

Numerical Analysis – Digital Signal Processing

Hanyang University

Jong-Il Park

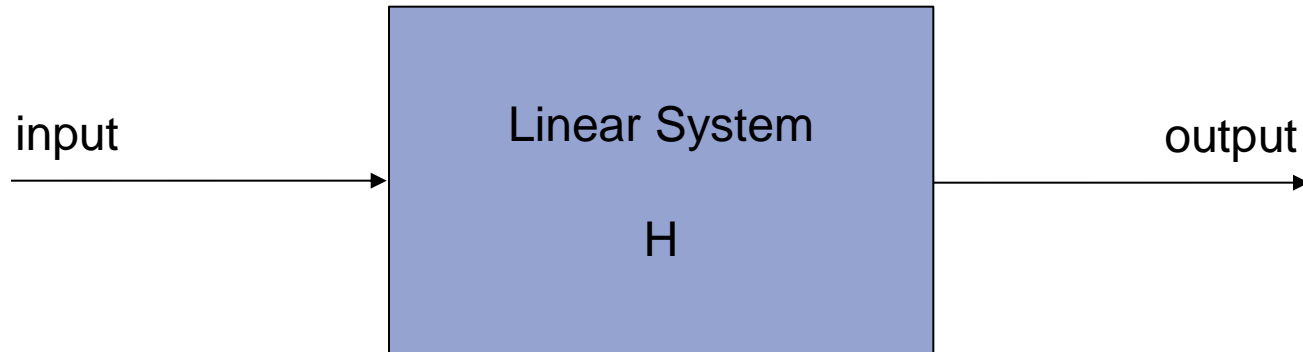


Digital Signal Processing

- Linear Systems
- Sampling and Reconstruction
- Convolution
- Discrete Fourier Transform
- Fast Fourier Transform(FFT)
- Multi-dimensional FFT



Linear Systems



A general [deterministic system](#) can be described by an operator, H , that maps an input, $x(t)$, as a function of t to an output, $y(t)$, a type of [black box](#) description. Linear systems satisfy the property of [superposition](#). Given two valid inputs

$$x_1(t)$$

$$x_2(t)$$

as well as their respective outputs

$$y_1(t) = H \{x_1(t)\}$$

$$y_2(t) = H \{x_2(t)\}$$

then a linear system must satisfy

$$\alpha y_1(t) + \beta y_2(t) = H \{\alpha x_1(t) + \beta x_2(t)\}$$

for any [scalar](#) values α and β .

[from Wikipedia]



Notation and definitions

■ One-dimensional signal

- ❖ Continuous signal : $f(x), u(x), s(t), \dots$
- ❖ Sampled signal : $u_n, u(n), \dots$

■ Two-dimensional signal

- ❖ Continuous signal : $u(x, y), v(x, y), f(x, y), \dots$
- ❖ Sampled signal : $u_{m,n}, v(m, n), u(i, j), \dots$
 - i, j, k, l, m, n, \dots are usually used to specify integer indices
- ❖ Separable form : $f(x, y) = f(x)f(y)$



Delta function

■ 2-D delta function

❖ Dirac : $\delta(x, y) = \delta(x)\delta(y)$

➤ Property

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x', y') \delta(x - x', y - y') dx' dy' = f(x, y),$$

$$\lim_{\varepsilon \rightarrow 0} \int_{-\varepsilon}^{\varepsilon} \int_{-\varepsilon}^{\varepsilon} \delta(x, y) dx dy = 1$$

➤ Scaling : $\delta(ax) = \delta(x) / |a|,$

$$\delta(ax, by) = \delta(x, y) / |ab|,$$

❖ Kronecker delta : $\delta(m, n) = \delta(m)\delta(n)$

➤ Property

$$x(m, n) = \sum_{m'=-\infty}^{\infty} \sum_{n'=-\infty}^{\infty} x(m', n') \delta(m - m', n - n'), \quad \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} \delta(m, n) = 1$$



