

Fourier Transform - Part II

- Discrete Fourier Transform - 1D
- Discrete Fourier Transform - 2D
- Fourier Properties
- Convolution Theorem
- FFT
- Examples

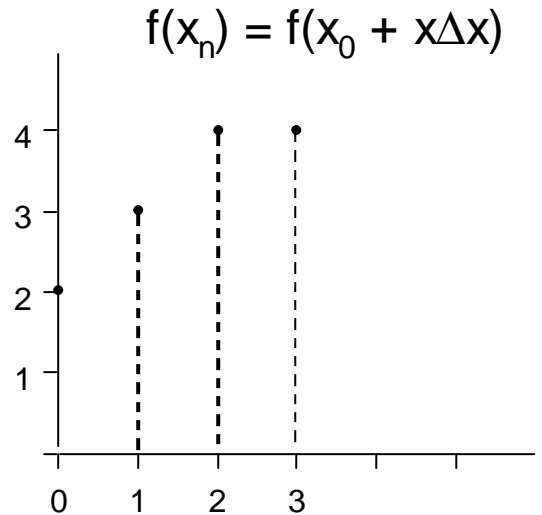
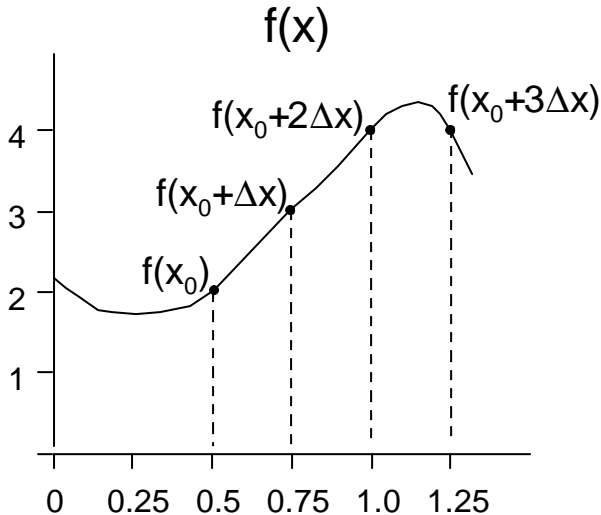
Discrete Fourier Transform

Move from $f(x)$ ($x \in \mathbb{R}$) to $f(x)$ ($x \in \mathbb{Z}$) by sampling at equal intervals.

$f(x_0), f(x_0+\Delta x), f(x_0+2\Delta x), \dots, f(x_0+[n-1]\Delta x),$

Given N samples at equal intervals, we redefine f as:

$$f(x) = f(x_0+x\Delta x) \quad x = 0, 1, 2, \dots, N-1$$



Discrete Fourier Transform

The **Discrete Fourier Transform** (DFT) is defined as:

$$F(u) = \frac{1}{N} \sum_{x=0}^{N-1} f(x) e^{-\frac{2\pi i u x}{N}} \quad u = 0, 1, 2, \dots, N-1$$

Matlab: `F=fft(f);`

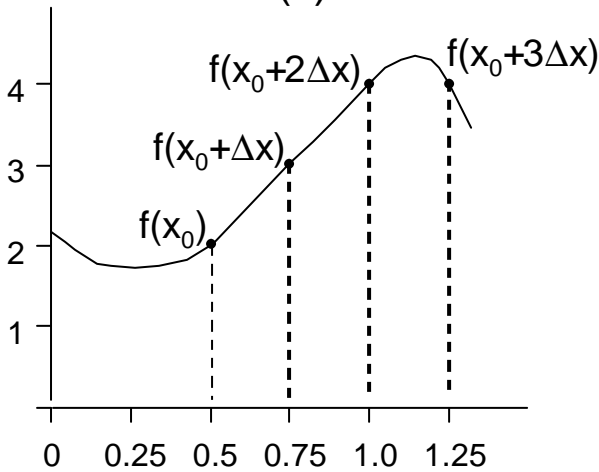
The **Inverse Discrete Fourier Transform** (IDFT) is defined as:

$$f(x) = \sum_{u=0}^{N-1} F(u) e^{\frac{2\pi i u x}{N}} \quad x = 0, 1, 2, \dots, N-1$$

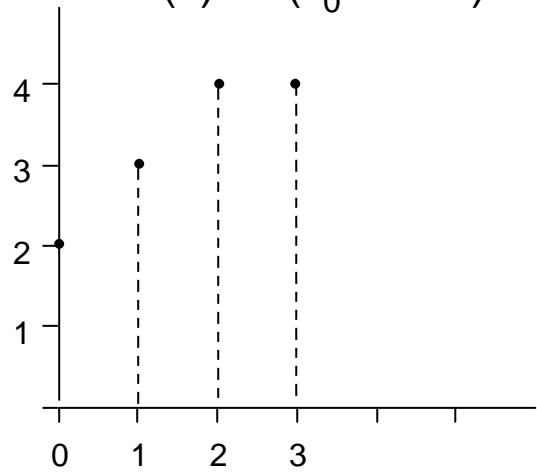
Matlab: `F=ifft(f);`

Discrete Fourier Transform - Example

$f(x)$



$f(x) = f(x_0 + x\Delta x)$



$$F(0) = 1/4 \sum_{x=0}^3 f(x) e^{\frac{-2\pi i 0 x}{4}} = 1/4 \sum_{x=0}^3 f(x) 1$$

$$= 1/4(f(0) + f(1) + f(2) + f(3)) = 1/4(2+3+4+4) = 3.25$$

$$F(1) = 1/4 \sum_{x=0}^3 f(x) e^{\frac{-2\pi i x}{4}} = 1/4 [2e^0 + 3e^{-i\pi/2} + 4e^{-\pi i} + 4e^{-i3\pi/2}] = \frac{1}{4} [-2+i]$$

$$F(2) = 1/4 \sum_{x=0}^3 f(x) e^{\frac{-4\pi i x}{4}} = 1/4 [2e^0 + 3e^{-i\pi} + 4e^{-2\pi i} + 4e^{-3\pi i}] = \frac{-1}{4} [-1-0i] = \frac{-1}{4}$$

$$F(3) = 1/4 \sum_{x=0}^3 f(x) e^{\frac{-6\pi i x}{4}} = 1/4 [2e^0 + 3e^{-i3\pi/2} + 4e^{-3\pi i} + 4e^{-i9\pi/2}] = \frac{1}{4} [-2-i]$$

Fourier Spectrum:

$$|F(0)| = 3.25$$

$$|F(1)| = [(-1/2)^2 + (1/4)^2]^{0.5}$$

$$|F(2)| = [(-1/4)^2 + (0)^2]^{0.5}$$

$$|F(3)| = [(-1/2)^2 + (-1/4)^2]^{0.5}$$

Discrete Fourier Transform - 2D

Image $f(x,y)$ $x = 0,1,\dots,N-1$ $y = 0,1,\dots,M-1$

The **Discrete Fourier Transform** (DFT) is defined as:

$$F(u,v) = \frac{1}{MN} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} f(x,y) e^{-2\pi i \left(\frac{ux}{N} + \frac{vy}{M} \right)} \quad \begin{array}{l} u = 0, 1, 2, \dots, N-1 \\ v = 0, 1, 2, \dots, M-1 \end{array}$$

Matlab: `F=fft2(f);`

The **Inverse Discrete Fourier Transform** (IDFT) is defined as:

$$f(x,y) = \sum_{u=0}^{N-1} \sum_{v=0}^{M-1} F(u,v) e^{2\pi i \left(\frac{ux}{N} + \frac{vy}{M} \right)} \quad \begin{array}{l} x = 0, 1, 2, \dots, N-1 \\ y = 0, 1, 2, \dots, M-1 \end{array}$$

