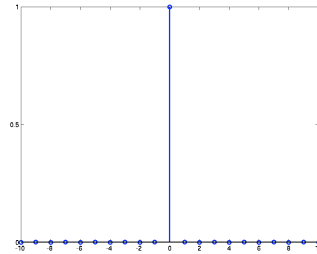
$$k_x = 1/\text{FOV}$$

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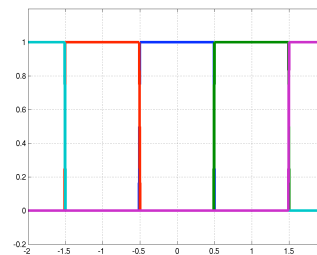
Aliasing Example



$$\Delta k_x = 1$$



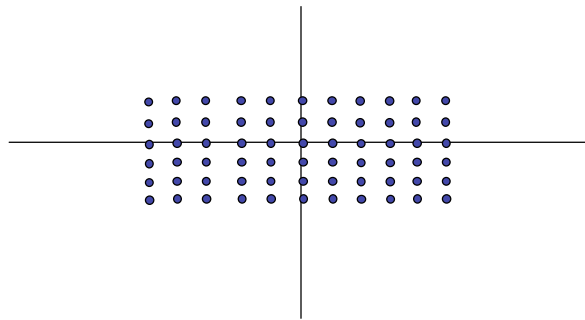
$$1/\Delta k_x = 1$$



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2D Comb Function

$$\begin{aligned} \text{comb}(x, y) &= \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} \delta(x - m, y - n) \\ &= \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} \delta(x - m) \delta(y - n) \\ &= \text{comb}(x) \text{comb}(y) \end{aligned}$$

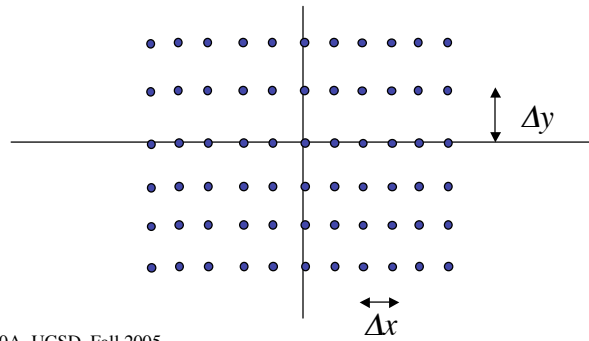


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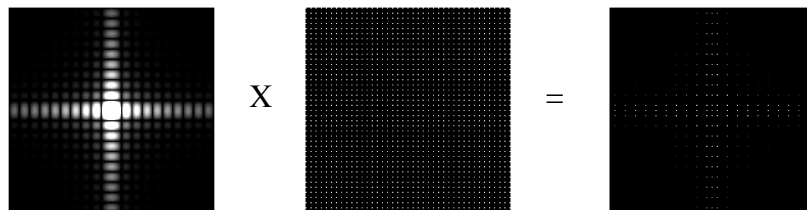
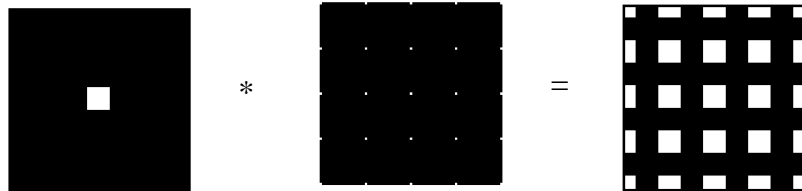
Scaled 2D Comb Function

$$\text{comb}(x/\Delta x, y/\Delta y) = \text{comb}(x/\Delta x)\text{comb}(y/\Delta y)$$

$$= \Delta x \Delta y \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} \delta(x - m\Delta x)\delta(y - n\Delta y)$$



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2D k-space sampling

$$\begin{aligned}
 G_S(k_x, k_y) &= G(k_x, k_y) \frac{1}{\Delta k_x \Delta k_y} \text{comb}\left(\frac{k_x}{\Delta k_x}, \frac{k_y}{\Delta k_y}\right) \\
 &= G(k_x, k_y) \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} \delta(k_x - m\Delta k_x, k_y - n\Delta k_y) \\
 &= \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} G(m\Delta k_x, n\Delta k_y) \delta(k_x - m\Delta k_x, k_y - n\Delta k_y)
 \end{aligned}$$

