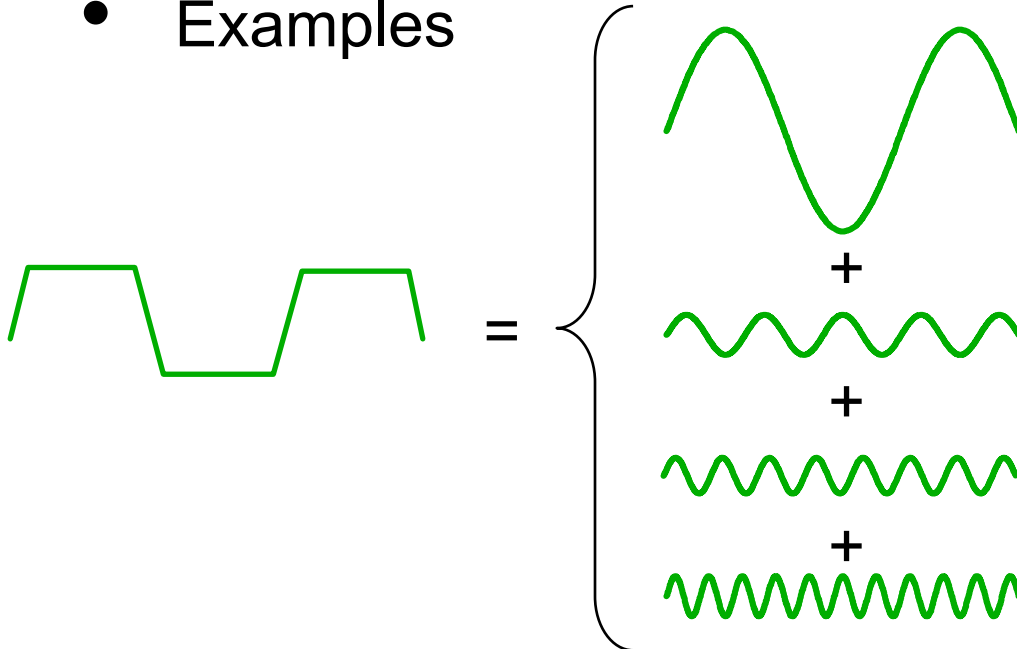


Fourier Transform 2D

- Discrete Fourier Transform - 2D
- Continuous Fourier Transform - 2D
- Fourier Properties
- Convolution Theorem
- Examples



The 2D Discrete Fourier Transform

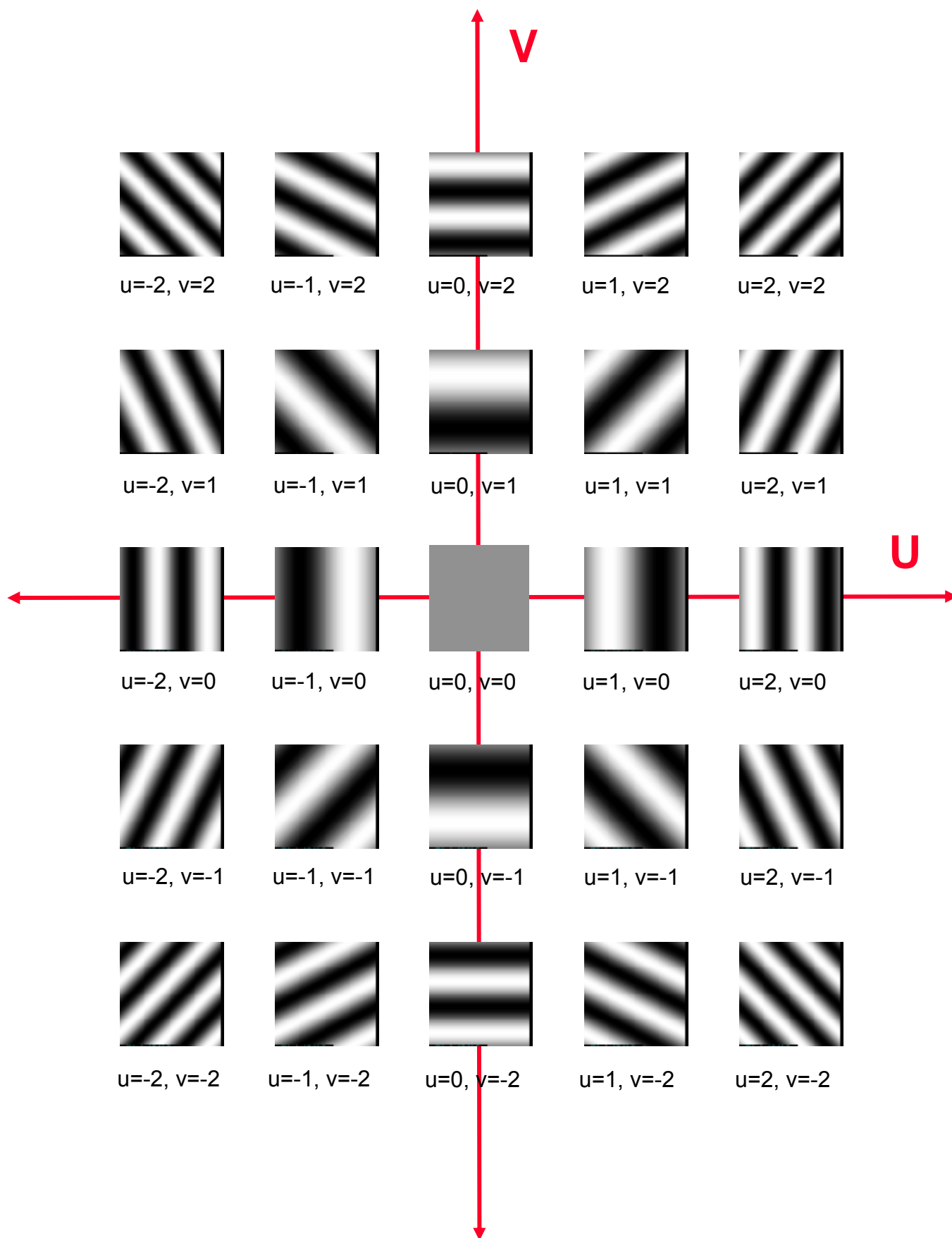
- For an image $f(x,y)$ $x=0..N-1$, $y=0..M-1$, there are two-indices basis functions $B_{u,v}(x,y)$:

$$B_{u,v}(x,y) = \frac{1}{\sqrt{MN}} e^{2\pi i \left(\frac{ux}{N} + \frac{vy}{M} \right)}$$

$$u=0..N-1, \quad v=0..M-1$$

- The inner product of 2 functions (in 2D) is defined similarly to the 1D case :

$$\begin{aligned} F(u,v) &= \langle f(x,y), B_{u,v}(x,y) \rangle = \\ &= \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} f(x,y) B_{u,v}^*(x,y) \end{aligned}$$



The 2D Discrete Fourier Transform

- Image $f(x,y)$ $x = 0,1,\dots,N-1$ $y=0,1,\dots,M-1$
- The **2D Discrete Fourier Transform** (DFT) is defined as:

$$F(u,v) = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} f(x,y) e^{-2\pi i (ux/N + vy/M)}$$

$u = 0, 1, 2, \dots, N-1$
 $v = 0, 1, 2, \dots, M-1$

Matlab: `F=fft2(f);`

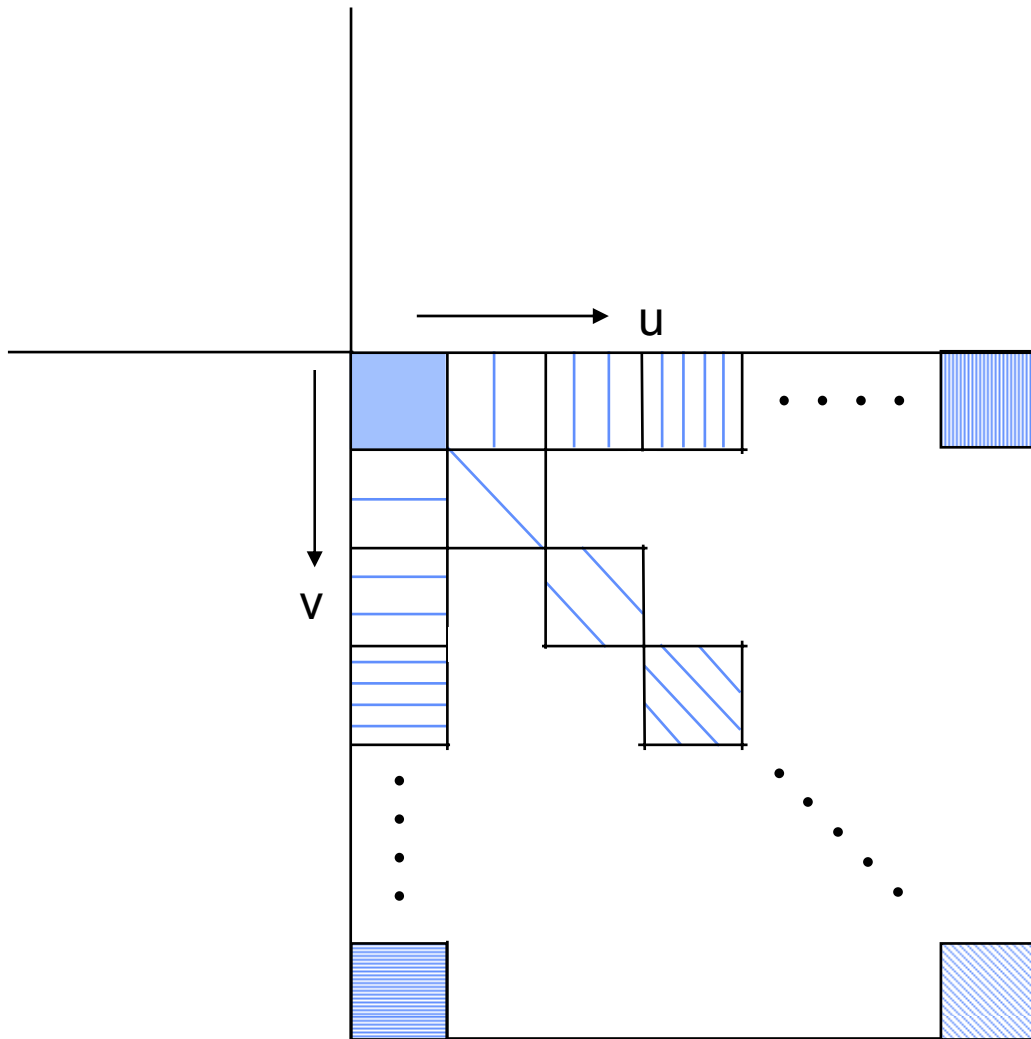
- The **Inverse Discrete Fourier Transform** (IDFT) is defined as:

$$f(x,y) = \frac{1}{MN} \sum_{u=0}^{N-1} \sum_{v=0}^{M-1} F(u,v) e^{2\pi i (ux/N + vy/M)}$$

$y = 0, 1, 2, \dots, N-1$
 $x = 0, 1, 2, \dots, M-1$

Matlab: `f=ifft2(F);`

Fourier Transform - Image

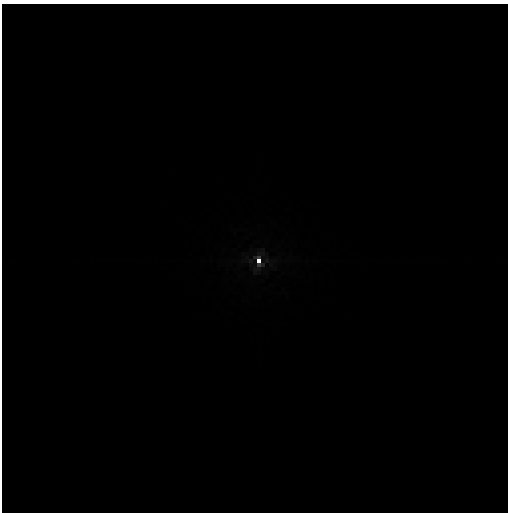
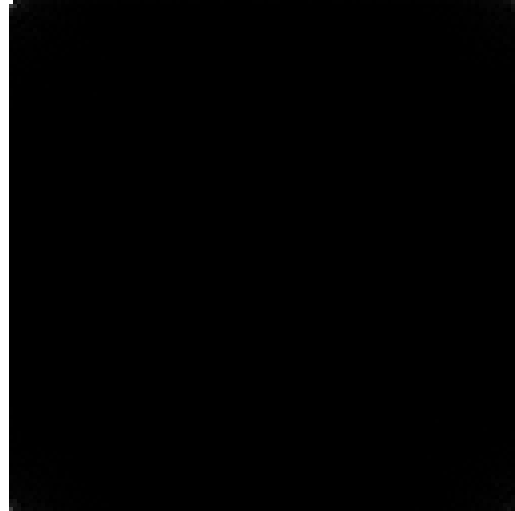


Fourier Image - Example

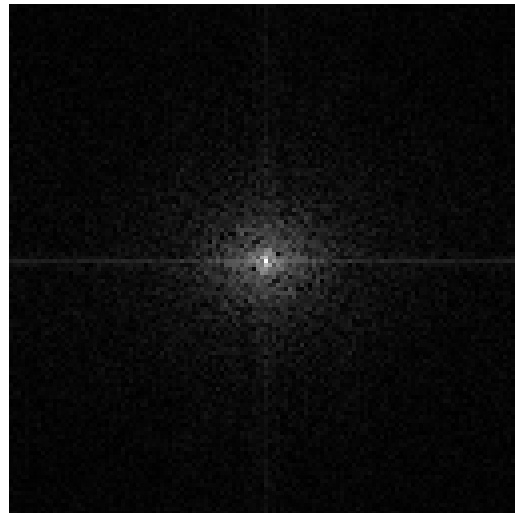
Original



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



Shifted Fourier Image



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

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

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

- Cyclically rotate the image so that $F(0,0)$ is in the center:

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

Example:

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

Display in Range([0..100]):

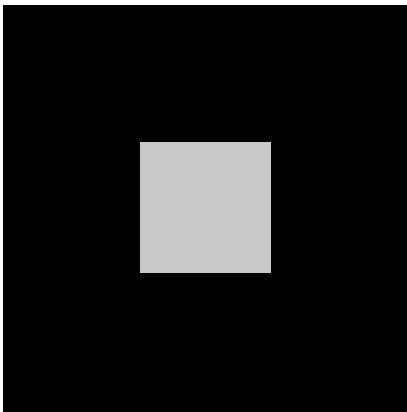
$$\log(1+|F(u)|) = 4.62 \quad 1.61 \quad 1.01 \quad 0.69 \quad 0 \quad 0 \quad 0.69 \quad 1.01 \quad 1.61$$

$$\log(1+|F(u)|)/0.0462 = 100 \quad 40 \quad 20 \quad 10 \quad 0 \quad 0 \quad 10 \quad 20 \quad 40$$