Matlab: `F=ifft2(f);`



$u=-2, v=2$



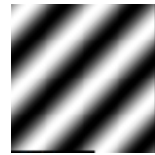
$u=-1, v=2$



$u=0, v=2$



$u=1, v=2$



$u=2, v=2$



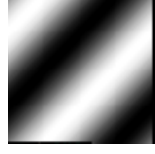
$u=-2, v=1$



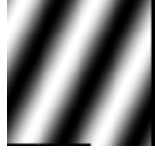
$u=-1, v=1$



$u=0, v=1$



$u=1, v=1$



$u=2, v=1$



$u=-2, v=0$



$u=-1, v=0$



$u=0, v=0$



$u=1, v=0$



$u=2, v=0$



$u=-2, v=-1$



$u=-1, v=-1$



$u=0, v=-1$



$u=1, v=-1$



$u=2, v=-1$



$u=-2, v=-2$



$u=-1, v=-2$



$u=0, v=-2$



$u=1, v=-2$



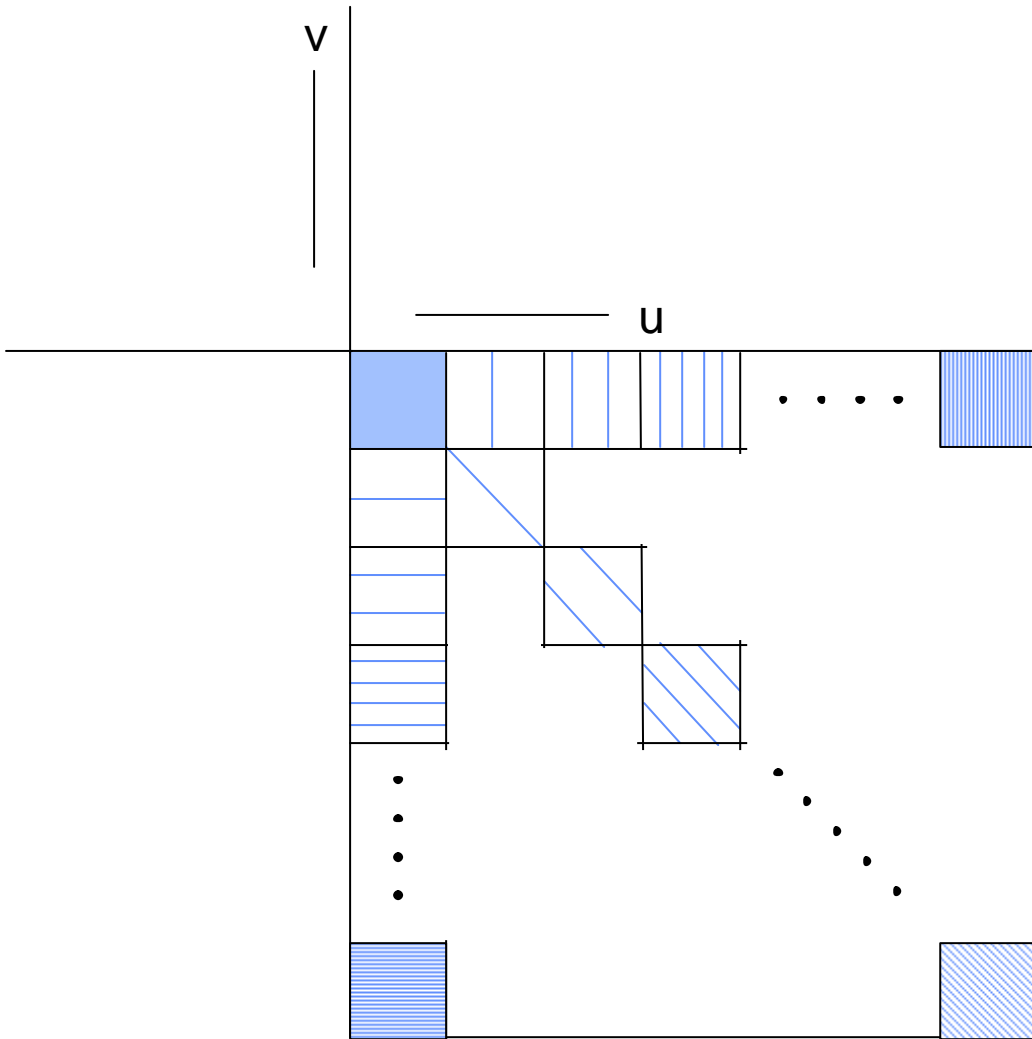
$u=2, v=-2$



U



Fourier Transform - Image



Visualizing the Fourier Transform Image using Matlab Routines

- $F(u,v)$ is a Fourier transform of $f(x,y)$ and it has complex entries.

$$F = \text{fft2}(f);$$

- In order to display the Fourier Spectrum $|F(u,v)|$
 - Cyclically rotate the image so that $F(0,0)$ is in the center:

$$F = \text{fftshift}(F);$$

- Reduce dynamic range of $|F(u,v)|$ by displaying the log:

$$D = \log(1+\text{abs}(F));$$

Example:

$$|F(u)| = 100 \quad 4 \quad 2 \quad 1 \quad 0 \quad 0 \quad 1 \quad 2 \quad 4$$

Cyclic $|F(u)| = 0 \quad 1 \quad 2 \quad 4 \quad 100 \quad 4 \quad 2 \quad 1 \quad 0$

Display in Range([0..10]):

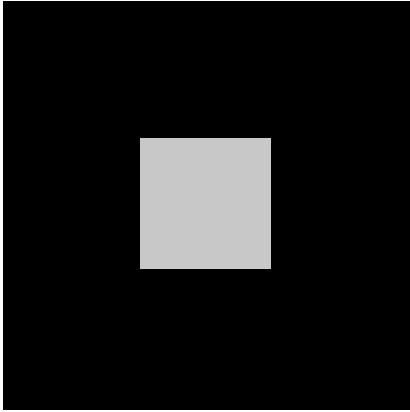
$$|F(u)|/10 = \boxed{0 \quad 0 \quad 0 \quad 0 \quad 10 \quad 0 \quad 0 \quad 0 \quad 0}$$

$$\log(1+|F(u)|) = 0 \quad 0.69 \quad 1.01 \quad 1.61 \quad 4.62 \quad 1.61 \quad 1.01 \quad 0.69 \quad 0$$

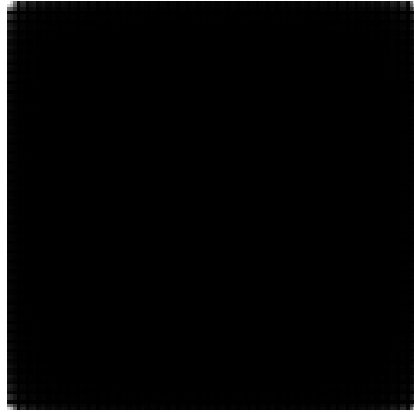
$$\log(1+|F(u)|)/0.462 = \boxed{0 \quad 1 \quad 2 \quad 4 \quad 10 \quad 4 \quad 2 \quad 1 \quad 0}$$

Visualizing the Fourier Image - Example

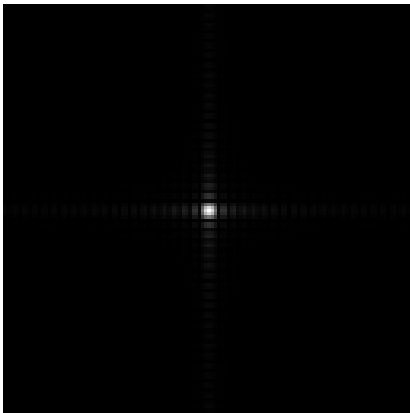
Original



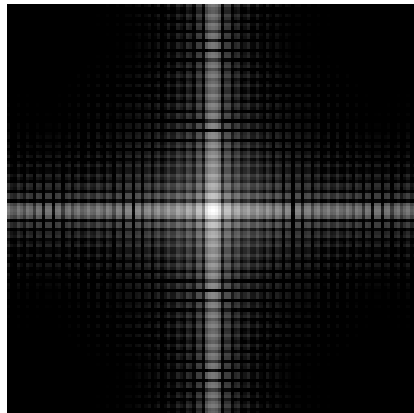
$|F(u,v)|$



$|F(0,0)|$ at center



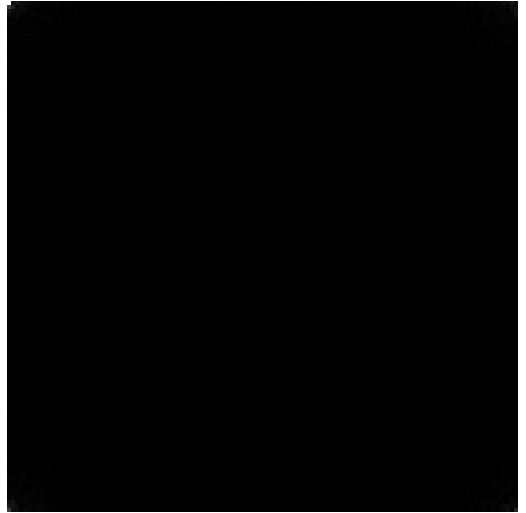
$\log(1 + |F(u,v)|)$



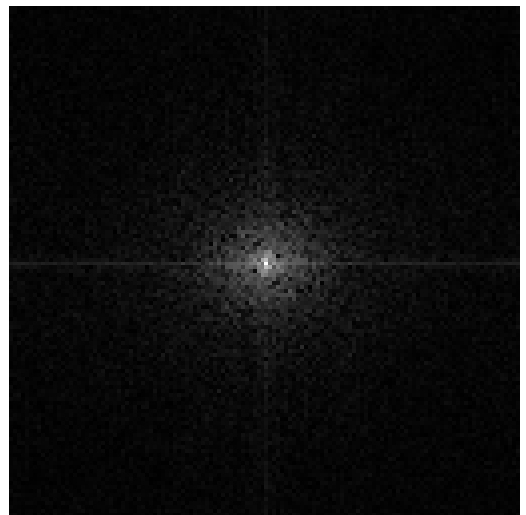
Original



Fourier Image = $|F(u,v)|$



Shifted Fourier Image



Shifted Log Fourier Image = $\log(1+ |F(u,v)|)$

Properties of The Fourier Transform

Distributive (addition)

$$\tilde{F} [f_1(x,y) + f_2(x,y)] = \tilde{F} [f_1(x,y)] + \tilde{F} [f_2(x,y)]$$