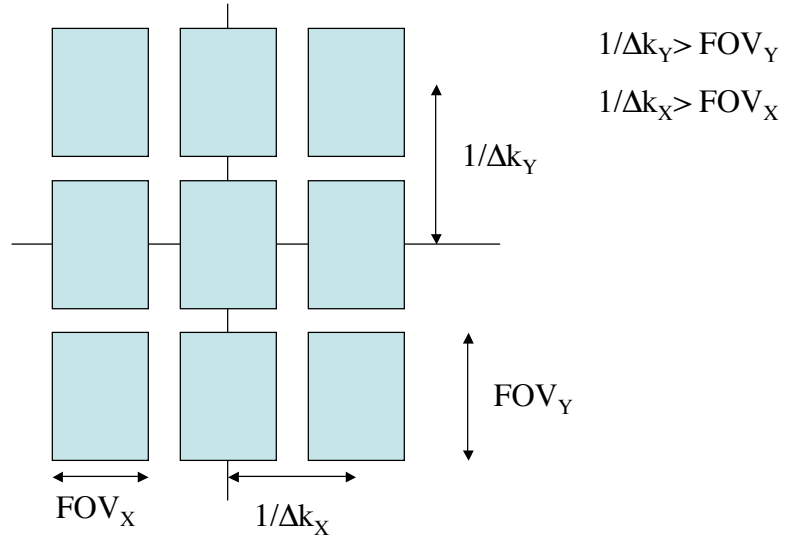
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2D k-space sampling

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

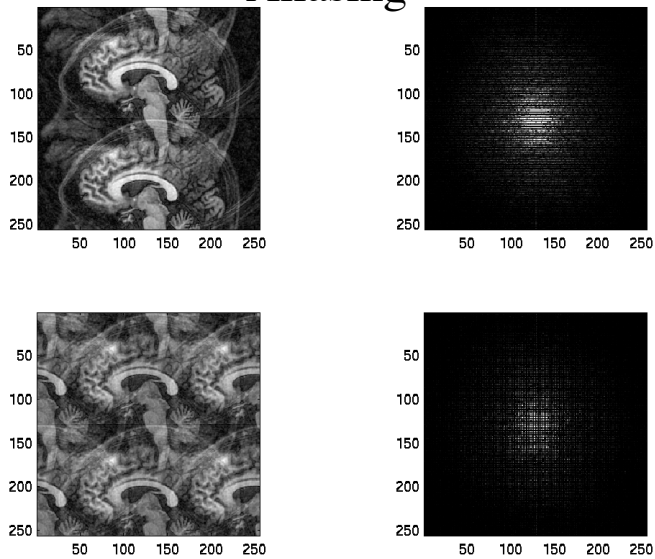
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Nyquist Conditions



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Aliasing



T1

Windowing

Windowing the data in Fourier space

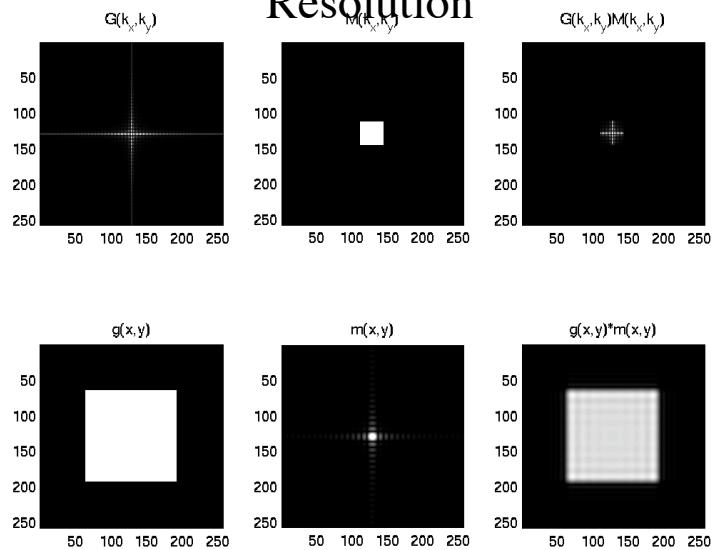
$$G_w(k_x, k_y) = G(k_x, k_y)W(k_x, k_y)$$