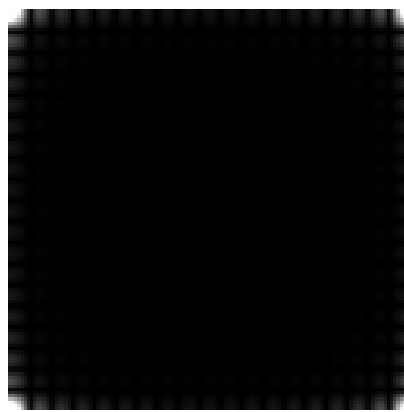
$$\text{fftshift}(\log(1+|F(u)|)) = 0 \quad 10 \quad 20 \quad 40 \quad 100 \quad 40 \quad 20 \quad 10 \quad 0$$

Visualizing the Fourier Image - Example

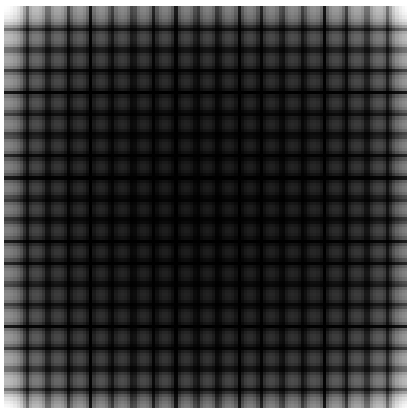
Original



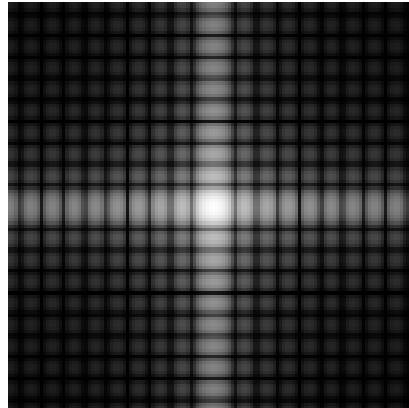
$|F(u,v)|$



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



$\text{fftshift}(\log(1 + |F(u,v)|))$



Properties of The Fourier Transform

- Linearity:

$$\tilde{F}[\alpha f] = \alpha \tilde{F}[f]$$

- Distributive (additivity):

$$\tilde{F}[f_1 + f_2] = \tilde{F}[f_1] + \tilde{F}[f_2]$$

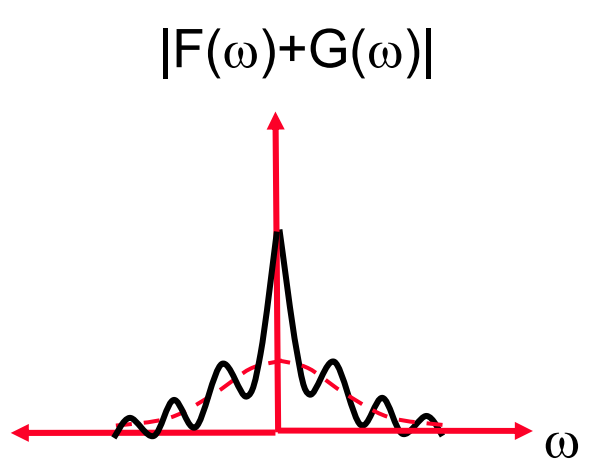
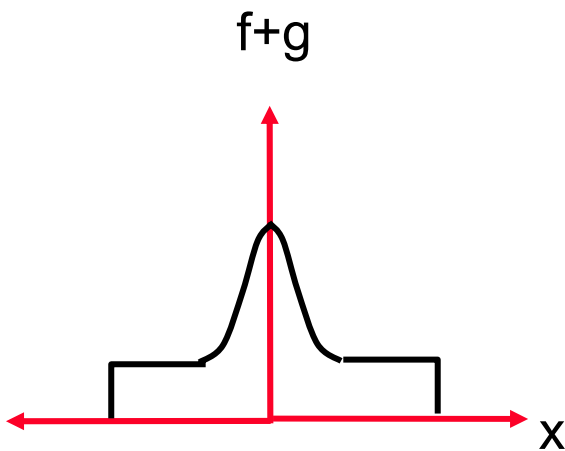
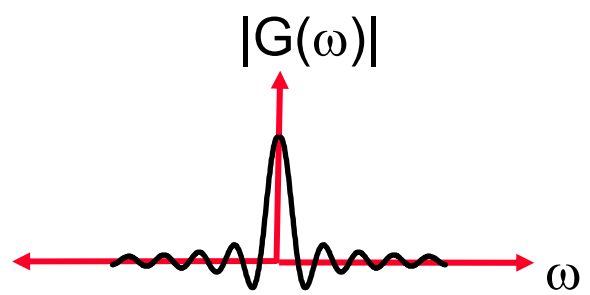
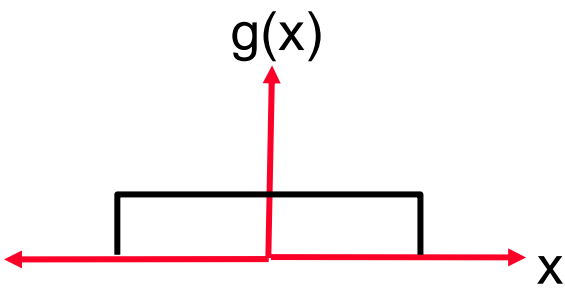
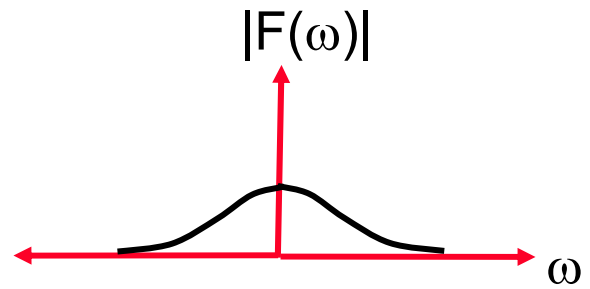
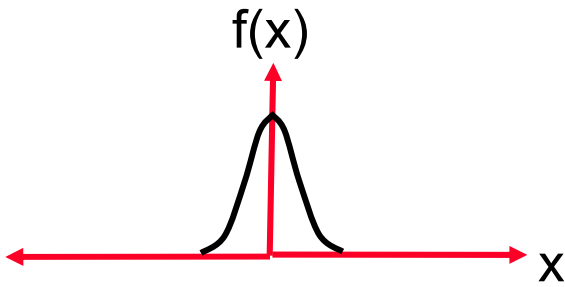
- DC (average):

$$F(0,0) = \sum_x \sum_y f(x,y) e^0$$

- Parseval

$$\sum_x \sum_y \|f(x,y)\|^2 = \sum_u \sum_v \|F(u,v)\|^2$$

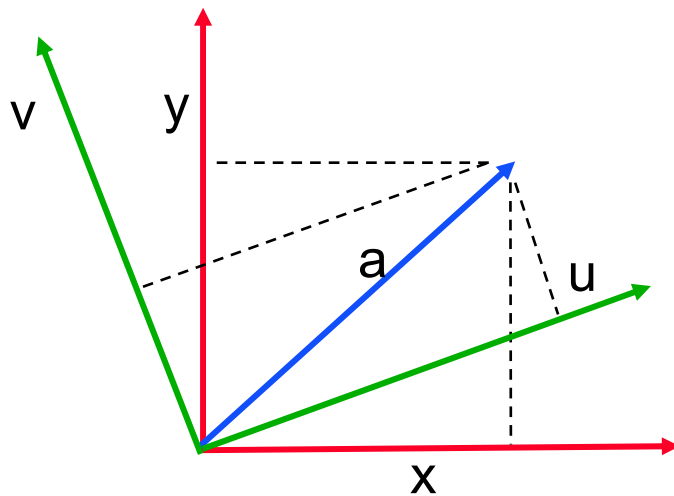
Distributive: $\tilde{F}\{f + g\} = \tilde{F}\{f\} + \tilde{F}\{g\}$



Parseval's Theorem

One more characteristic:

$$\sum_x \sum_y |f(x,y)|^2 = \sum_u \sum_v |F(u,v)|^2$$



Properties of The Fourier Transform

- Symmetric:

If $f(x,y)$ is real then,

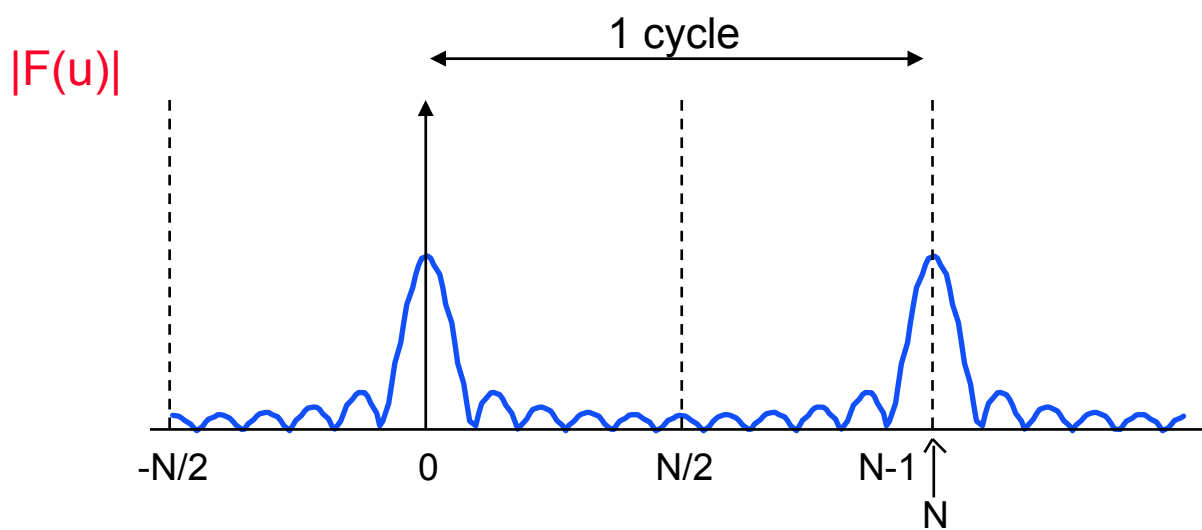
$$F(u,v) = F^*(-u,-v) \quad \text{thus} \quad |F(u,v)| = |F(-u,-v)|$$

- Cyclic:

if $f(x,y)$ is discrete

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

Cyclic and Symmetry of the Fourier Transform - 1D Example



Properties: Cont.

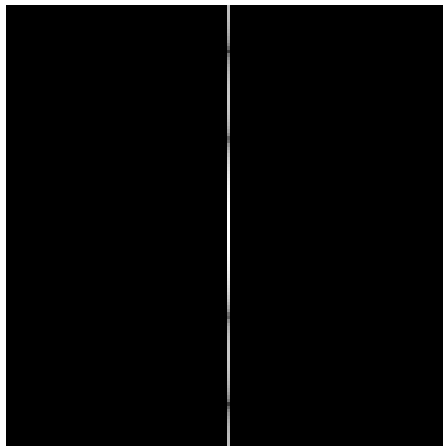
Separability

$$\begin{aligned} F(u,v) &= \sum_x \sum_y f(x,y) e^{-2\pi i \left(\frac{ux}{N} + \frac{vy}{M} \right)} = \\ &= \sum_x \left(\sum_y f(x,y) e^{-2\pi i \frac{vy}{N}} \right) e^{-2\pi i \frac{ux}{N}} = \sum_x F(x,v) e^{-2\pi i \frac{ux}{N}} \end{aligned}$$

- Thus, performing a **2D** Fourier Transform is equivalent to performing 2 **1D** transforms:
 1. Perform 1D transform on EACH column of image $f(x,y)$, obtaining $F(x,v)$.
 2. Perform 1D transform on EACH row of $F(x,v)$, obtaining $F(u,v)$.
- Higher Dimensions: Fourier in any dimension can be performed by applying 1D transform on each dimension.

Example - Separability

2D Image



Fourier Spectrum

Image Transformations

- **Translation:**

$$\tilde{F}[f(x-x_0, y-y_0)] = F(u, v) e^{-2\pi i \left(\frac{ux_0}{N} + \frac{vy_0}{M} \right)}$$

The Fourier Spectrum remains unchanged under translation:

$$|F(u, v)| = \left| F(u, v) e^{-2\pi i \left(\frac{ux_0}{N} + \frac{vy_0}{M} \right)} \right|$$

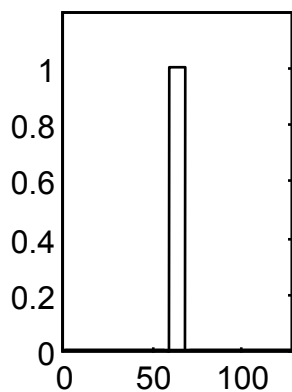
- **Rotation:** Rotation of $f(x, y)$ by $\theta \rightarrow$ rotation of $F(u, v)$ by θ

- **Scaling:**

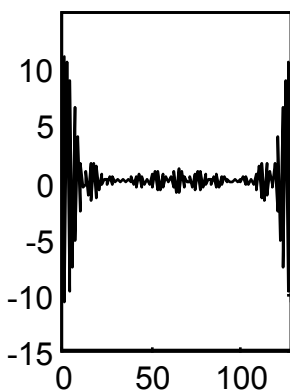
$$\tilde{F}[f(ax, by)] = \frac{1}{|ab|} F\left(\frac{u}{a}, \frac{v}{b}\right)$$

Example - Translation

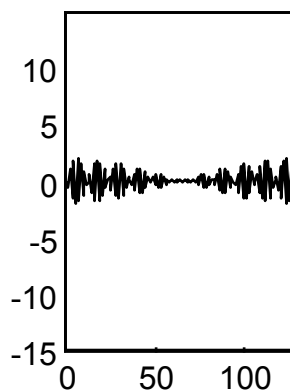
1D Image



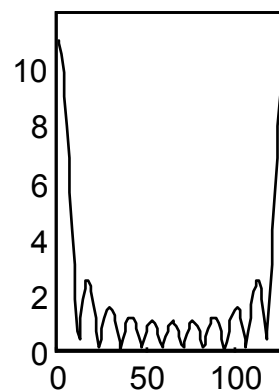
$\text{real}(F(u))$



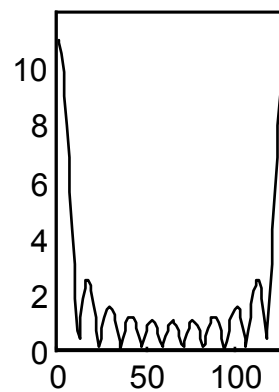
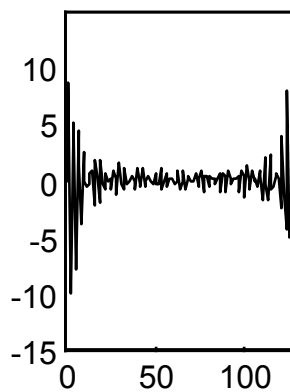
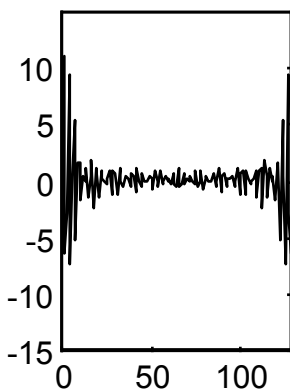
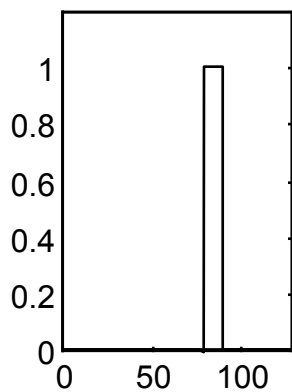
$\text{imag}(F(u))$