Linearity

$$\tilde{F} [a f(x,y)] = a \tilde{F} [f(x,y)]$$

$$a f(x,y) \text{ ————— } a F(u,v)$$

Cyclic

$$F(u,v) = F(u+N,v) = F(u,v+N) = F(u+N,v+N)$$

$$F(x,y) = F(x+N,y+N)$$

Symmetric if $f(x)$ is real:

$$F(u,v) = F^*(-u,-v)$$

thus:

$$|F(u,v)| = |F(-u,-v)|$$

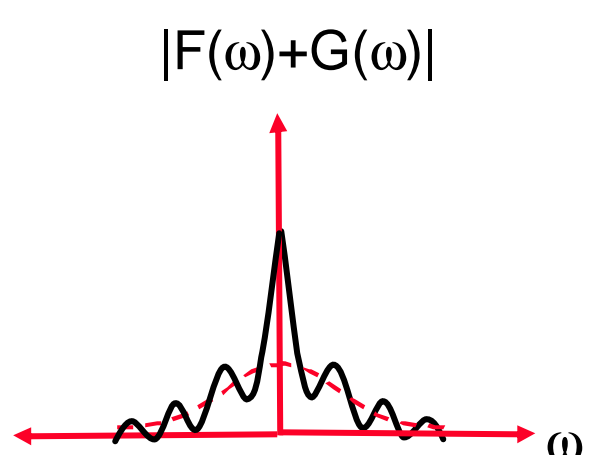
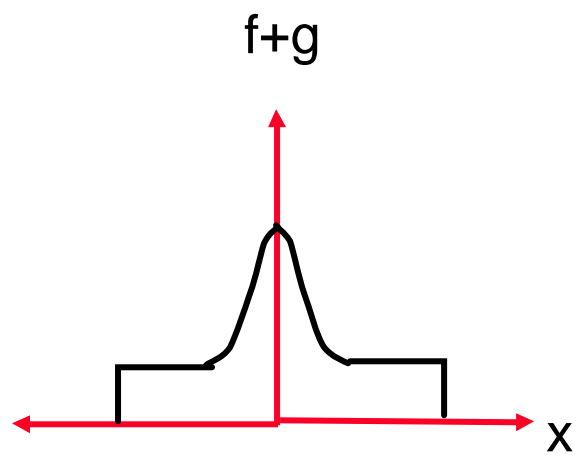
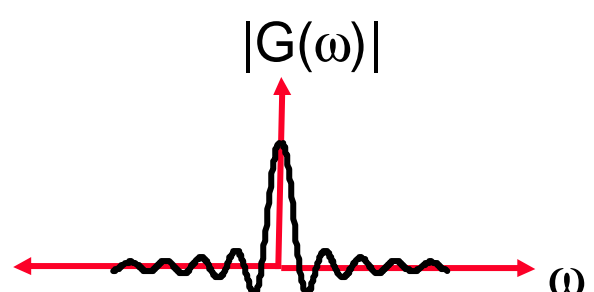
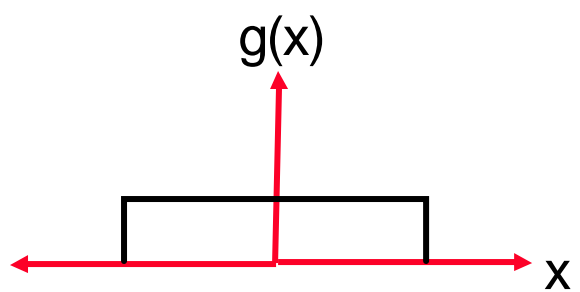
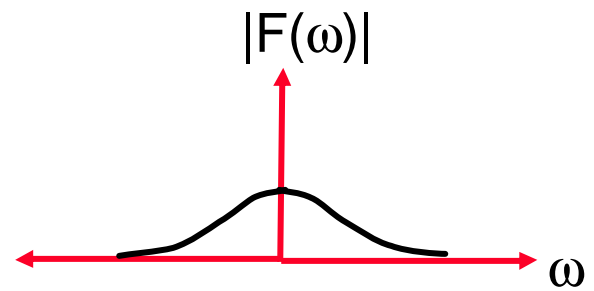
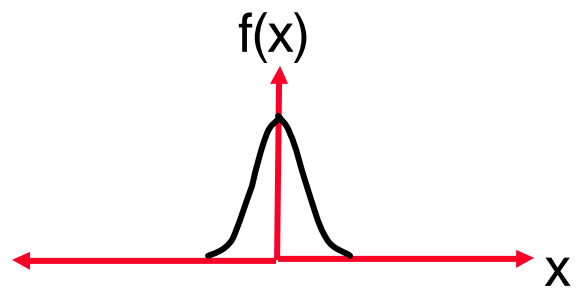
Fourier Spectrum
is symmetric

DC (Average)

$$F(0,0) = \frac{1}{N} \frac{1}{M} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} f(x) e^0$$

Distributive:

$$\tilde{F}\{f + g\} = \tilde{F}\{f\} + \tilde{F}\{g\}$$



Cyclic and Symmetry of the Fourier Transform - 1D Example

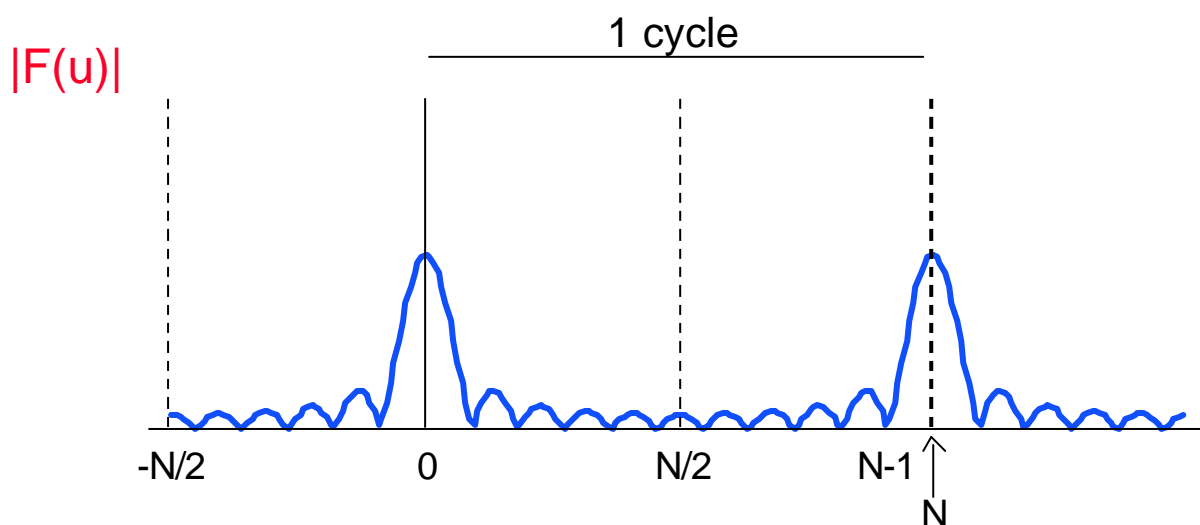


Image Transformations

Translation

$$f(x-x_0, y-y_0) \text{ ————— } F(u, v) e^{\frac{-2\pi i(u x_0 + v y_0)}{N}}$$

$$f(x, y) e^{\frac{2\pi i(u_0 x + v_0 y)}{N}} \text{ ————— } F(u-u_0, v-v_0)$$

The Fourier Spectrum remains unchanged under translation:

$$|F(u, v)| = |F(u, v) e^{\frac{-2\pi i(u x_0 + v y_0)}{N}}|$$

Rotation

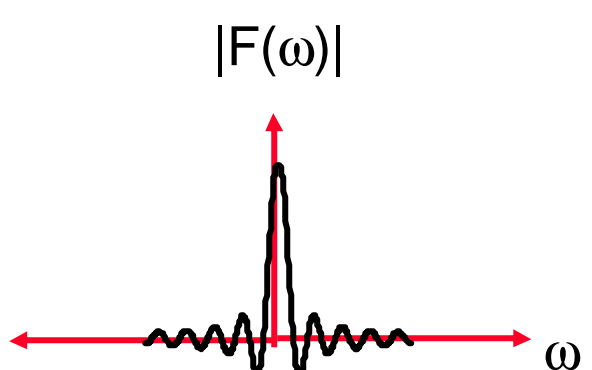
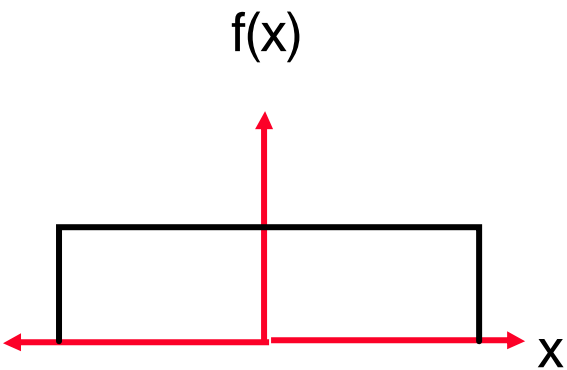
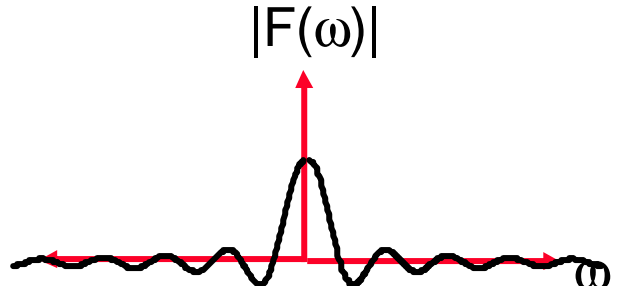
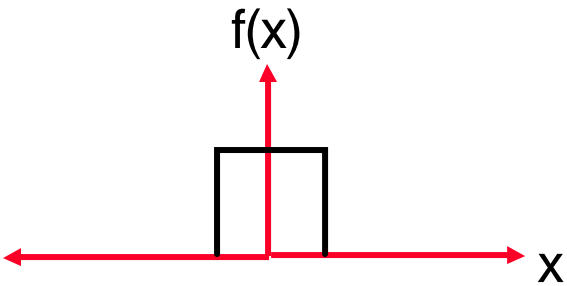
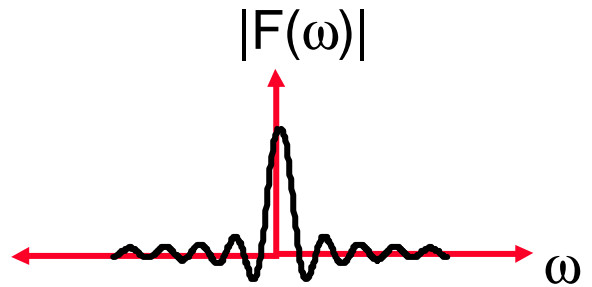
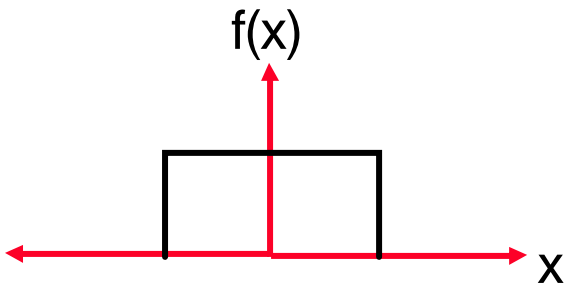
$$\begin{array}{ccc} \text{Rotation of } f(x, y) & \text{—————} & \text{Rotation of } F(u, v) \\ \text{by } \theta & & \text{by } \theta \end{array}$$

Scale

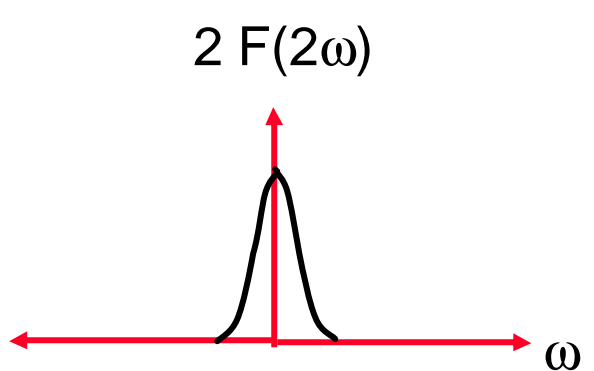
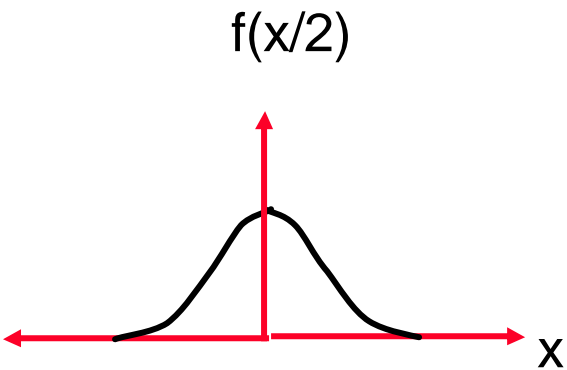
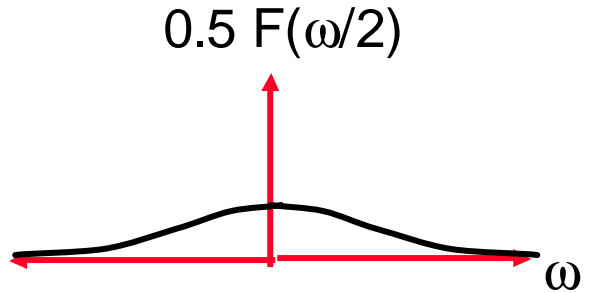
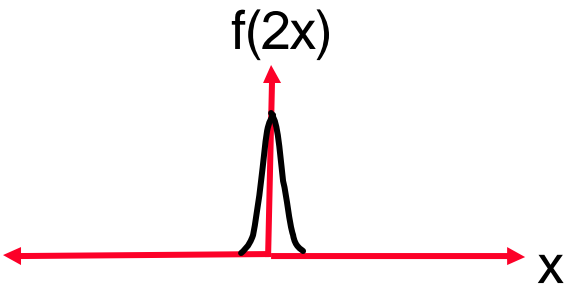
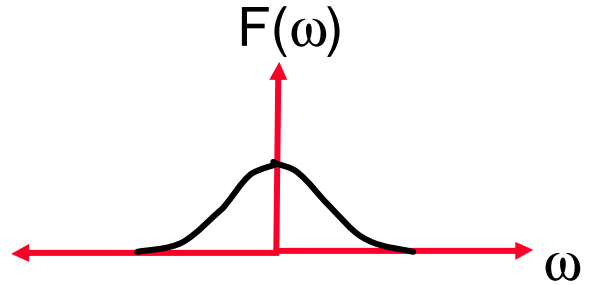
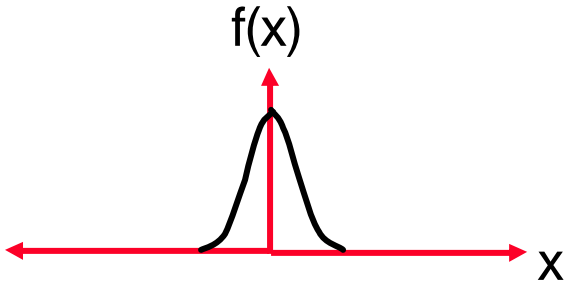
$$f(ax, by) \text{ ————— } \frac{1}{|ab|} F(u/a, v/b)$$

Change of Scale- 1D:

$$\text{if } \tilde{F}\{f(x)\} = F(\omega) \quad \text{then} \quad \tilde{F}\{f(ax)\} = \frac{1}{|a|} F\left(\frac{\omega}{a}\right)$$

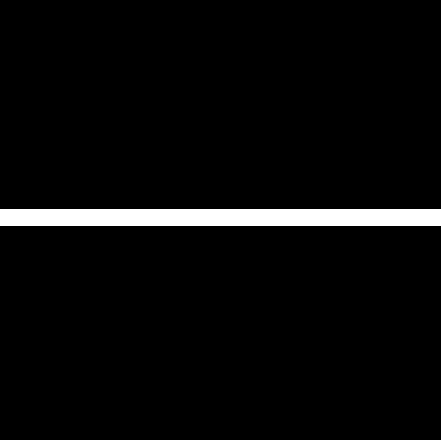


Change of Scale

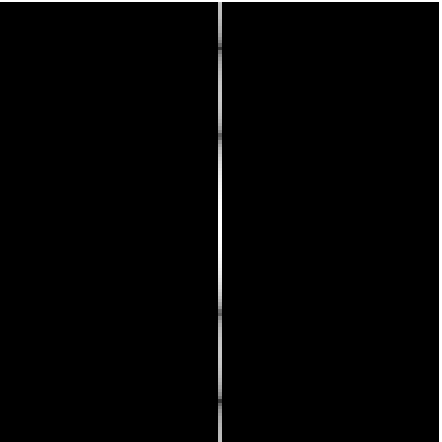
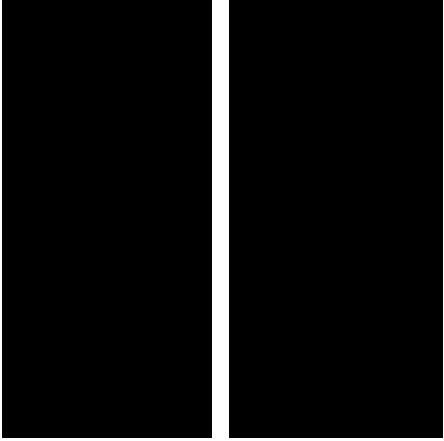