Results in convolution of the object with the inverse transform of the window

$$g_w(x, y) = g(x, y) * w(x, y)$$

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Resolution



1

Windowing Example

$$W(k_x, k_y) = \text{rect}\left(\frac{k_x}{W_{k_x}}\right) \text{rect}\left(\frac{k_y}{W_{k_y}}\right)$$

$$\begin{aligned} w(x, y) &= F^{-1} \left[\text{rect}\left(\frac{k_x}{W_{k_x}}\right) \text{rect}\left(\frac{k_y}{W_{k_y}}\right) \right] \\ &= W_{k_x} W_{k_y} \text{sinc}(W_{k_x} x) \text{sinc}(W_{k_y} y) \end{aligned}$$

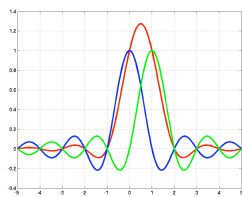
$$g_W(x, y) = g(x, y) ** W_{k_x} W_{k_y} \text{sinc}(W_{k_x} x) \text{sinc}(W_{k_y} y)$$

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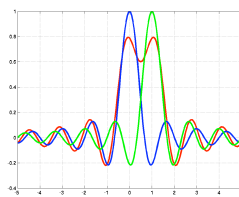
Windowing Example

$$g(x, y) = [\delta(x) + \delta(x-1)]\delta(y)$$

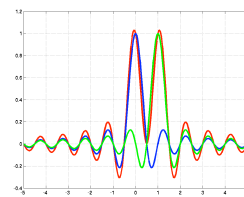
$$\begin{aligned} g_W(x, y) &= [\delta(x) + \delta(x-1)]\delta(y) ** W_{k_x} W_{k_y} \text{sinc}(W_{k_x} x) \text{sinc}(W_{k_y} y) \\ &= W_{k_x} W_{k_y} \left([\delta(x) + \delta(x-1)] * \text{sinc}(W_{k_x} x) \right) \text{sinc}(W_{k_y} y) \\ &= W_{k_x} W_{k_y} \left(\text{sinc}(W_{k_x} x) + \text{sinc}(W_{k_x} (x-1)) \right) \text{sinc}(W_{k_y} y) \end{aligned}$$



$W_{k_x} = 1$



$W_{k_x} = 1.5$



$W_{k_x} = 2$

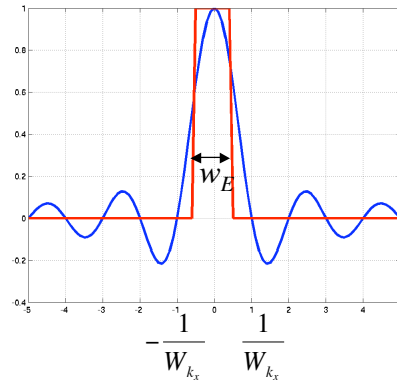
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Effective Width

$$w_E = \frac{1}{w(0)} \int_{-\infty}^{\infty} w(x) dx$$

Example

$$\begin{aligned} w_E &= \frac{1}{1} \int_{-\infty}^{\infty} \text{sinc}(W_{k_x} x) dx \\ &= F[\text{sinc}(W_{k_x} x)] \Big|_{k_x=0} \\ &= \frac{1}{W_{k_x}} \text{rect}\left(\frac{k_x}{W_{k_x}}\right) \Big|_{k_x=0} \\ &= \frac{1}{W_{k_x}} \end{aligned}$$

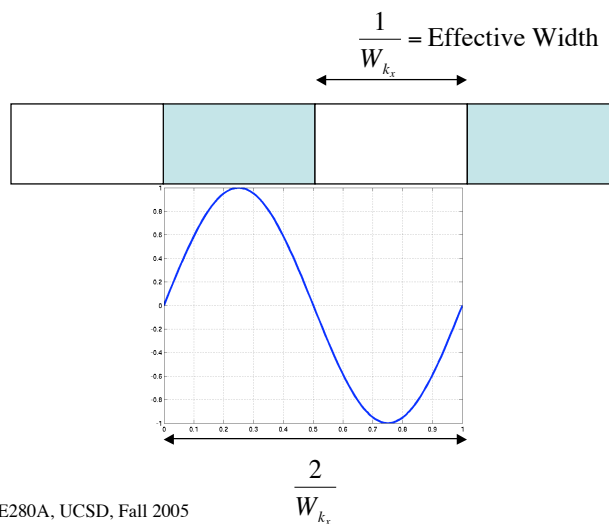


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Resolution and spatial frequency