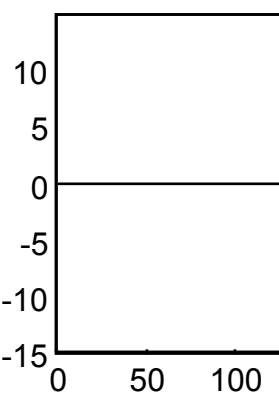
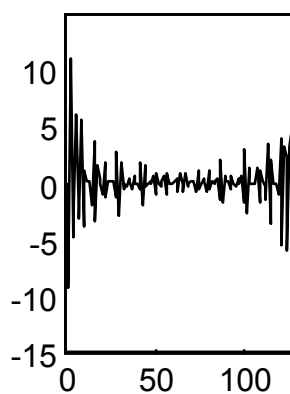
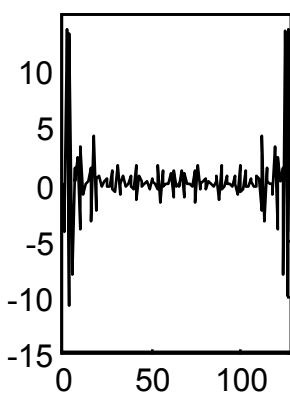
$|F(u)|$



Translated

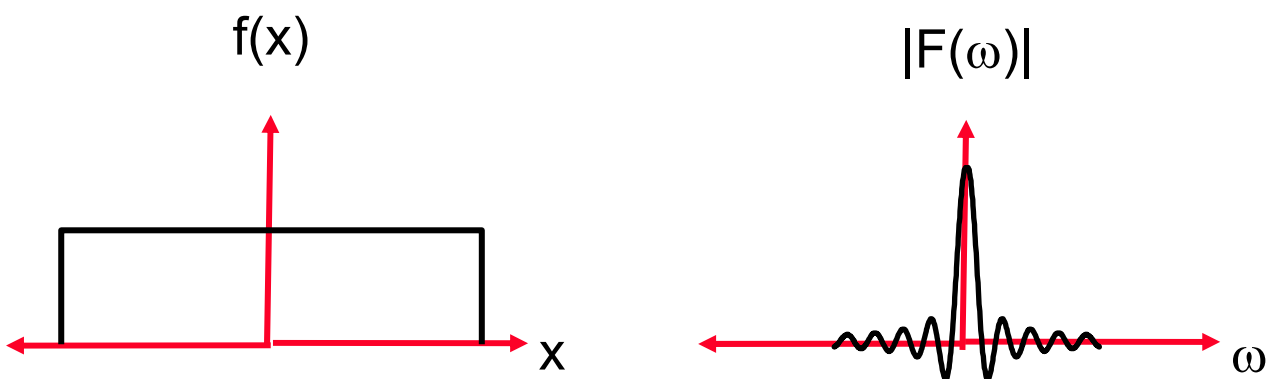
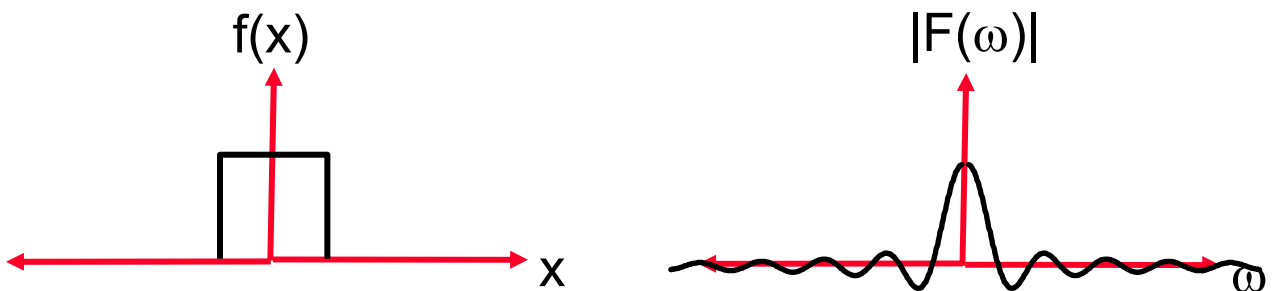
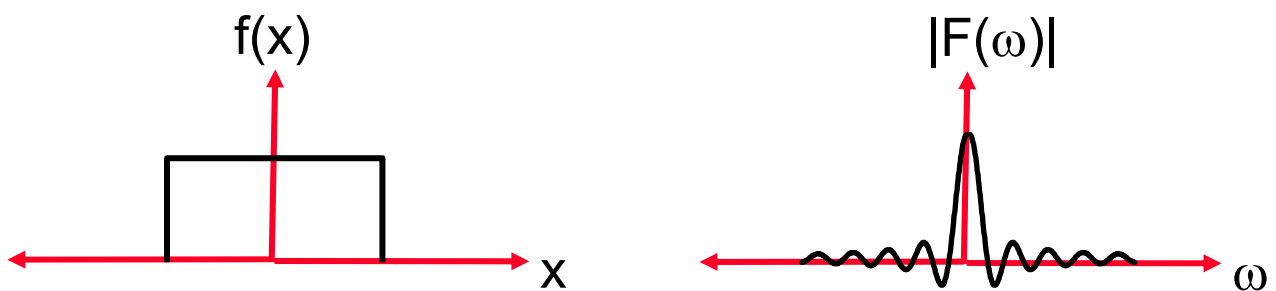


Differences:

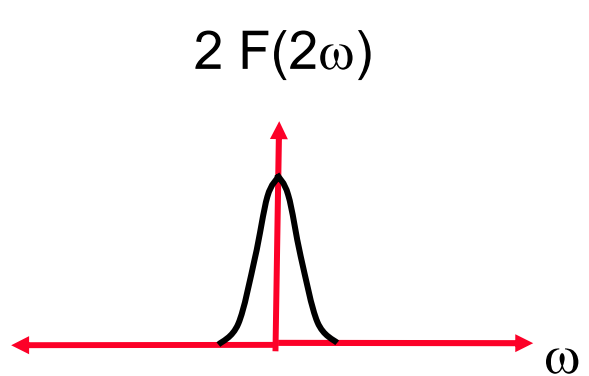
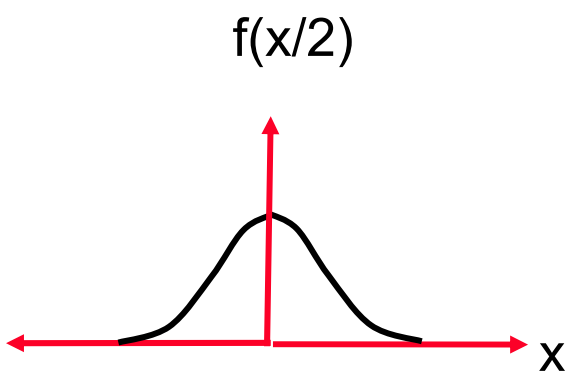
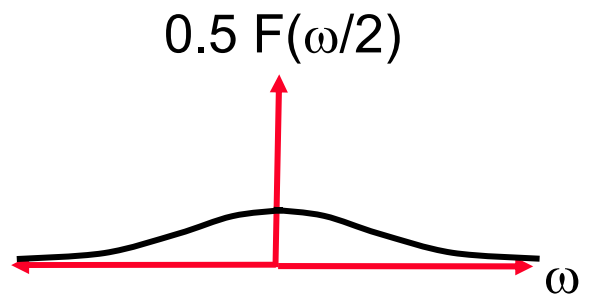
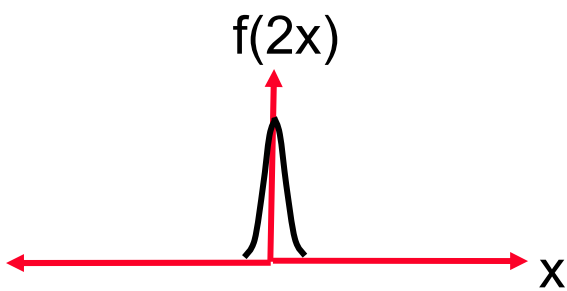
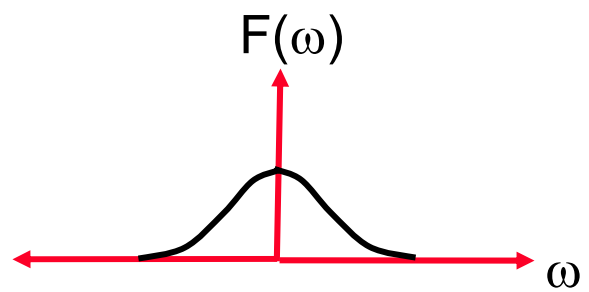
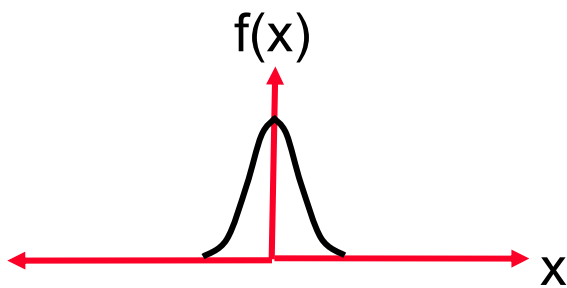


Change of Scale- 1D:

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

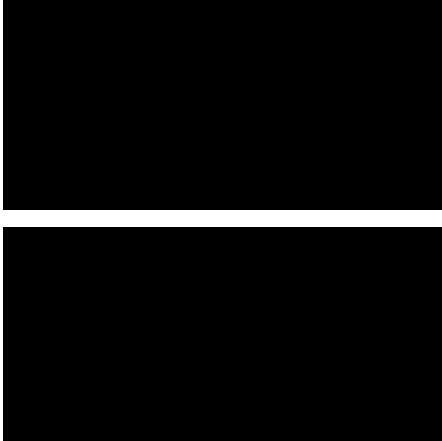


Change of Scale

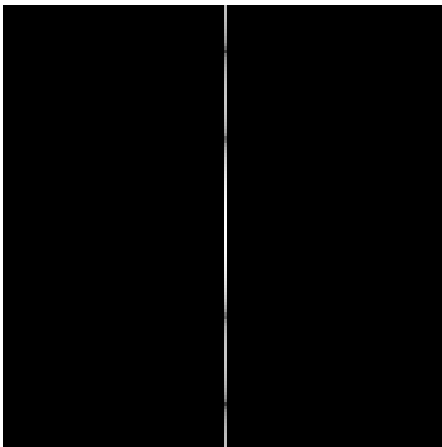
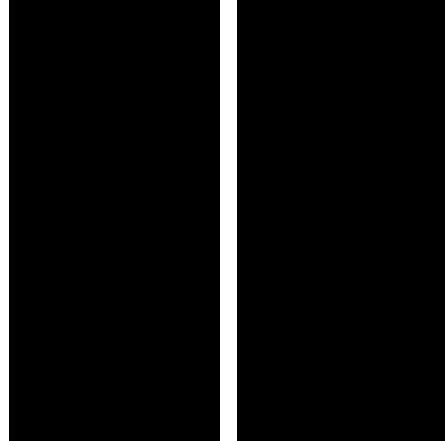


Example - Rotation

2D Image



2D Image - Rotated



Fourier Spectrum

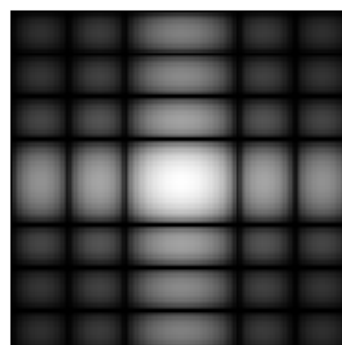
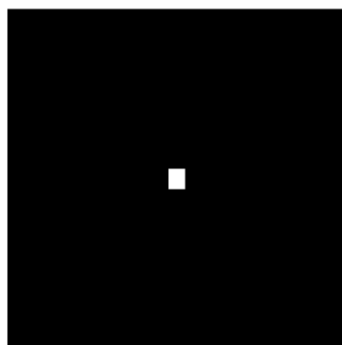
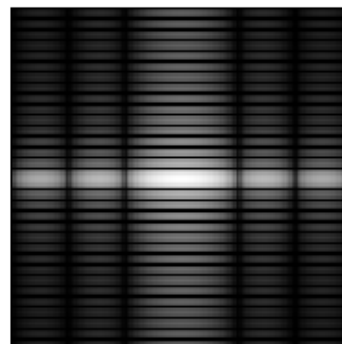
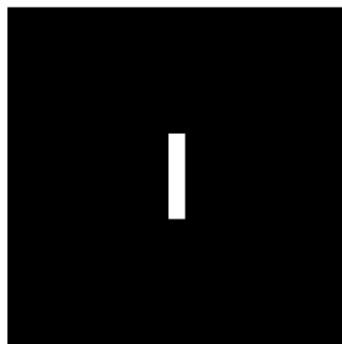
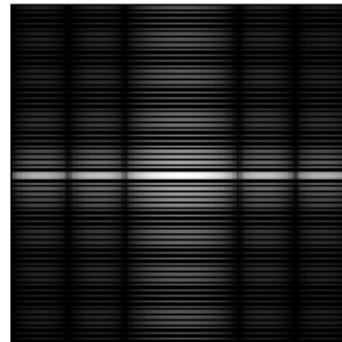
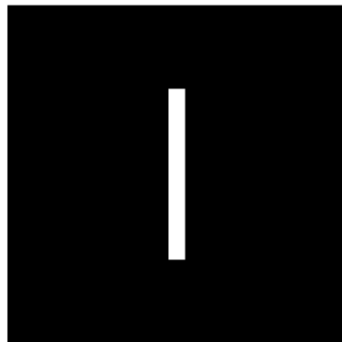
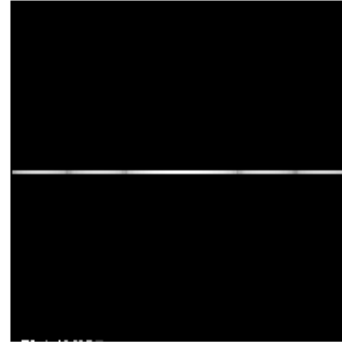
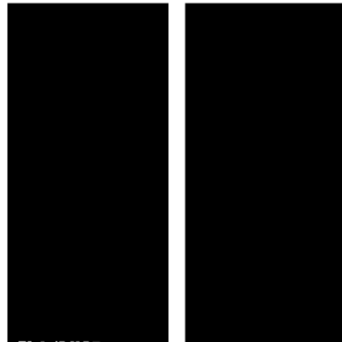