Example - Rotation

2D Image



2D Image - Rotated



Fourier Spectrum

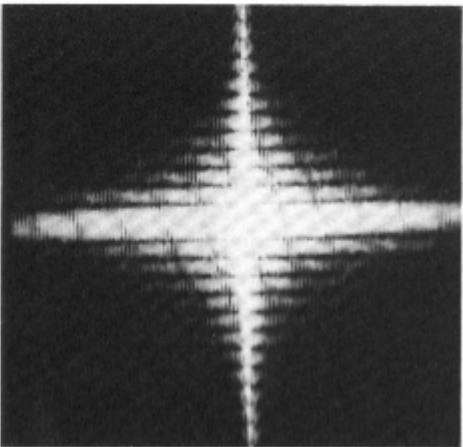
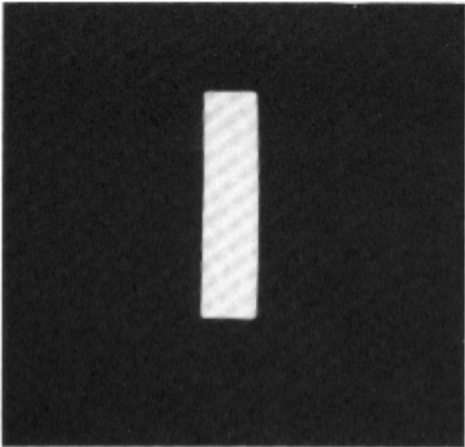
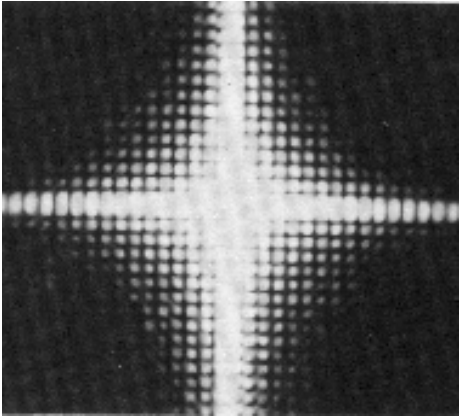
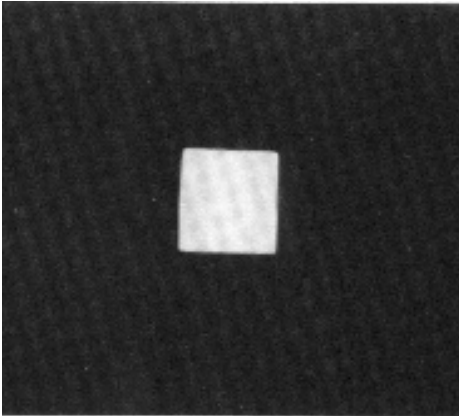


Fourier Spectrum

Fourier Transform Examples

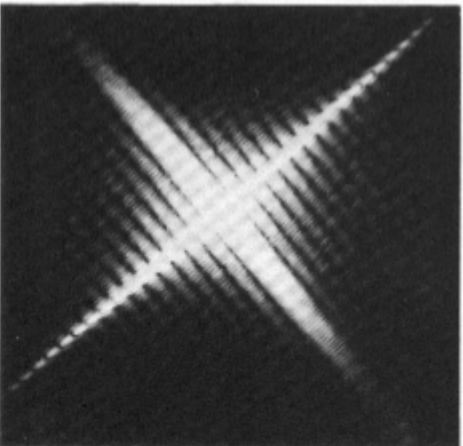
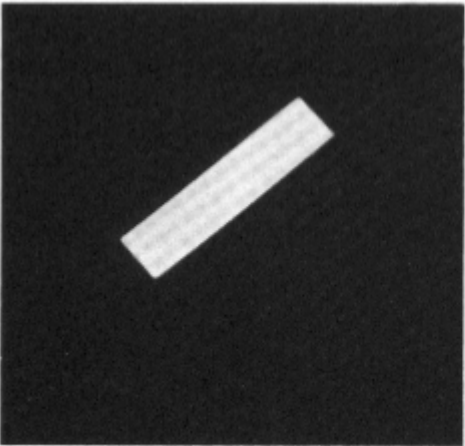
Image Domain

Frequency Domain



(a)

(b)



Separability

$$\begin{aligned} F(u,v) &= \frac{1}{N} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) e^{-2\pi i(ux+vy)/n} \\ &= \frac{1}{N} \sum_{x=0}^{N-1} \left(\sum_{y=0}^{N-1} f(x,y) e^{-2\pi i v y/n} \right) e^{-2\pi i u x/n} \\ &= \frac{1}{N} \sum_{x=0}^{N-1} F(x,v) e^{-2\pi i u x/n} \end{aligned}$$

Thus, to perform a **2D** Fourier Transform is equivalent to performing 2 **1D** transforms:

- 1) Perform 1D transform on EACH column of image $f(x,y)$. Obtain $F(x,v)$.
- 2) Perform 1D transform on EACH row of $F(x,v)$.

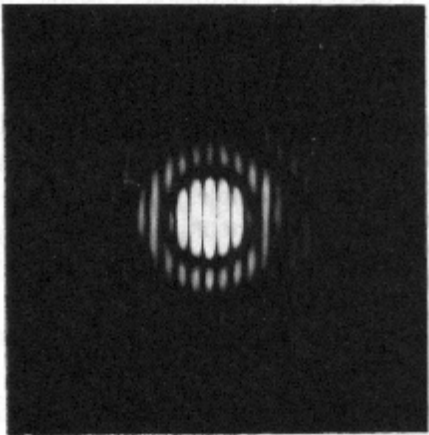
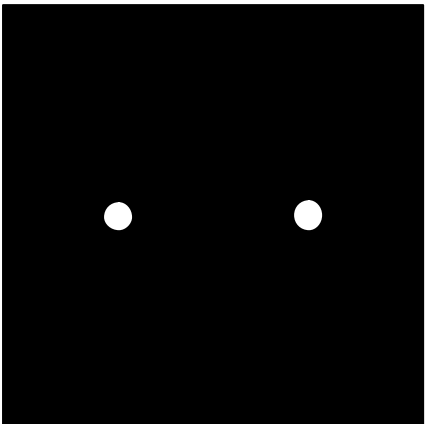
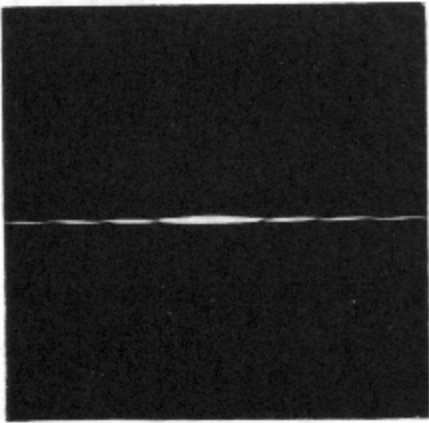
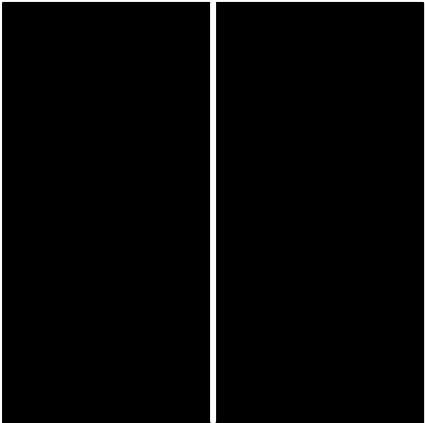
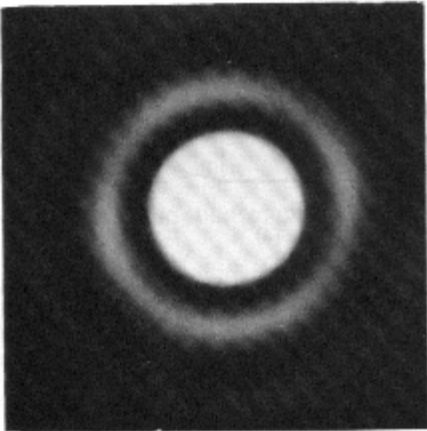
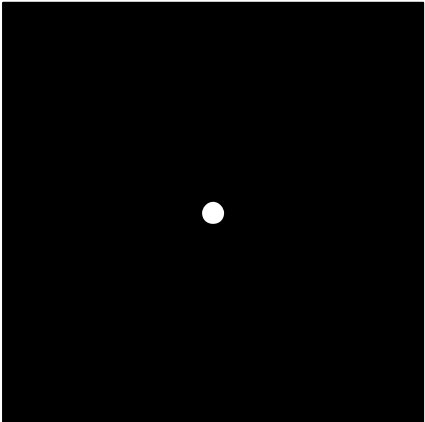
Higher Dimensions:

Fourier in any dimension can be performed by applying 1D transform on each dimension.