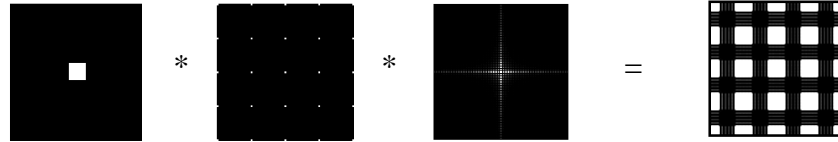
With a window of width W_{k_x} the highest spatial frequency is $W_{k_x}/2$.

This corresponds to a spatial period of $2/W_{k_x}$.



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Sampling and Windowing



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Sampling and Windowing

Sampling and windowing the data in Fourier space

$$G_{SW}(k_x, k_y) = G(k_x, k_y) \frac{1}{\Delta k_x \Delta k_y} \text{comb}\left(\frac{k_x}{\Delta k_x}, \frac{k_y}{\Delta k_y}\right) \text{rect}\left(\frac{k_x}{W_{k_x}}, \frac{k_y}{W_{k_y}}\right)$$

Results in replication and convolution in object space.

$$g_{SW}(x, y) = W_{k_x} W_{k_y} g(x, y) ** \text{comb}(\Delta k_x x, \Delta k_y y) ** \text{sinc}(W_{k_x} x) \text{sinc}(W_{k_y} y)$$

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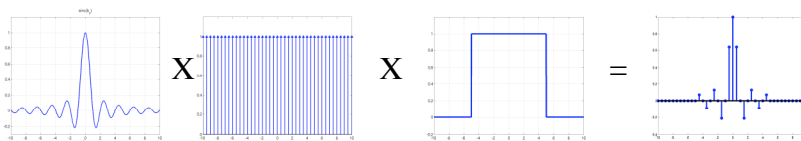
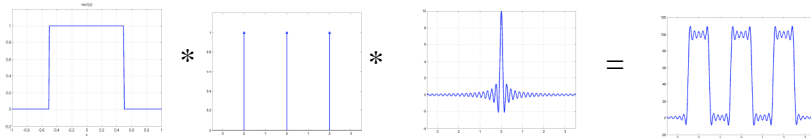
Discrete Fourier Transform

Idea: If we sample and window in the Fourier domain, we obtain a finite number of discrete Fourier samples. When we reconstruct the object, we should have the same number of pixels in our object.

Also, the windowing process, has band-limited the sampled Fourier transform, so this allows us to sample the replicated object at discrete points.

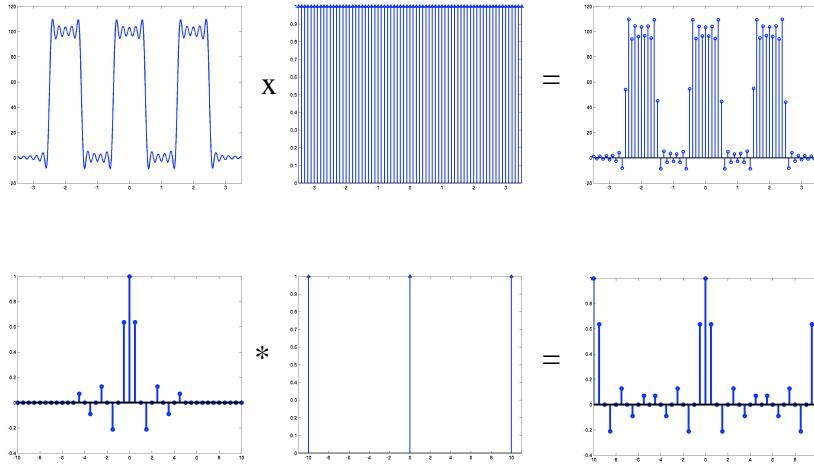
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1D Sampling and Windowing