Fourier Spectrum

Fourier Transform Examples

Image Domain

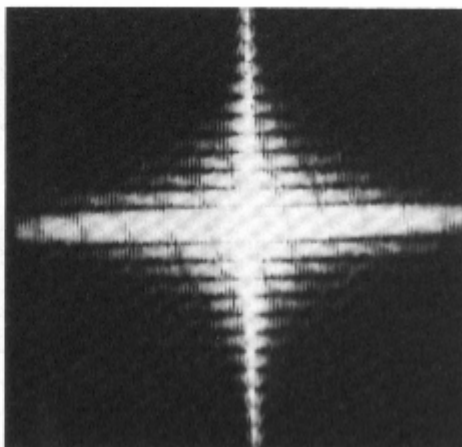
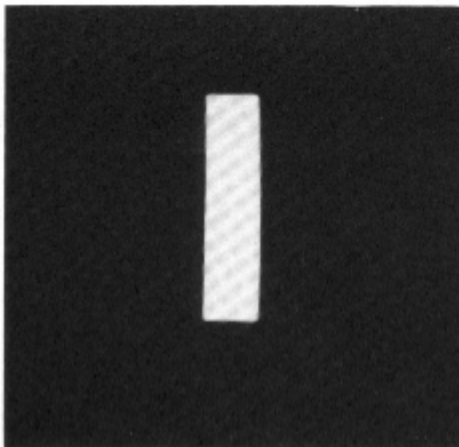
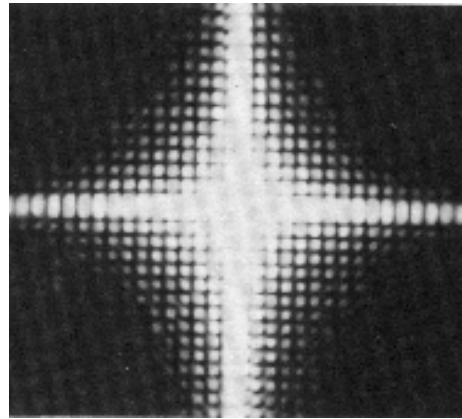
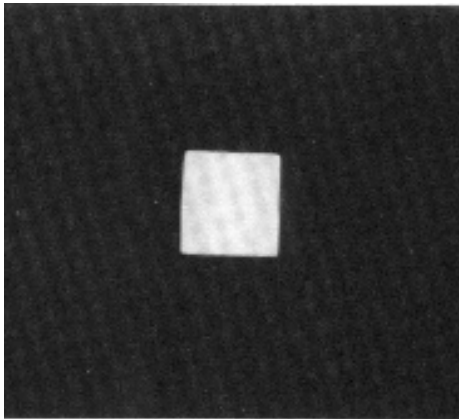
Frequency Domain



Fourier Transform Examples

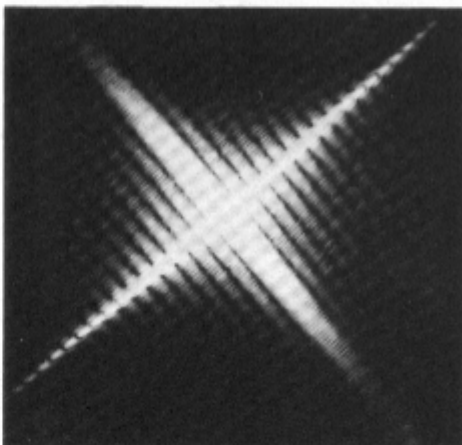
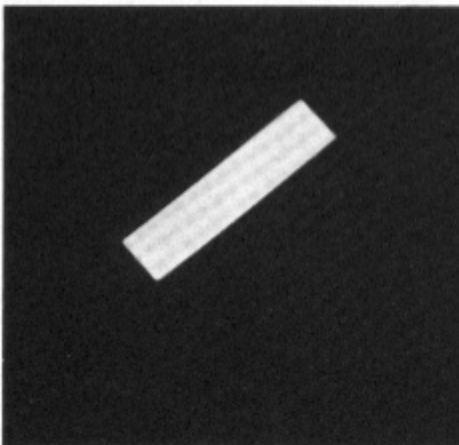
Image Domain

Frequency Domain



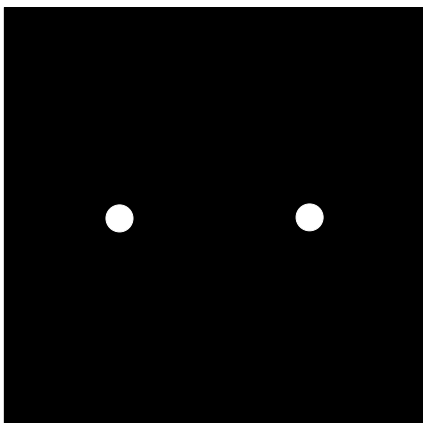
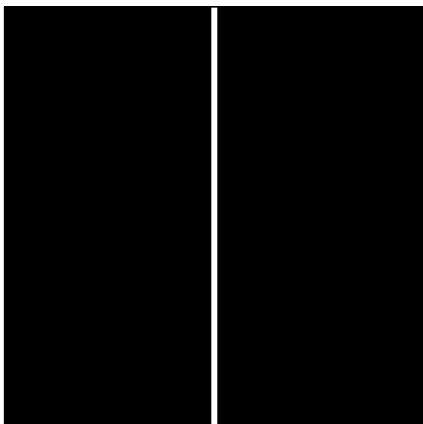
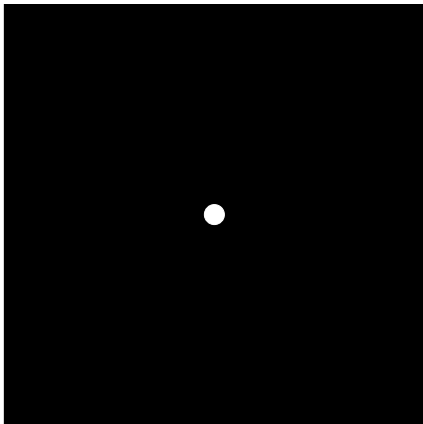
(a)

(b)

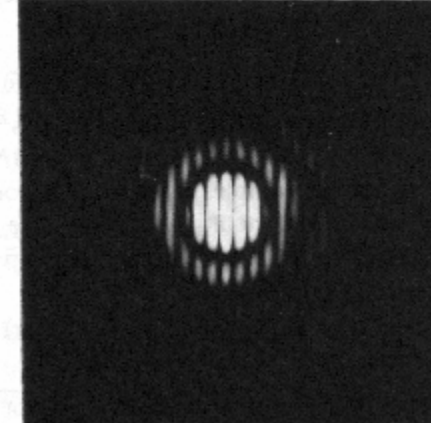
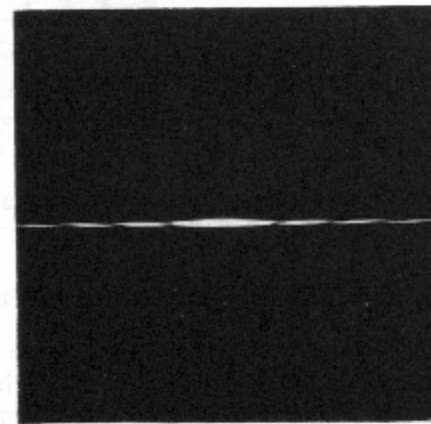
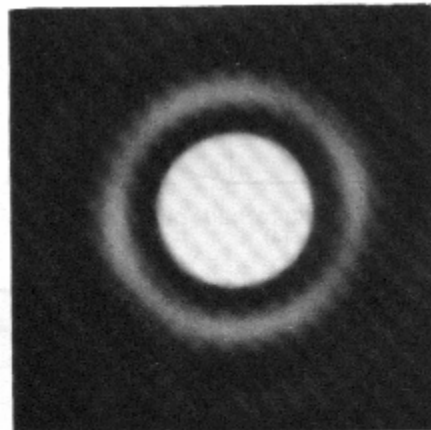


Fourier Transform Examples

Image Domain

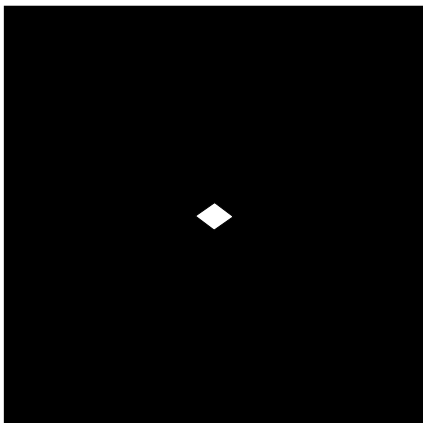
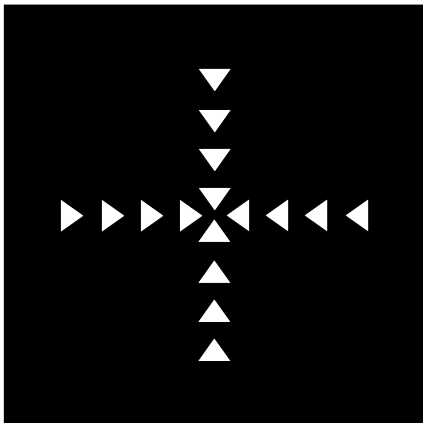
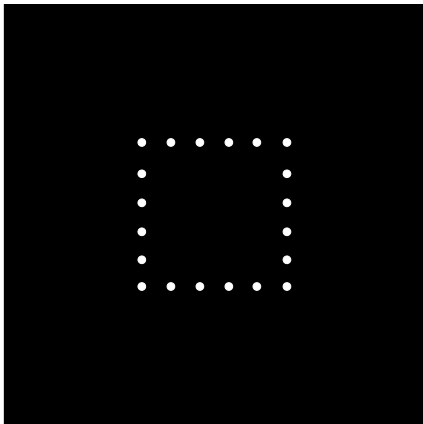


Frequency Domain

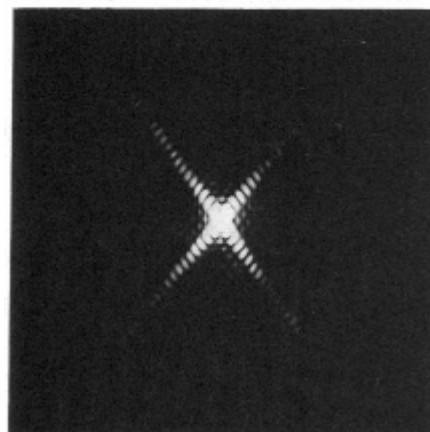
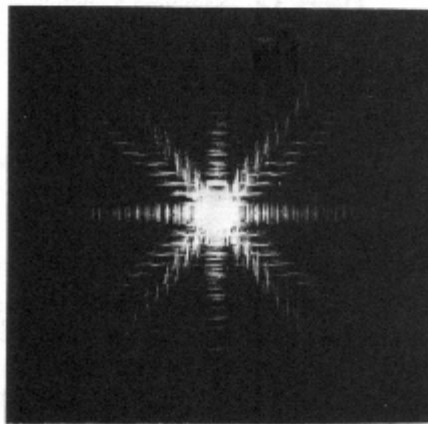
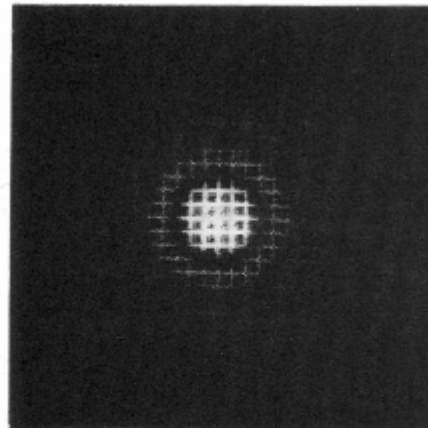


Fourier Transform Examples

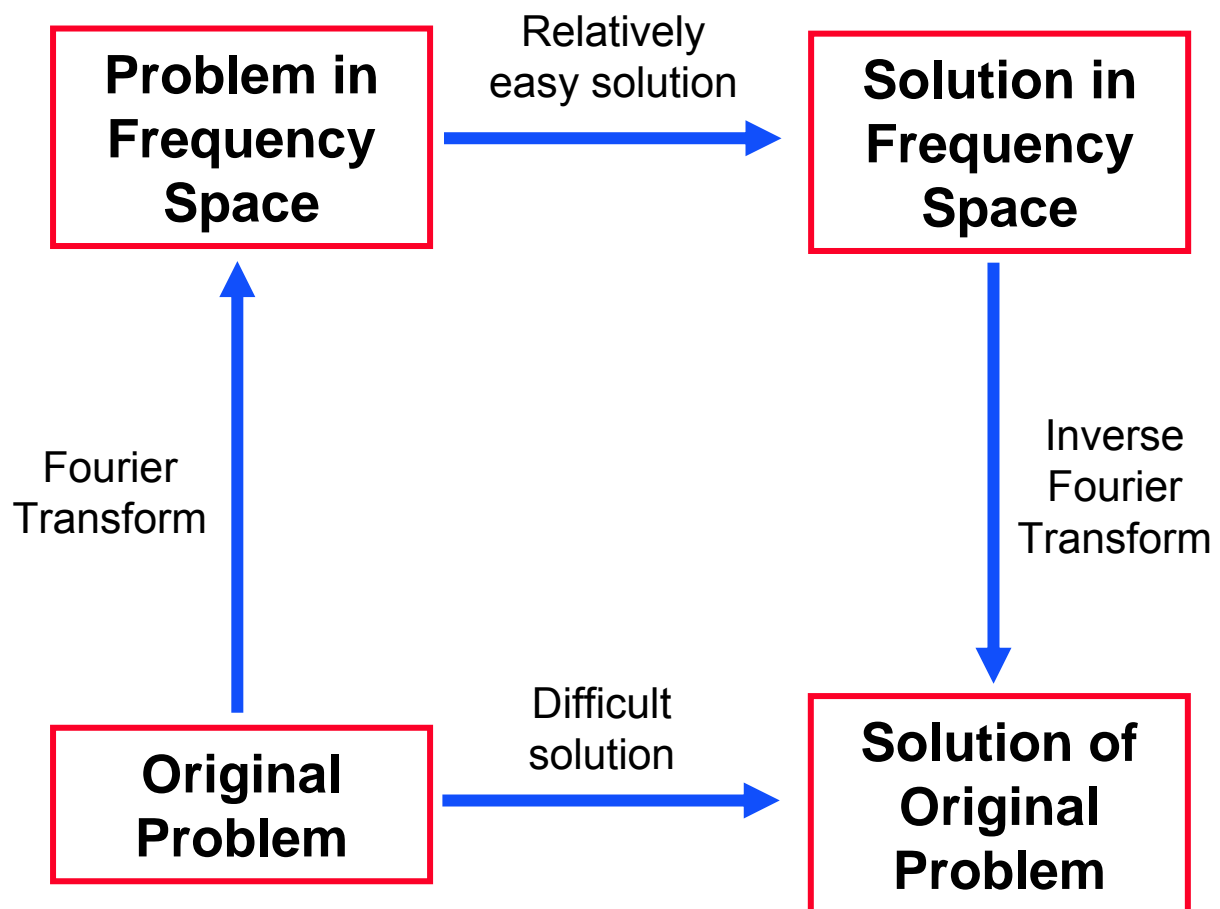
Image Domain



Frequency Domain



Why do we need representation in the frequency domain?