Fourier Transform Examples

Image Domain

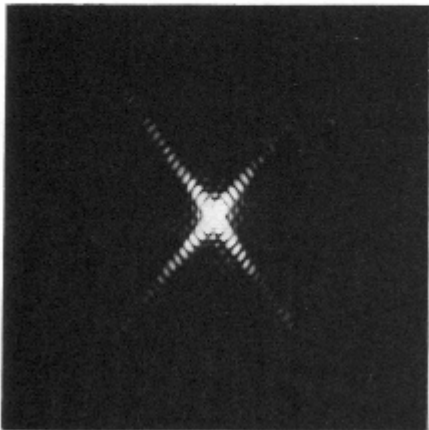
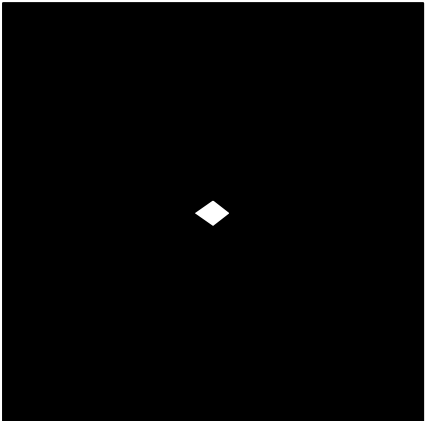
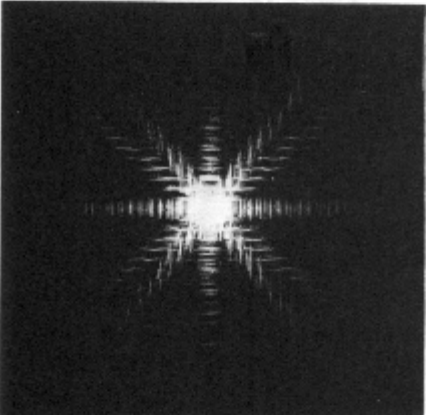
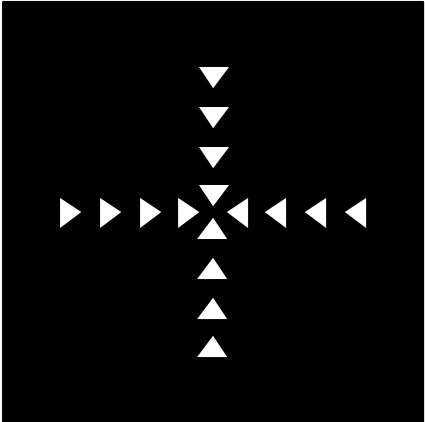
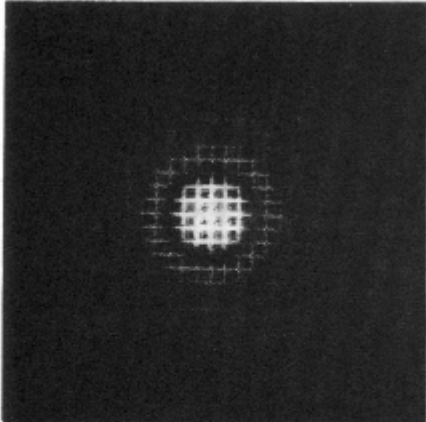
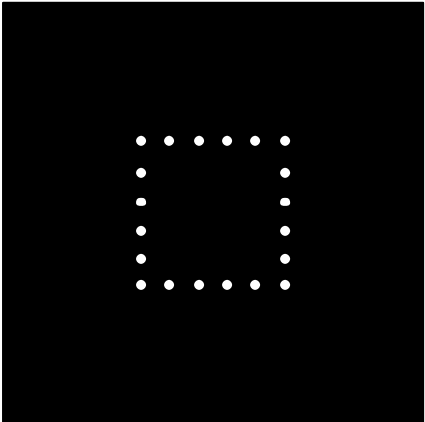
Frequency Domain



Fourier Transform Examples

Image Domain

Frequency Domain



Linear Systems and Responses

	Spatial Domain	Frequency Domain
Input	f	F
Output	g	G
Impulse Response	h	
Freq. Response		H
Relationship	$g=f*h$	$G=FH$

The Convolution Theorem

$$g = f * h$$

implies

$$G = F H$$

$$g = f h$$

implies

$$G = F * H$$

Convolution in one domain is
multiplication in the other and vice
versa

The Convolution Theorem

$$\tilde{F}\{f(\mathbf{x}) * g(\mathbf{x})\} = \tilde{F}\{f(\mathbf{x})\} \tilde{F}\{g(\mathbf{x})\}$$

and likewise

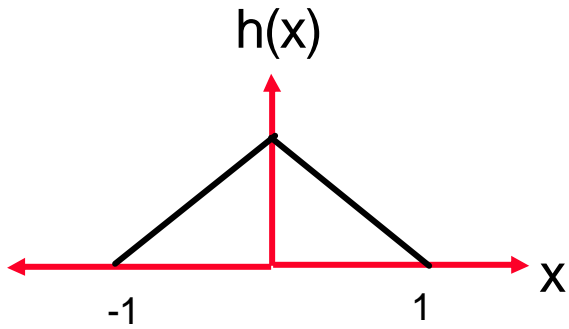
$$\tilde{F}\{f(\mathbf{x})g(\mathbf{x})\} = \tilde{F}\{f(\mathbf{x})\} * \tilde{F}\{g(\mathbf{x})\}$$

$$f(x,y) * g(x,y) \quad \text{————} \quad F(u,v) G(u,v)$$

$$f(x,y) g(x,y) \quad \text{————} \quad F(u,v) * G(u,v)$$

Convolution in one domain is
multiplication in the other and vice
versa

Example:



$$h(x) = \text{rect}(x) * \text{rect}(x)$$

The diagram illustrates the convolution of two rectangular functions $f(x)$. Each $f(x)$ is a rectangle centered at $x=0$ with a width of 1, extending from $x=-0.5$ to $x=0.5$. The convolution operation is represented by an asterisk $*$. The resulting function $h(x)$ is the triangular function shown in the first figure.

$$H(\omega) = F(\omega) \cdot F(\omega)$$

The diagram illustrates the multiplication of two sinc-like functions $F(\omega)$ in the frequency domain. Each $F(\omega)$ has a central peak at $\omega=0$ and decaying oscillations on either side. The multiplication operation is represented by a dot \cdot . The resulting function $H(\omega)$ is a narrower, taller sinc-like function centered at $\omega=0$.

$$=$$

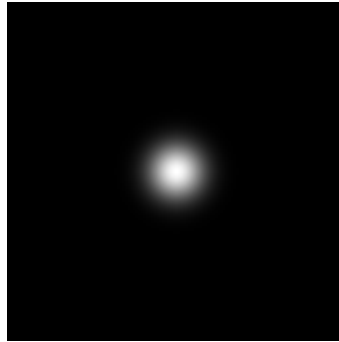
The final result is a single, narrower, taller sinc-like function centered at $\omega=0$, representing $H(\omega)$.