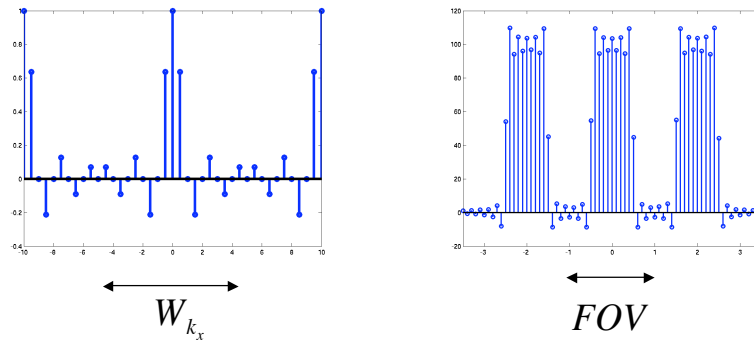
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Discrete Fourier Transform



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Discrete Fourier Transform



$$N_x = \frac{W_{k_x}}{\Delta k_x}$$

$$N_x = \frac{FOV_X}{1/W_{k_x}} = \frac{W_{k_x}}{\Delta k_x}$$

Note that $\frac{FOV_X}{N_x} = \frac{1}{W_{k_x}} = \delta_x$, our measure for resolution.

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DFT

Sampling, windowing, and replication in Fourier space

$$G_{DFT}(k_x, k_y) = G(k_x, k_y) \frac{1}{\Delta k_x \Delta k_y} \text{comb}\left(\frac{k_x}{\Delta k_x}, \frac{k_y}{\Delta k_y}\right) \text{rect}\left(\frac{k_x}{W_{k_x}}, \frac{k_y}{W_{k_y}}\right) ** \text{comb}\left(\frac{k_x}{W_{k_x}}, \frac{k_y}{W_{k_y}}\right)$$

Replication, convolving, sampling in object space

$$g_{DFT}(x, y) = W_{k_x} W_{k_y} g(x, y) ** \text{comb}(\Delta k_x x, \Delta k_y y) ** \text{sinc}(W_{k_x} x) \text{sinc}(W_{k_y} y) \\ \times W_{k_x} W_{k_y} \text{comb}(W_{k_x} x, W_{k_y} y)$$

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DFT

$$\begin{aligned} F[g_D(x)] &= \int_0^{FOV} g_D(x) e^{-j2\pi n \Delta k_x x} dx \\ &= \int_0^{FOV} \sum_{n=-\infty}^{\infty} g_D(n/W_x) \delta(x - n/W_x) e^{-j2\pi n \Delta k_x x} dx \\ &= \sum_{n=0}^{N-1} \int_{-\infty}^{\infty} g_D(n/W_x) \delta(x - n/W_x) e^{-j2\pi n \Delta k_x x} dx \\ &= \sum_{n=0}^{N-1} g_D(n/W_x) e^{-j2\pi n n \Delta k_x / W_x} \\ &= \sum_{n=0}^{N-1} g_D[n] e^{-j2\pi n n / N} \end{aligned}$$

This is what MATLAB computes when you use fft

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DFT Basis Functions

$$\text{DFT: } G[m] = \sum_{n=0}^{N-1} g[n] e^{-j2\pi mn/N}$$

Basis Functions are therefore :

$$b_m[n] = e^{j2\pi mn/N}$$

Are these orthonormal??

$$\text{Inverse DFT: } g[n] = \frac{1}{N} \sum_{m=0}^{N-1} G[m] e^{j2\pi mn/N}$$

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2D DFT

$$\text{DFT: } G[r,s] = \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} g[m,n] e^{-j2\pi(rm+sn)/N}$$

Basis Functions are therefore :

$$b_{r,s}[m,n] = e^{j2\pi(rm+sn)/N}$$

Are these orthonormal??

$$\text{Inverse DFT: } g[m,n] = \frac{1}{N^2} \sum_{r=0}^{N-1} \sum_{s=0}^{N-1} G[r,s] e^{j2\pi(rm+sn)/N}$$

In general, the number of points along each dimension need not be the same (e.g. $N_1 \neq N_2$). How does this change the expressions?

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