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

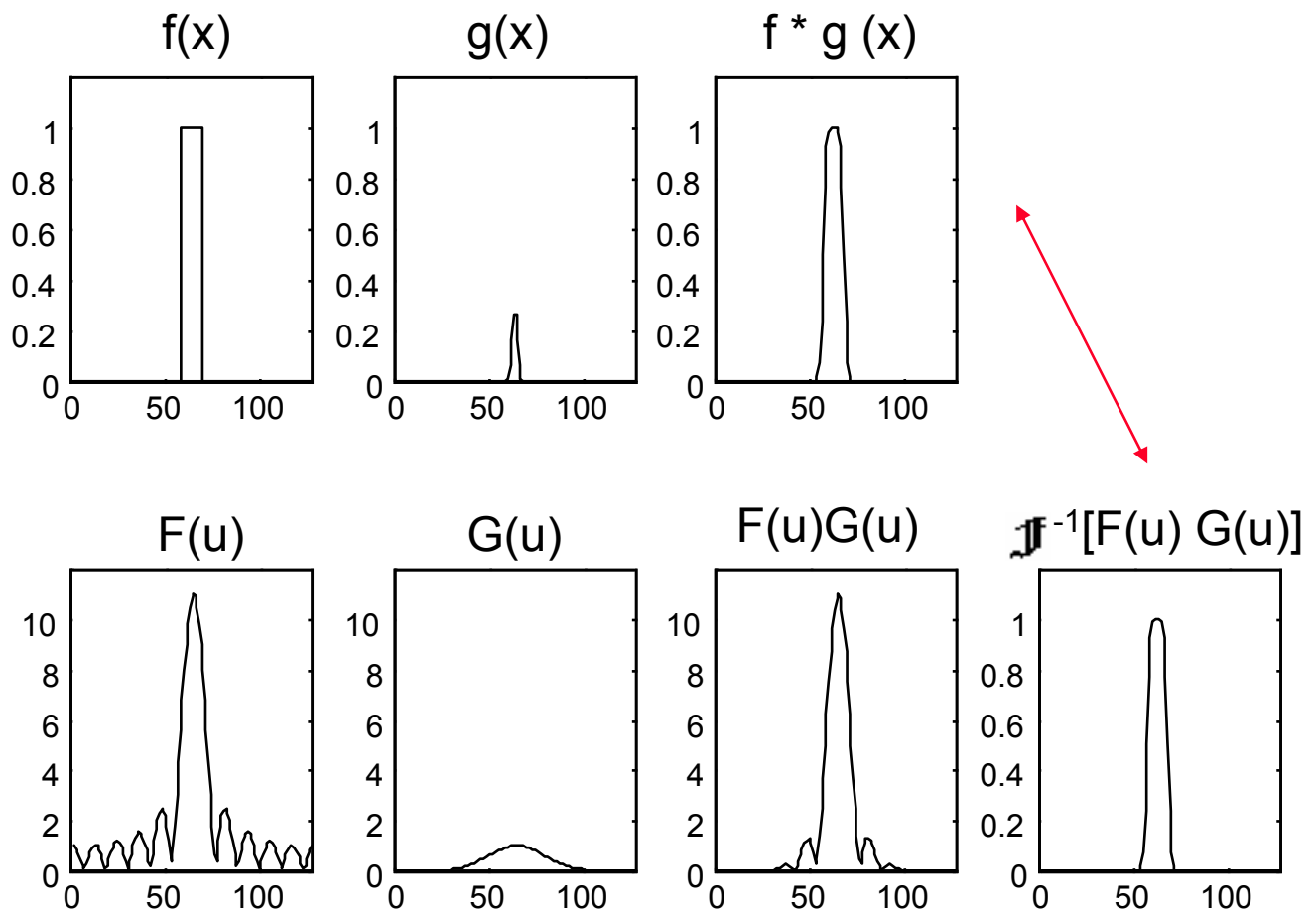
The Convolution Theorem

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

and likewise

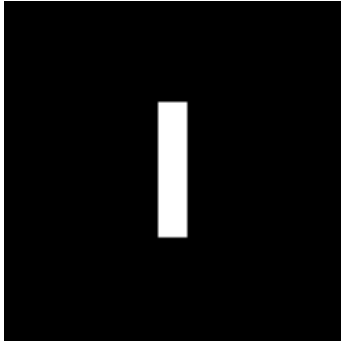
$$\tilde{F}\{f(x)g(x)\} = \tilde{F}\{f(x)\} * \tilde{F}\{g(x)\}$$

Convolution Theorem - Example

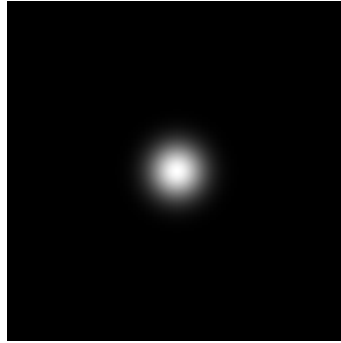


Convolution Theorem - 2D Example

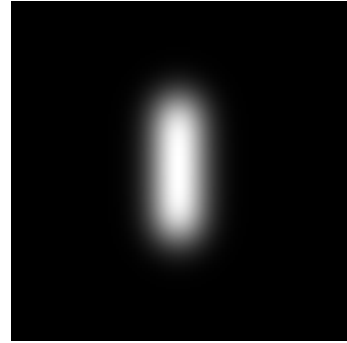
$f(x,y)$



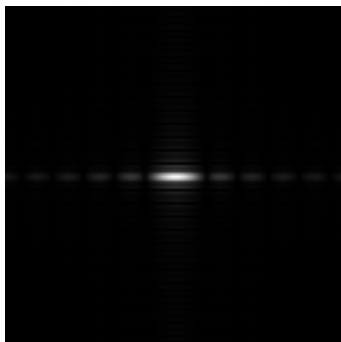
$g(x,y)$



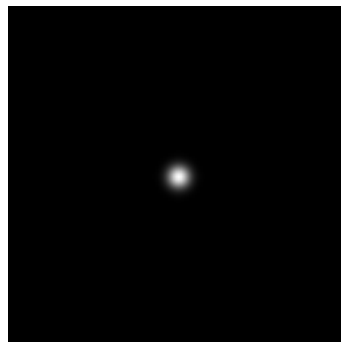
$f * g(x,y)$



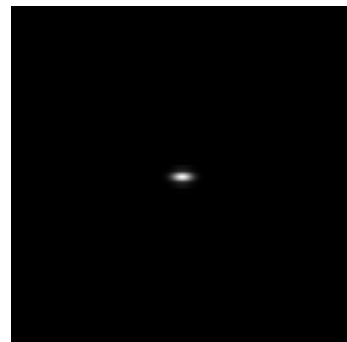
$F(u,v)$



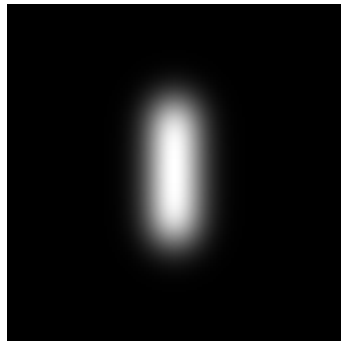
$G(u,v)$



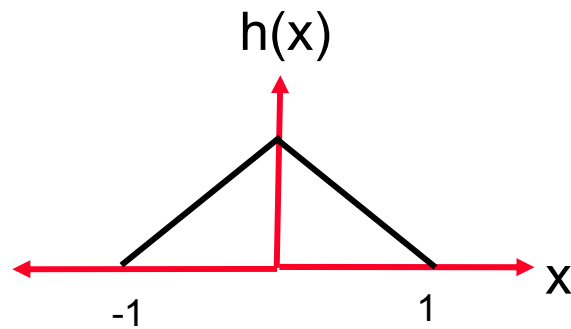
$F(u,v) \cdot G(u,v)$



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



Example: What is the Fourier Transform of:



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

The equation $h(x) = \text{rect}(x) * \text{rect}(x)$ is shown. The first $\text{rect}(x)$ is a rectangular pulse from $x = -0.5$ to $x = 0.5$ with a height of 1. The second $\text{rect}(x)$ is identical. The asterisk $*$ represents convolution. The result $h(x)$ is the triangular function shown in the previous figure.

$$H(\omega) = \text{sinc}(\omega) \cdot \text{sinc}(\omega)$$

The equation $H(\omega) = \text{sinc}(\omega) \cdot \text{sinc}(\omega)$ is shown. The first $\text{sinc}(\omega)$ is a sinc function centered at $\omega = 0$. The second $\text{sinc}(\omega)$ is identical. The dot \cdot represents multiplication. The result $H(\omega)$ is the squared sinc function shown in the next figure.

$$= \text{sinc}^2(\omega)$$

The equation $= \text{sinc}^2(\omega)$ is shown. The graph of $H(\omega)$ is a squared sinc function centered at $\omega = 0$, which is the product of the two sinc functions shown in the previous figure.

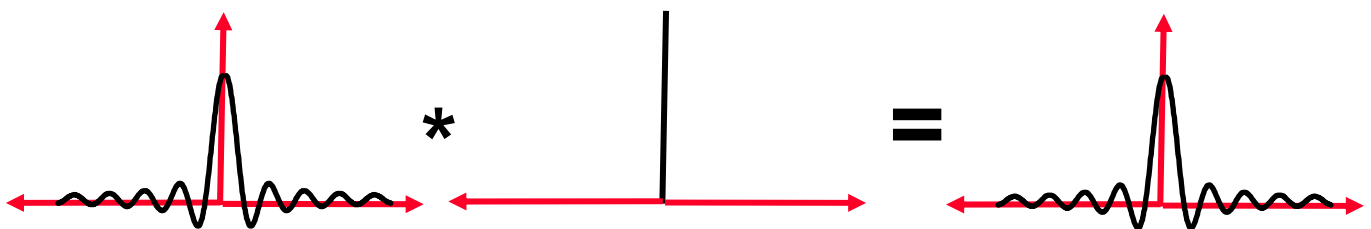
Example: What is the Fourier Transform of the Dirac Function?

$$\delta(x) = \begin{cases} 1 & \text{if } x = 0 \\ 0 & \text{otherwise} \end{cases}$$

Proof : Consider any function **f(x)**

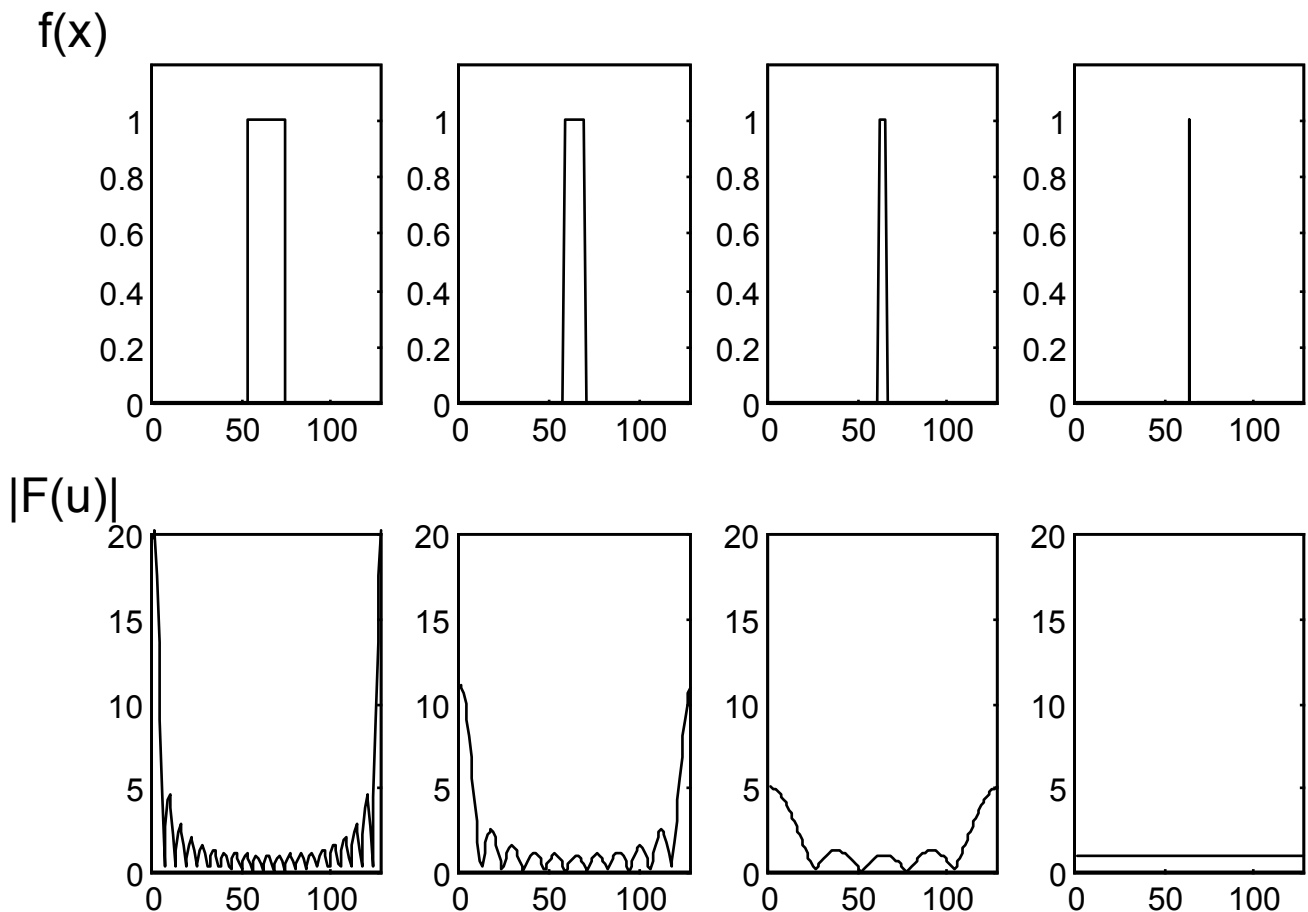
$$f(x) * \delta(x) = f(x)$$

$$\begin{array}{ccc} \downarrow & & \downarrow \\ F(u) \cdot F[\delta(x)] & = & F(u) \end{array}$$