Convolution Theorem - 2D Example

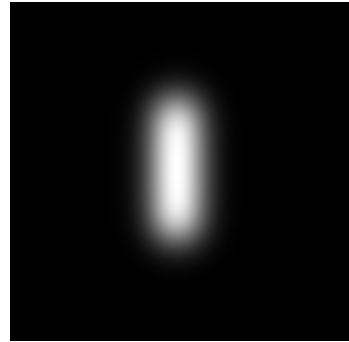
$f(x,y)$



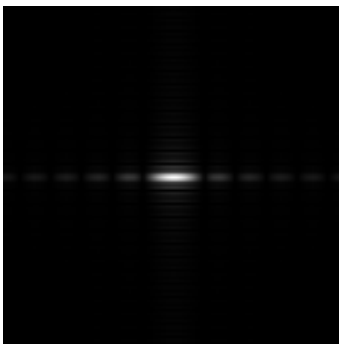
$g(x,y)$



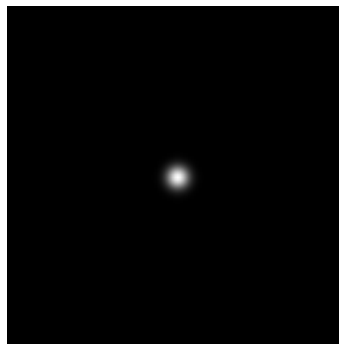
$f * g(x,y)$



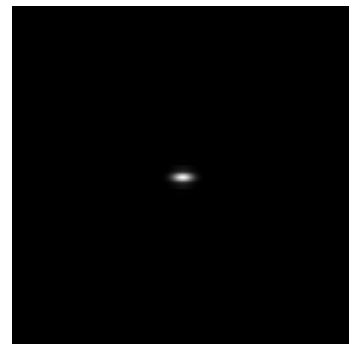
$F(u,v)$



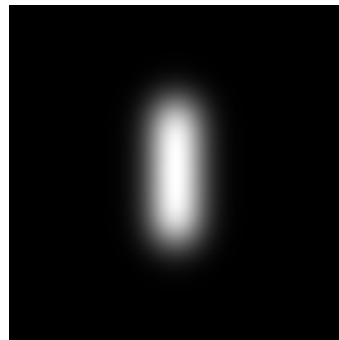
$G(u,v)$



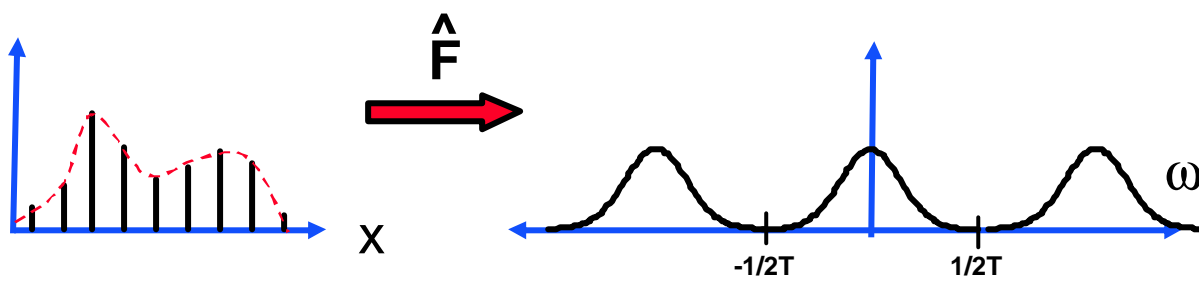
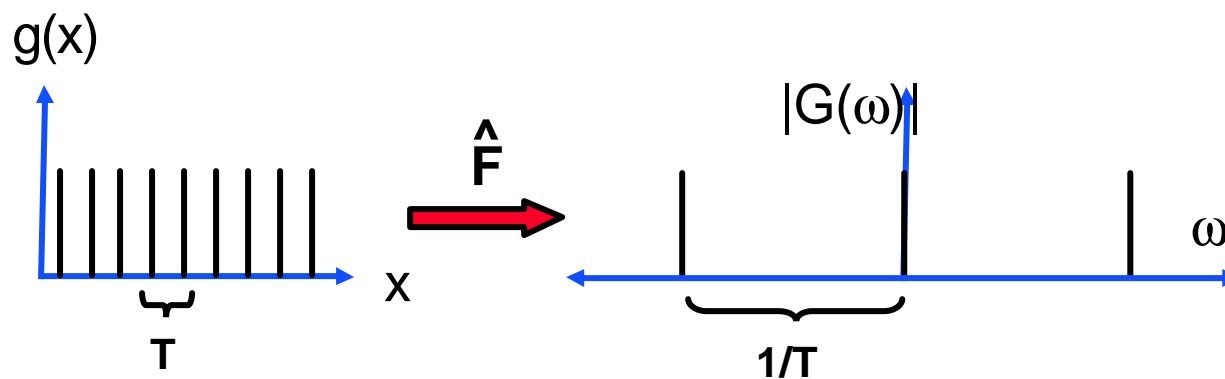
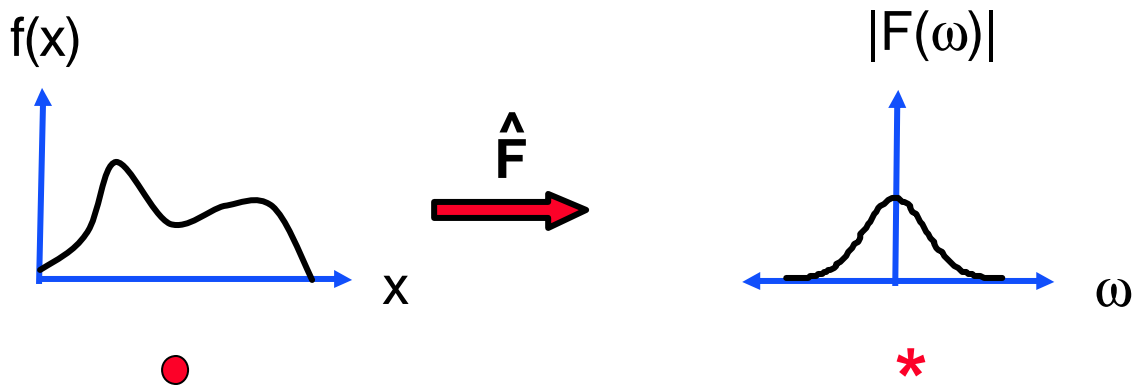
$F(u,v) G(u,v)$



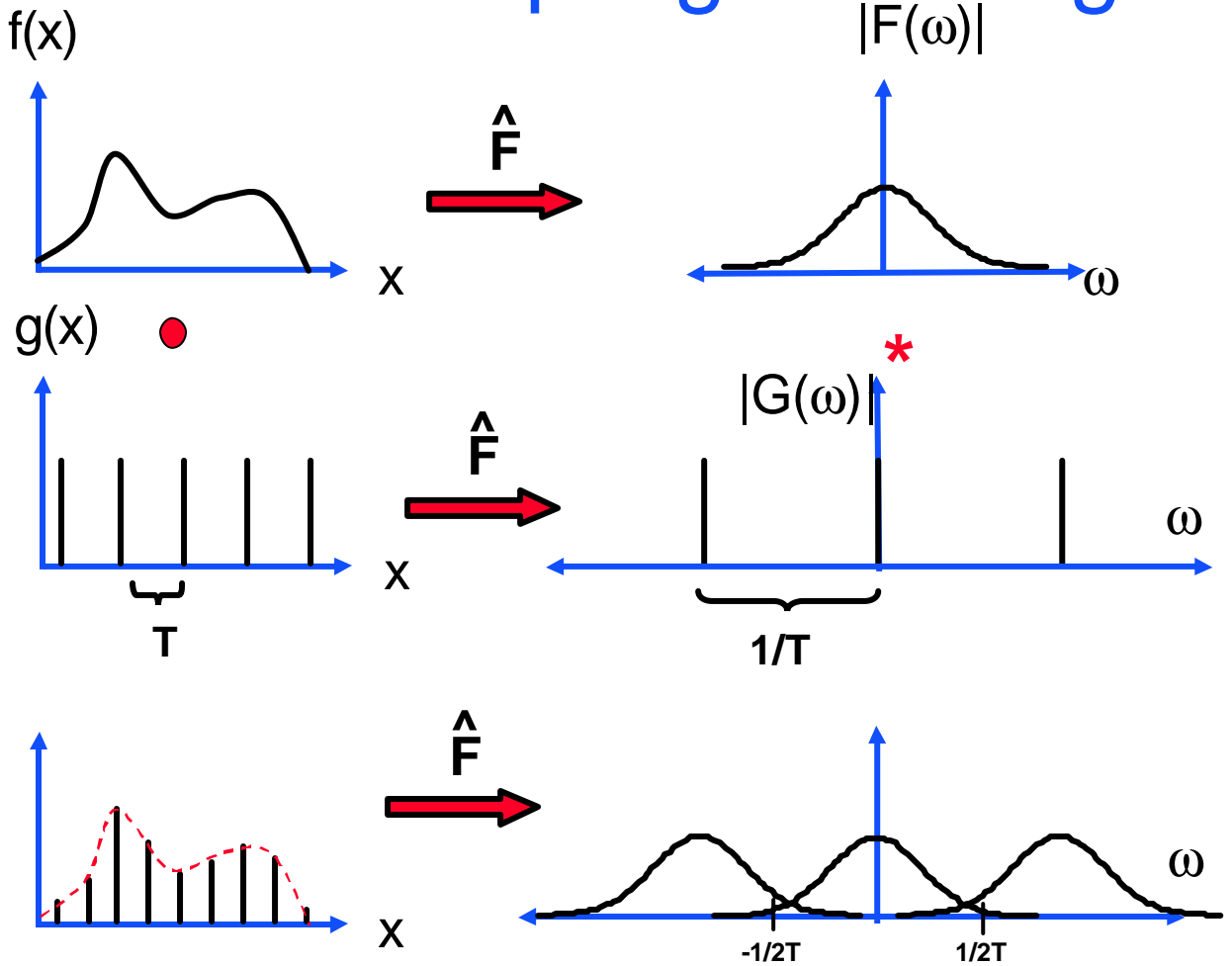
$$\mathcal{S}^{-1}[F(u,v) G(u,v)]$$



Sampling the Image



Undersampling the Image

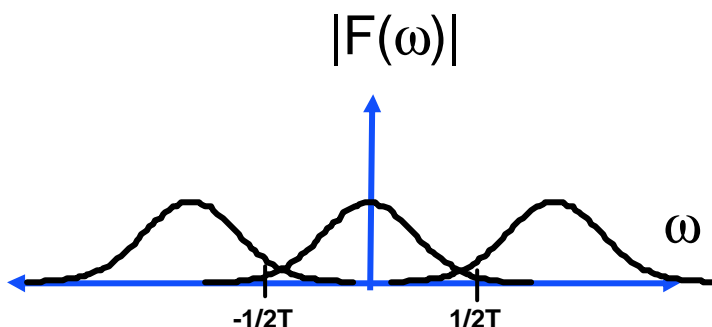


Critical Sampling

- If the maximal frequency of $f(x)$ is ω_{\max} , it is clear from the above replicas that ω_{\max} should be smaller than $1/2T$.
- Alternatively:

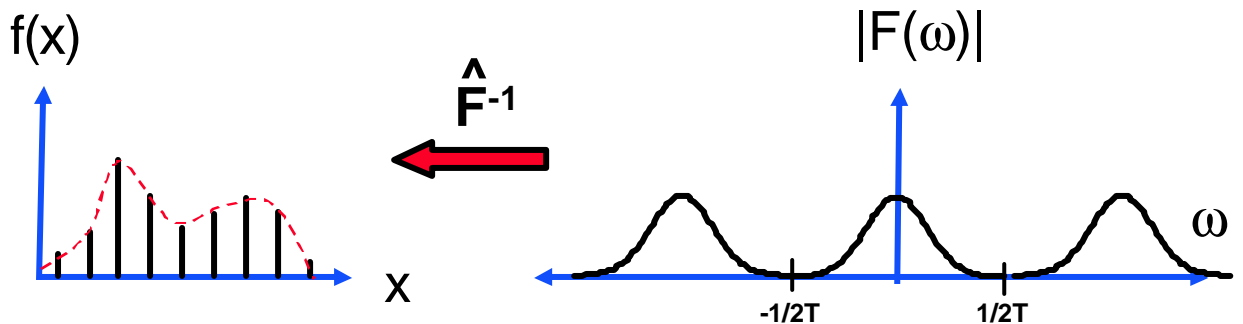
$$\frac{1}{T} > 2\omega_{\max}$$

- **Nyquist Theorem**: If the maximal frequency of $f(x)$ is ω_{\max} the sampling rate should be larger than $2\omega_{\max}$ in order to fully reconstruct $f(x)$ from its samples.
- If the sampling rate is smaller than $2\omega_{\max}$ overlapping replicas produce **aliasing**.



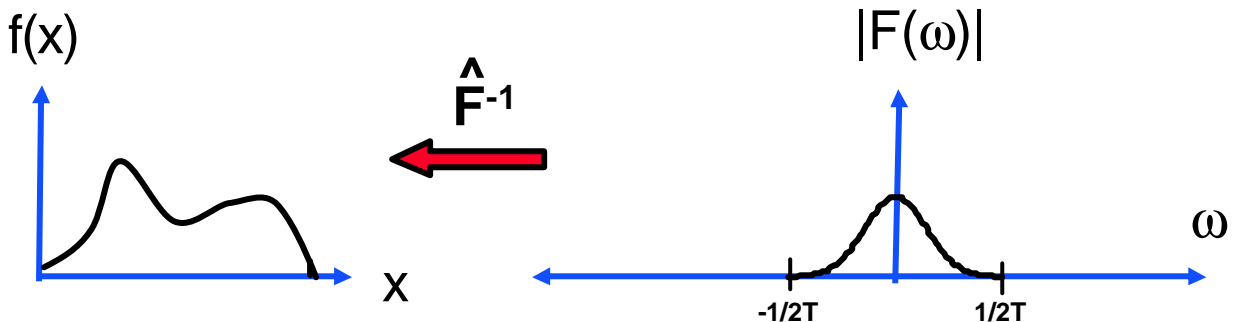
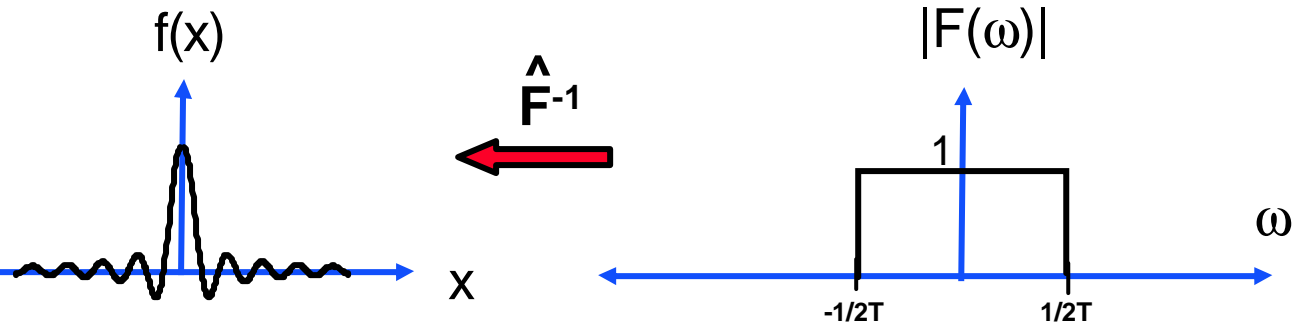
Optimal Interpolation

- It is possible to fully reconstruct $f(x)$ from its samples:



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Fast Fourier Transform - FFT

$$F(u) = \frac{1}{N} \sum_{x=0}^{N-1} f(x) e^{\frac{-2\pi i u x}{N}} \quad u = 0, 1, 2, \dots, N-1$$

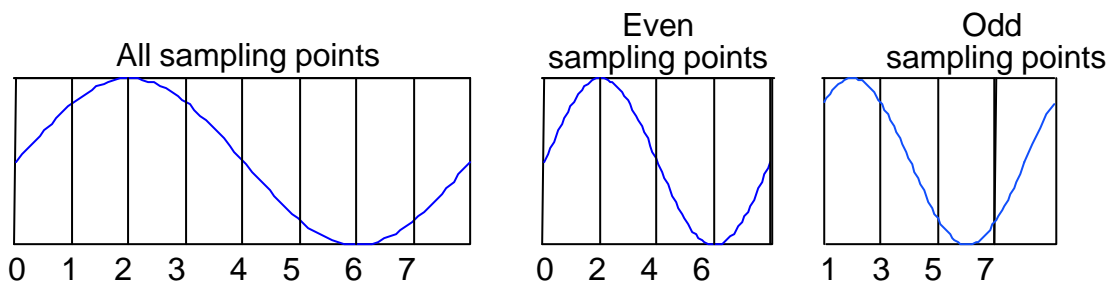
$O(n^2)$ operations

$$F(u) = \frac{1}{N} \sum_{x=0}^{N/2-1} f(2x) e^{\frac{-2\pi i u 2x}{N}} + \frac{1}{N} \sum_{x=0}^{N/2-1} f(2x+1) e^{\frac{-2\pi i u (2x+1)}{N}}$$

$$= \frac{1}{2} \left[\underbrace{\frac{1}{N/2} \sum_{x=0}^{N/2-1} f(2x) e^{\frac{-2\pi i u x}{N/2}}}_{\text{even } x} + e^{\frac{-2\pi i u}{N}} \underbrace{\frac{1}{N/2} \sum_{x=0}^{N/2-1} f(2x+1) e^{\frac{-2\pi i u x}{N/2}}}_{\text{odd } x} \right]$$

Fourier Transform of
of $N/2$ even points

Fourier Transform of
of $N/2$ odd points



The Fourier transform of N inputs, can be performed as 2 Fourier Transforms of $N/2$ inputs each + one complex multiplication and addition for each value i.e. $O(N)$.

Note, that only $N/2$ different transform values are obtained for the $N/2$ point transforms.

$$F_N(u) = \frac{1}{2} \left[\frac{1}{N/2} \sum_{x=0}^{N/2-1} f(2x) e^{\frac{-2\pi i u x}{N/2}} + e^{\frac{-2\pi i u}{N}} \frac{1}{N/2} \sum_{x=0}^{N/2-1} f(2x+1) e^{\frac{-2\pi i u x}{N/2}} \right]$$

$$F_N(u) = \frac{1}{2} \left[F_{N/2}^e(u) + e^{\frac{-2\pi i u}{N}} F_{N/2}^o(u) \right]$$

For $u' = u + N/2$:

$$e^{\frac{-2\pi i u'}{N}} = e^{\frac{-2\pi i (u + N/2)}{N}} = e^{\frac{-2\pi i u}{N}} e^{-\pi i} = -e^{\frac{-2\pi i u}{N}}$$

obtain :

$$F_N(u) = \frac{1}{2} \left[F_{N/2}^e(u) + e^{\frac{-2\pi i u}{N}} F_{N/2}^o(u) \right] \quad \text{For } u = 0, 1, 2, \dots, N/2-1$$

$$F_N(u + \frac{N}{2}) = \frac{1}{2} \left[F_{N/2}^e(u) - e^{\frac{-2\pi i u}{N}} F_{N/2}^o(u) \right]$$

Thus: only one complex multiplication is needed for two terms.

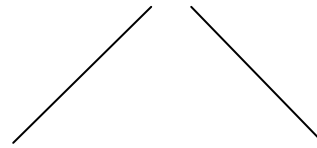
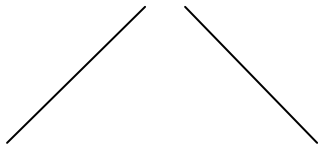
Calculating $F_{N/2}^e(u)$ and $F_{N/2}^o(u)$ is done recursively by calculating $F_{N/4}^e(u)$ and $F_{N/4}^o(u)$.

F(0) F(1) F(2) F(3) F(4) F(5) F(6) F(7)



F(0) F(2) F(4) F(6)

F(1) F(3) F(5) F(7)



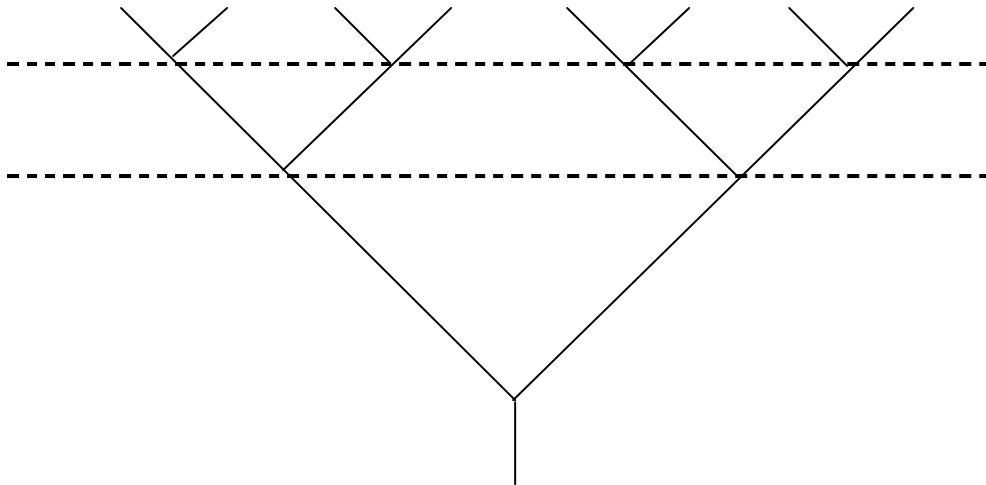
F(0) F(4)

F(2) F(6)

F(1) F(5)

F(3) F(7)

F(0) F(1) F(2) F(3) F(4) F(5) F(6) F(7)



2-point transform

4-point transform

FFT

FFT : $O(n \log(n))$ operations

FFT of NxN Image: $O(n^2 \log(n))$ operations

Frequency Enhancement