$$F[\delta(x)] = 1$$

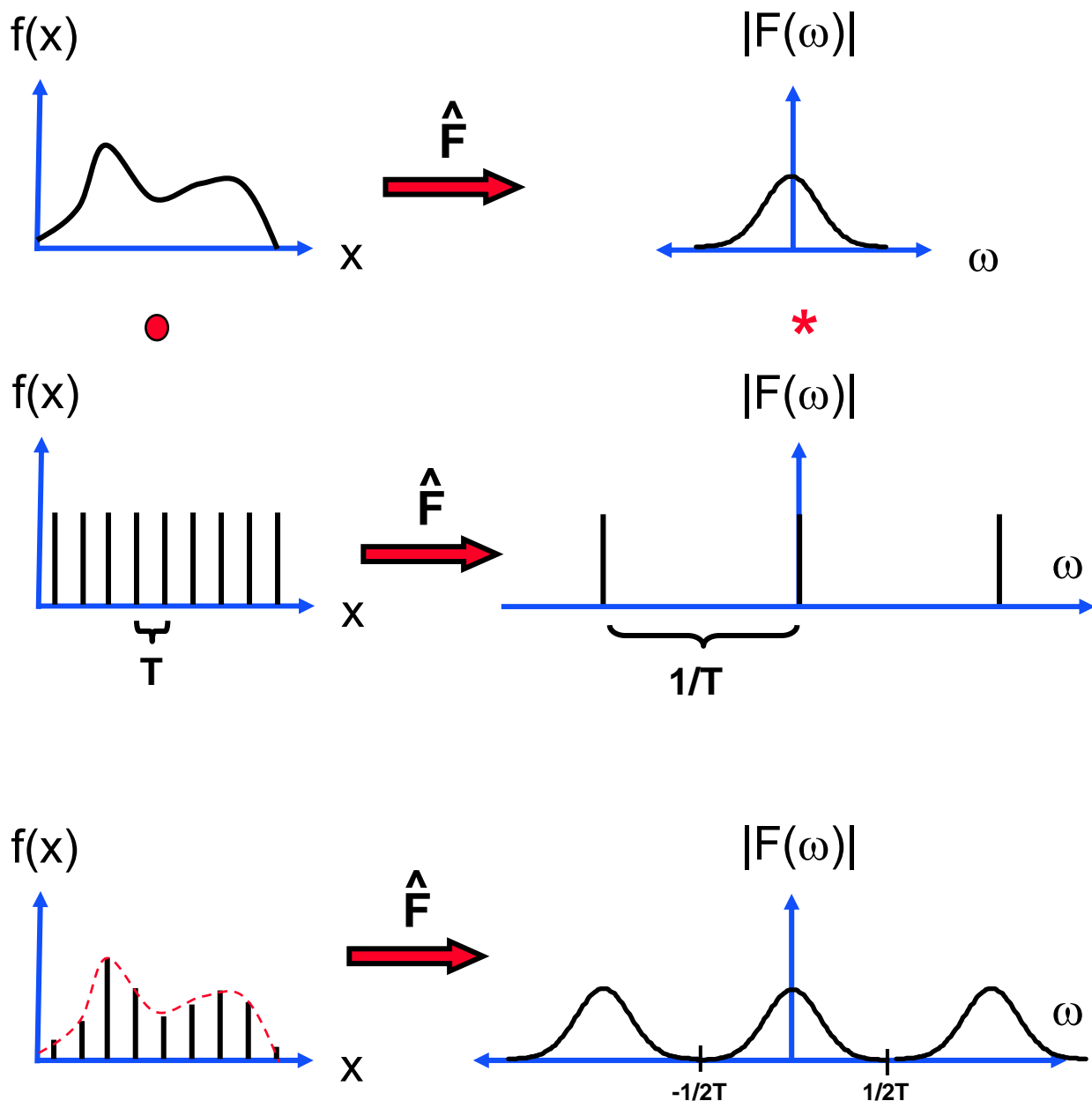
What is the Fourier Transform of the Dirac Function? Answer II:



What is the Fourier Transform of an image with constant gray value?

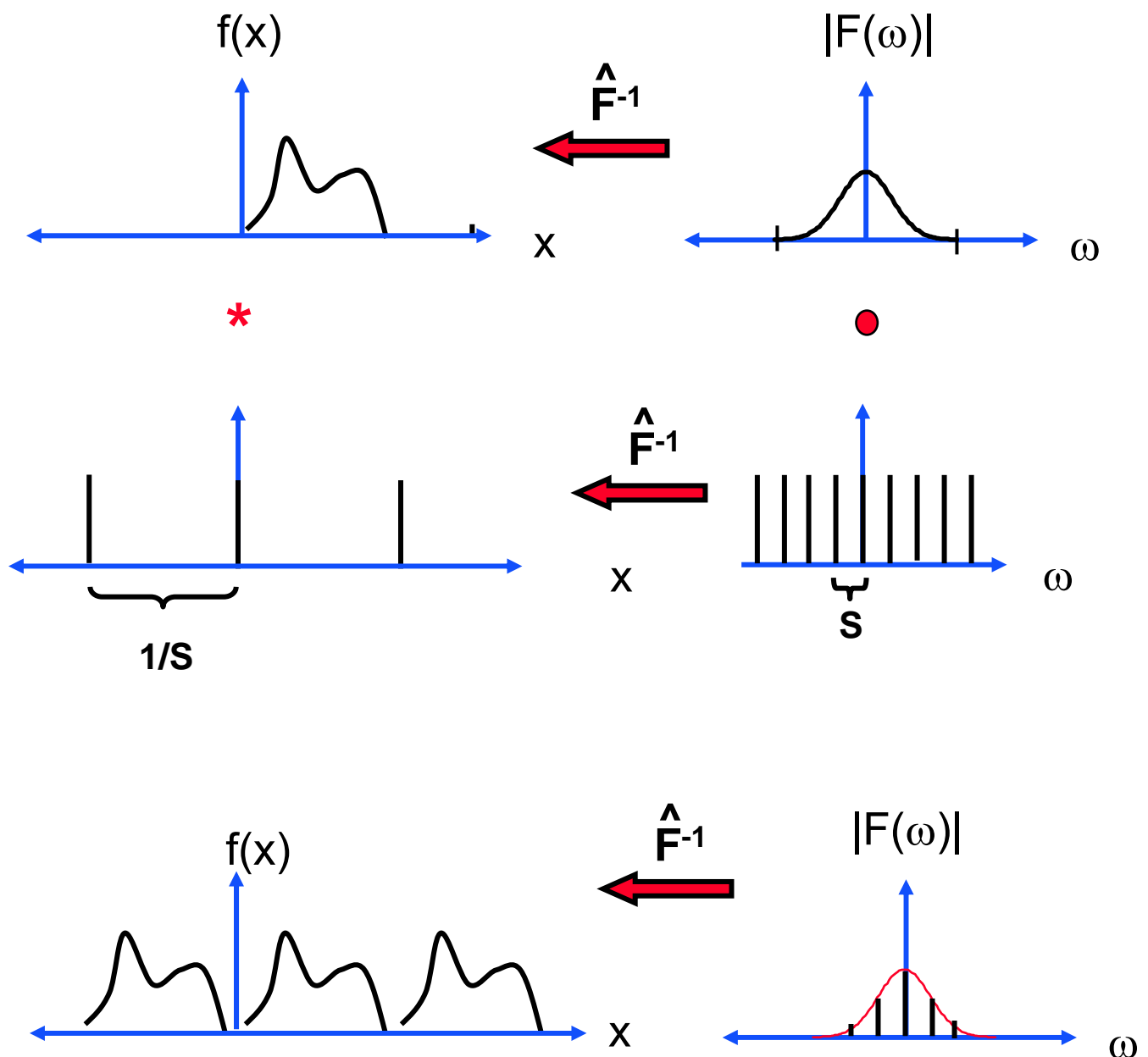
Sampling The Image

- Sampling a function $f(x)$ with impulse train of cycle T produces replicas in the frequency domain with cycle $1/T$:



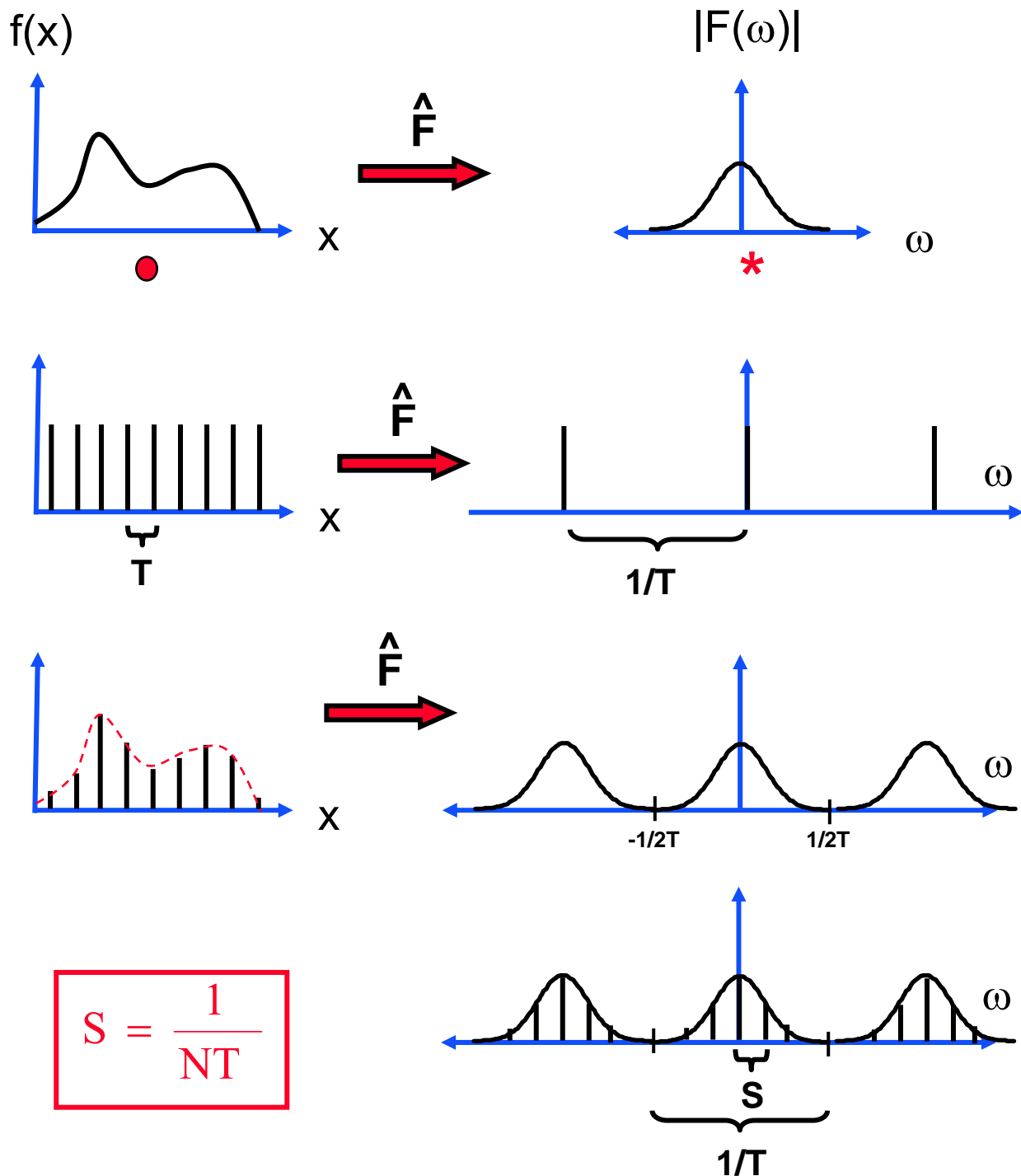
Sampling the Transform

- Sampling a function $F(\omega)$ with impulse train of cycle S produces replicas in the image domain with cycle $1/S$:

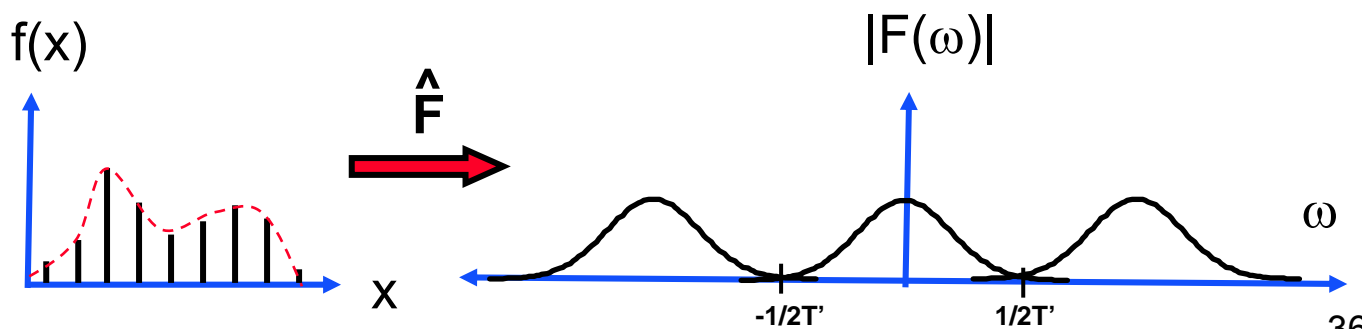
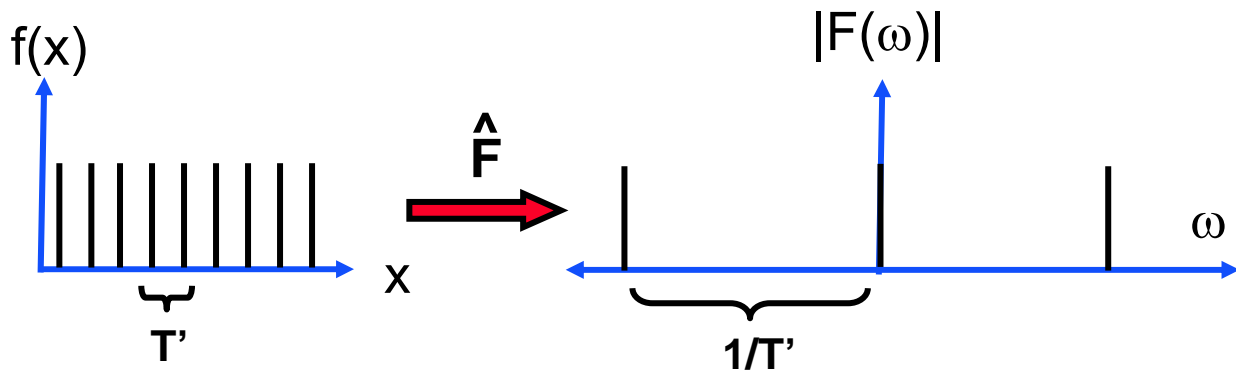
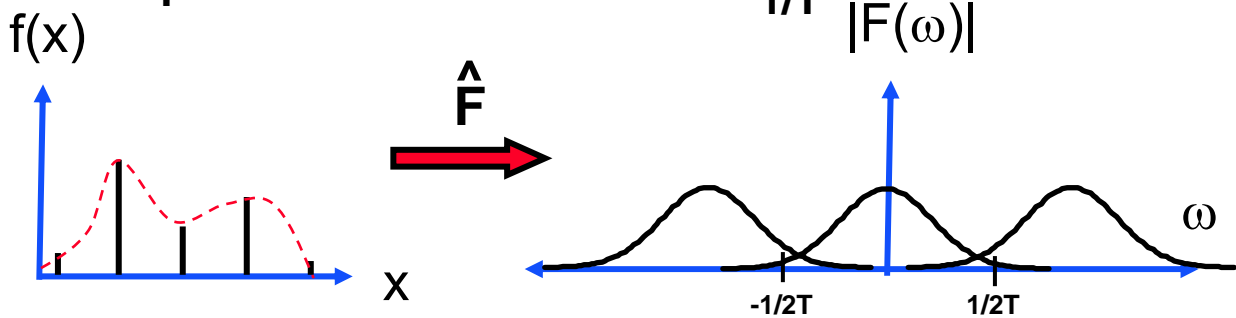
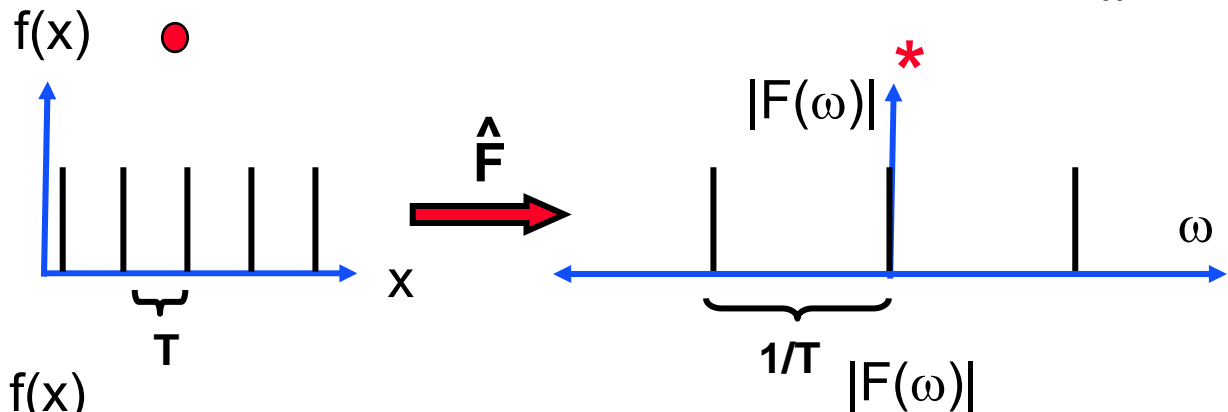
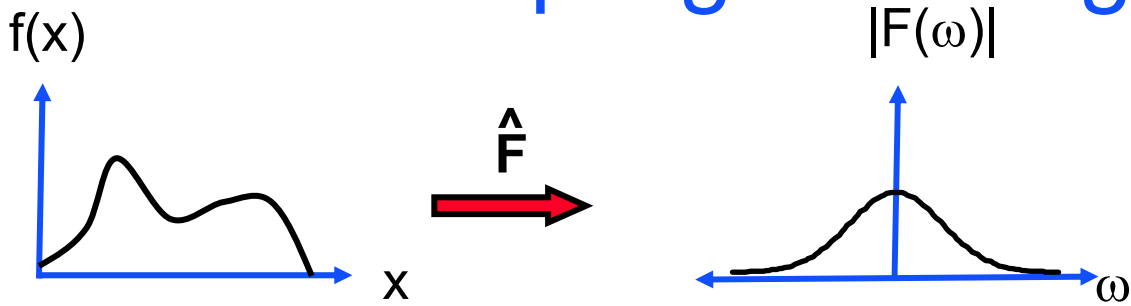


Sampling Image & Transform

- Sampling both $f(x)$ with impulse train of cycle T and $F(\omega)$ with impulse train of cycle S :



Undersampling the Image



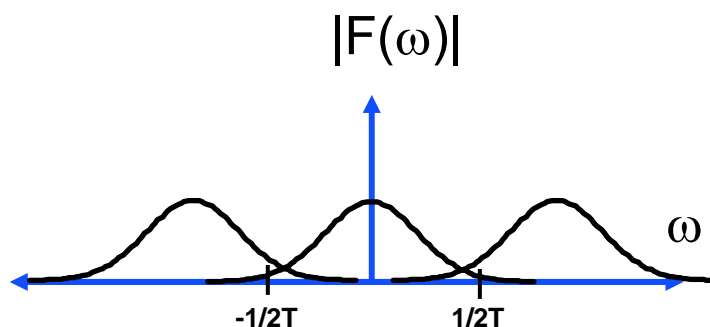
Critical Sampling

- 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:

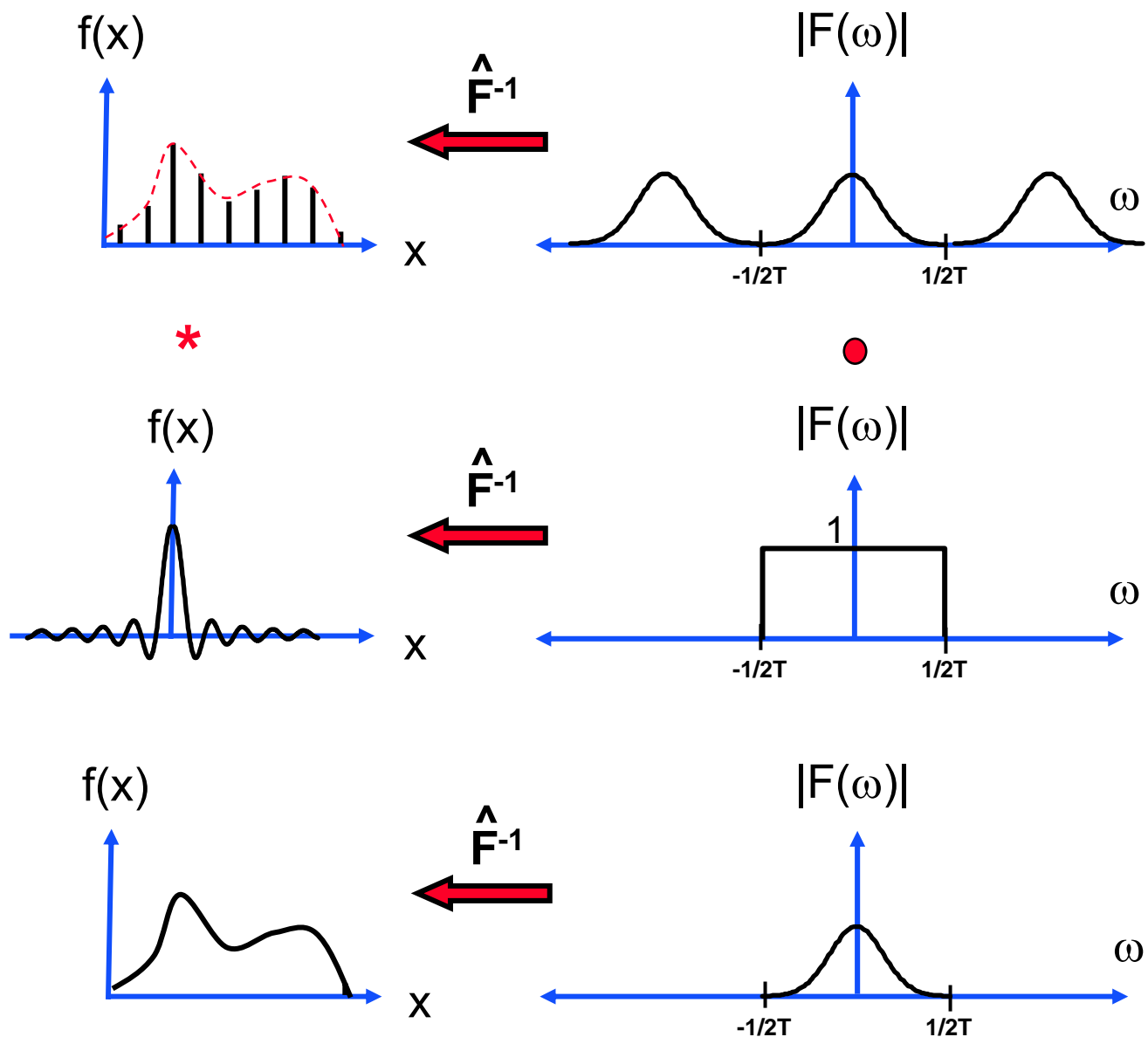
$$\frac{1}{T} > 2\omega_{\max}$$

- **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**.

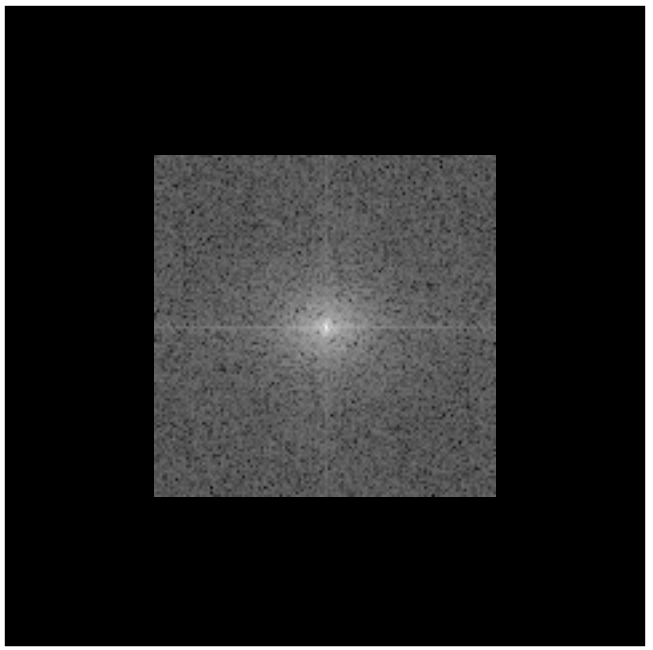
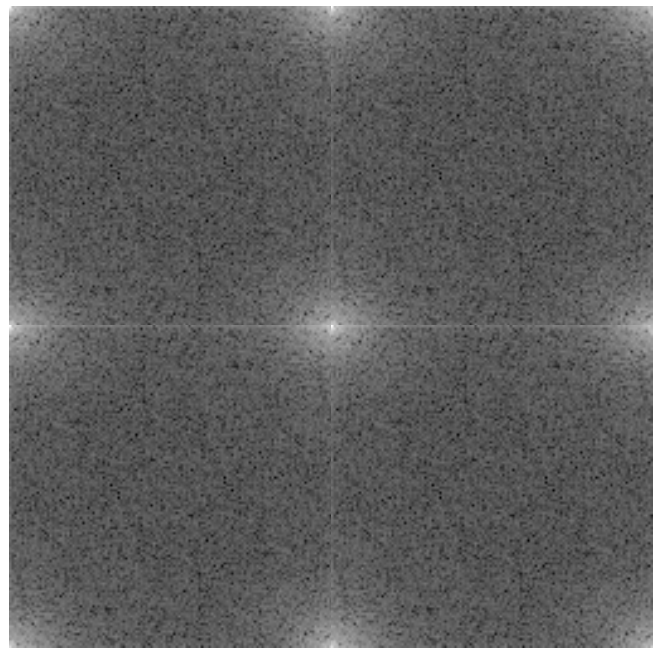
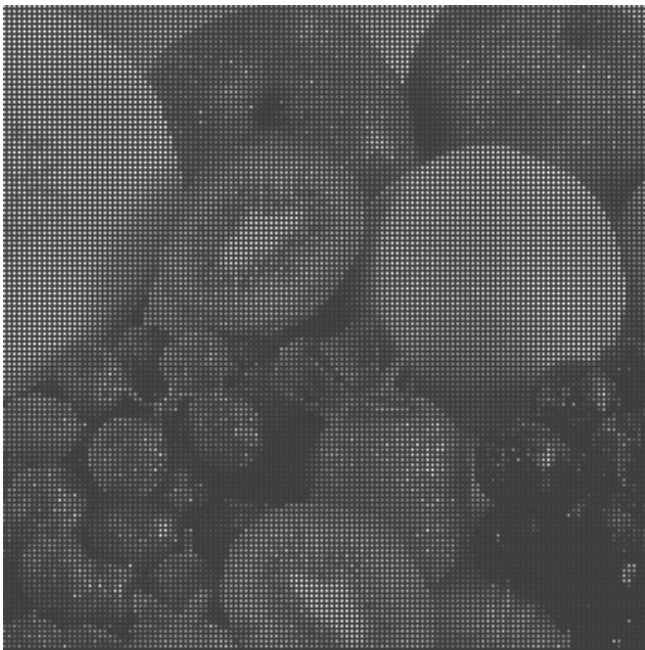
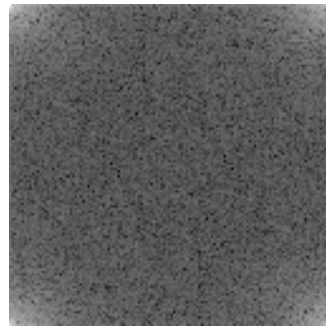
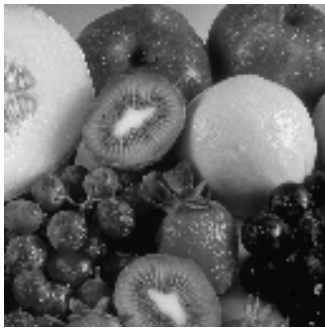


Optimal Interpolation

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



Optimal Interpolation- Example



Optimal Interpolation- Example

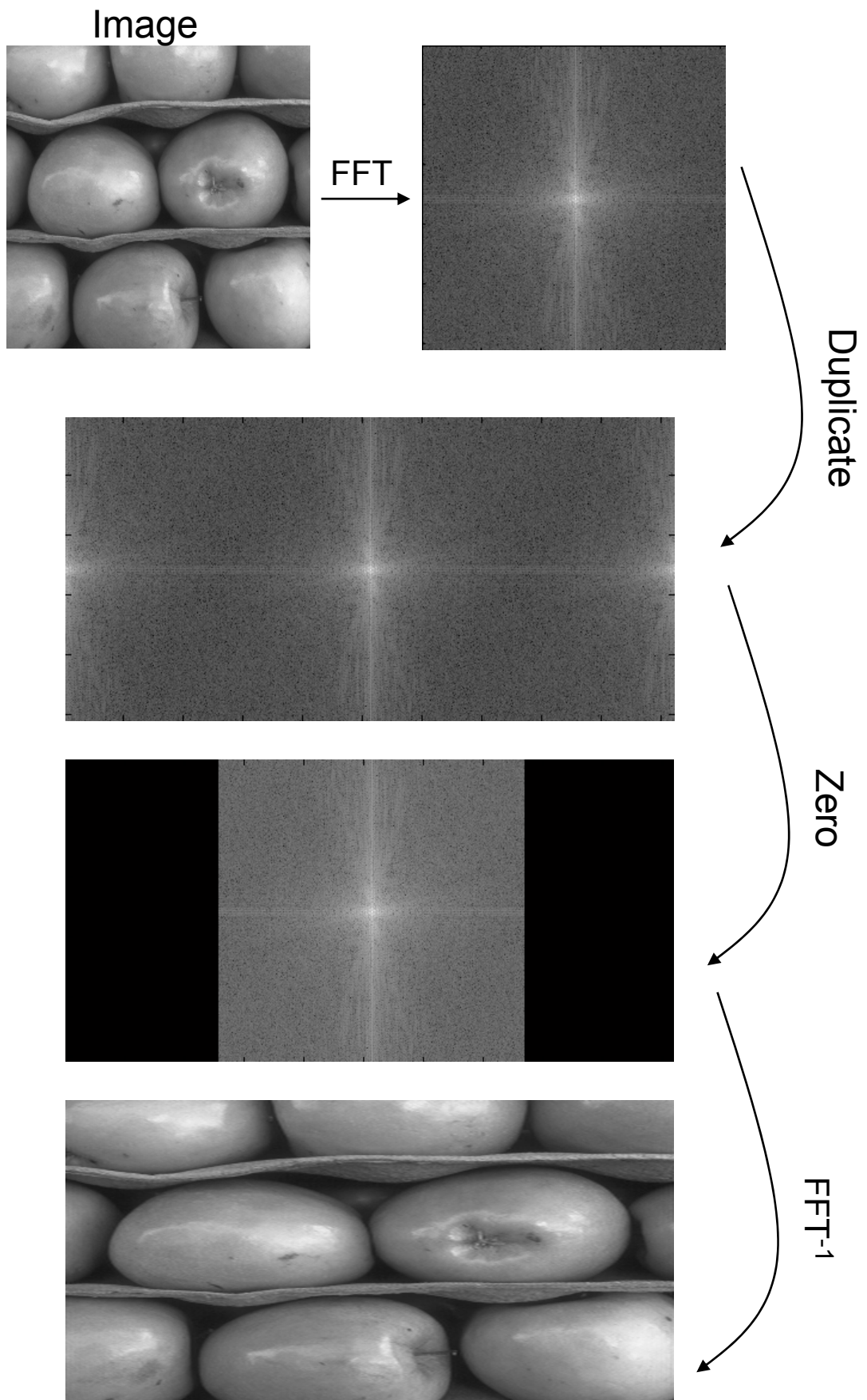
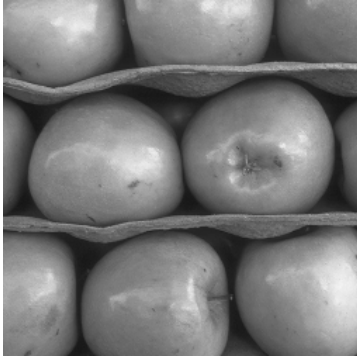
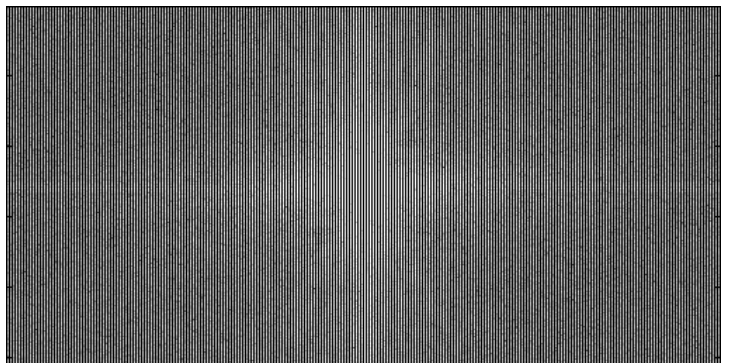
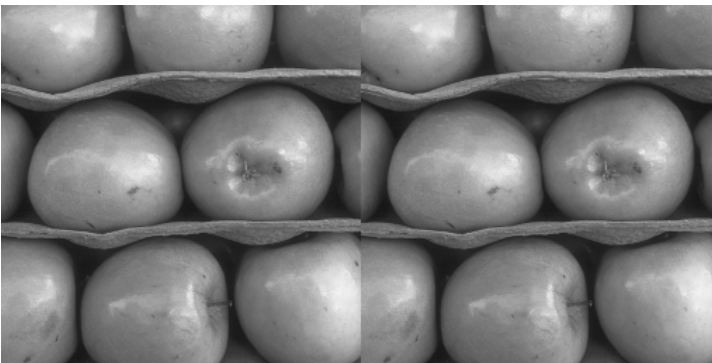
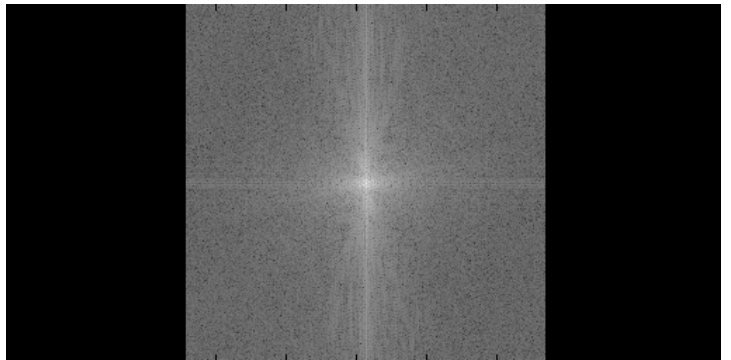
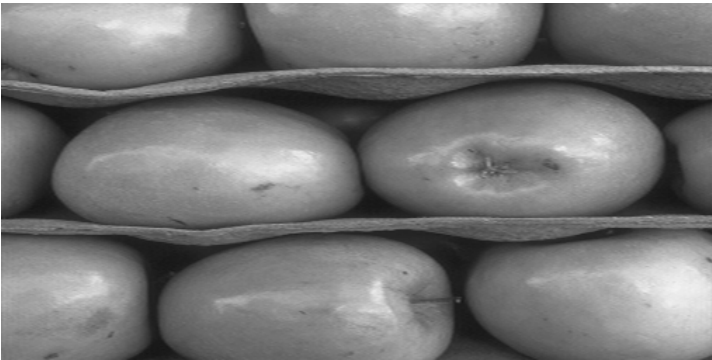
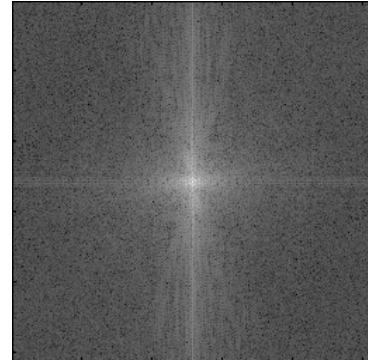


Image Domain



Frequency Domain



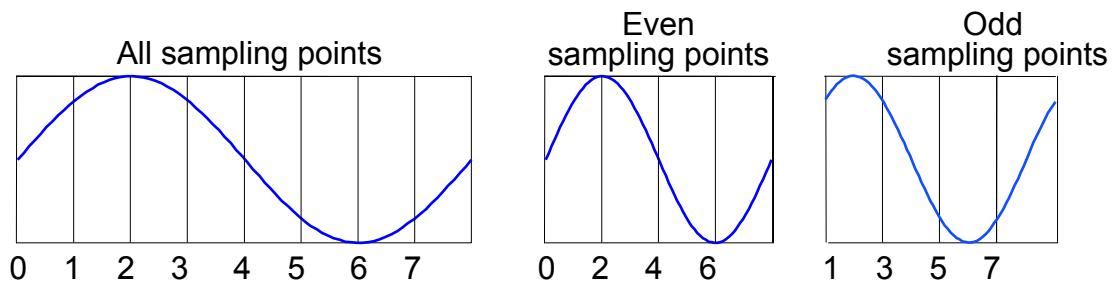
Fast Fourier Transform - FFT

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

$O(n^2)$ operations

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

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



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.

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

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

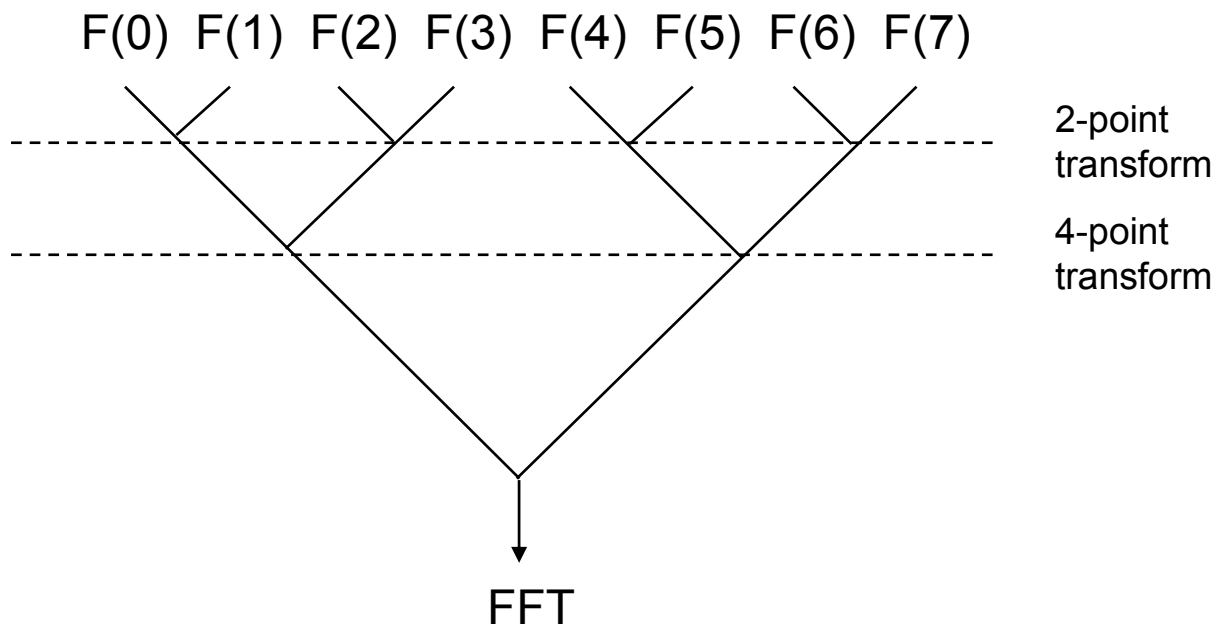
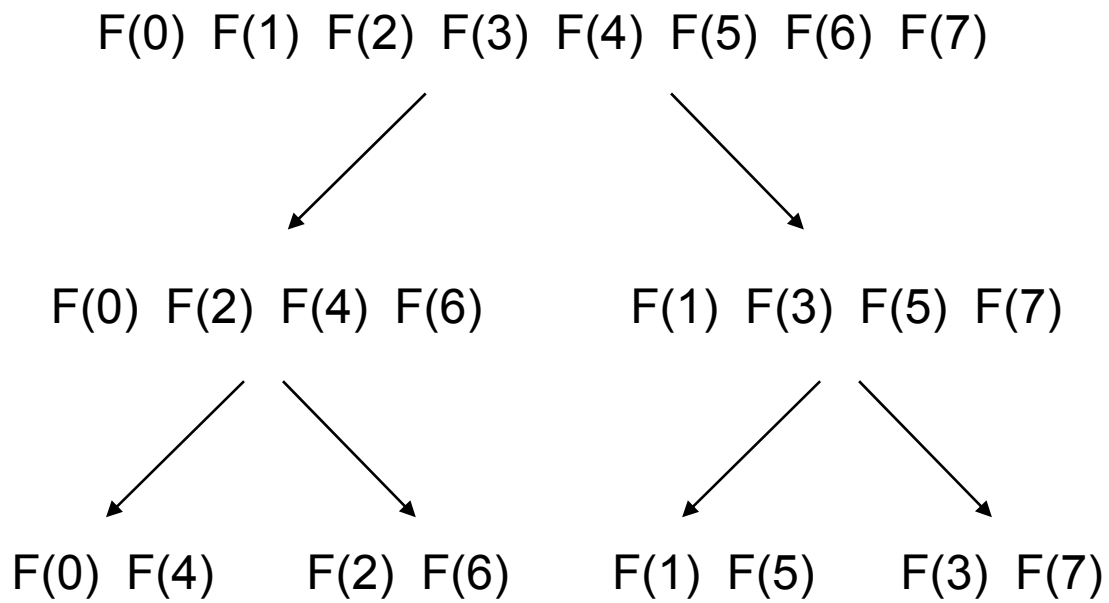
For $u' = u + N/2$: $e^{\frac{-2\pi i u'}{N}} = e^{\frac{-2\pi i (u + N/2)}{N}} = e^{\frac{-2\pi i u}{N}} e^{-\pi i} = -e^{\frac{-2\pi i u}{N}}$

obtain :

$$\left. \begin{aligned} F_N(u) &= \frac{1}{2} \left[F_{N/2}^e(u) + e^{\frac{-2\pi i u}{N}} F_{N/2}^o(u) \right] \\ F_N(u + \frac{N}{2}) &= \frac{1}{2} \left[F_{N/2}^e(u) - e^{\frac{-2\pi i u}{N}} F_{N/2}^o(u) \right] \end{aligned} \right\} \begin{array}{l} \text{For} \\ u = 0, 1, 2, \dots, N/2-1 \end{array}$$

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 $F_{N/4}^o(u)$.



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

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

Frequency Enhancement