Special signals

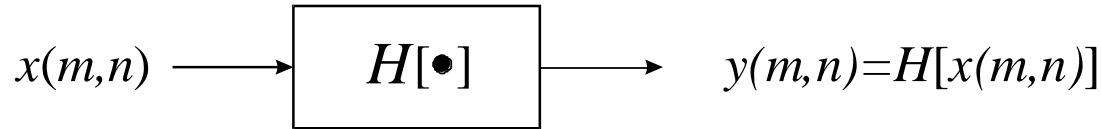
■ Some special signals(or functions)

TABLE 2.1 Some Special Functions

Function	Definition	Function	Definition
<i>Dirac delta</i>	$\delta(x) = 0, x \neq 0$	<i>Rectangle</i>	$\text{rect}(x) = \begin{cases} 1, & x \leq 1/2 \\ 0, & x > 1/2 \end{cases}$
	$\lim_{\epsilon \rightarrow 0} \int_{-\epsilon}^{\epsilon} \delta(x) dx = 1$	<i>Signum</i>	$\text{sgn}(x) = \begin{cases} 1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases}$
<i>Sifting property</i>	$\int_{-\infty}^{\infty} f(x') \delta(x - x') dx' = f(x)$	<i>Sinc</i>	$\text{sinc}(x) = \frac{\sin \pi x}{\pi x}$
<i>Scaling property</i>	$\delta(ax) = \frac{\delta(x)}{ a }$	<i>Comb</i>	$\text{comb}(x) = \sum_{n=-\infty}^{\infty} \delta(x - n)$
<i>Kronecker delta</i>	$\delta(n) = \begin{cases} 0, & n \neq 0 \\ 1, & n = 0 \end{cases}$	<i>Triangle</i>	$\text{tri}(x) = \begin{cases} 1 - x , & x \leq 1 \\ 0, & x > 1 \end{cases}$
<i>Sifting property</i>	$\sum_{m=-\infty}^{\infty} f(m) \delta(n - m) = f(n)$		



Linear and shift invariant systems



■ Linearity

$$\begin{aligned} H[a_1 x_1(m,n) + a_2 x_2(m,n)] &= a_1 H[x_1(m,n)] + a_2 H[x_2(m,n)] \\ &= a_1 y_1(m,n) + a_2 y_2(m,n), \text{ for } \forall a_1, a_2, x_1(\cdot), x_2(\cdot) \end{aligned}$$

• Output of linear systems

$$\begin{aligned} y(m,n) &= H[x(m,n)] = H\left[\sum_{m'} \sum_{n'} x(m',n') \delta(m-m', n-n')\right] \\ &= \sum_{m'} \sum_{n'} x(m',n') \underbrace{H[\delta(m-m', n-n')]}_{\text{impulse response, unit sample response, point spread function(PSF)}} \end{aligned}$$

by superposition

impulse response, unit sample response,
point spread function(PSF)

• Definition of impulse response

$$h(m,n;m',n') \equiv H[\delta(m-m', n-n')]$$



Shift invariance

■ Shift invariance

If $y(m, n) = H[x(m, n)]$ and $y(m - m_0, n - n_0) = H[x(m - m_0, n - n_0)]$, for $\forall m_0, n_0$ } definition of shift invariance
then, $h(m, n; m_0, n_0) = h(m - m_0, n - n_0)$

Output of LSI(linear shift invariant) systems

$$y(m, n) = \sum_{m'} \sum_{n'} x(m', n') h(m - m', n - n') \quad (2\text{-D convolution})$$

$$\begin{aligned} \because y(m, n) &= H[x(m, n)] = H\left[\sum_{m'} \sum_{n'} x(m', n') \delta(m - m', n - n')\right] && \text{by superposition of linearity} \\ &= \sum_{m'} \sum_{n'} x(m', n') H[\delta(m - m', n - n')] && \text{by definition of impulse response} \\ &= \sum_{m'} \sum_{n'} x(m', n') h(m, n; m', n') \\ &= \sum_{m'} \sum_{n'} x(m', n') h(m - m', n - n') && \text{by shift invariance} \end{aligned}$$



Stability

■ Stability

- ❖ Definition : bounded input, bounded output

$$\text{if } |x(m, n)| < \infty, \quad \text{then } |H[x(m, n)]| < \infty$$

- ❖ Stable LSI systems(necessary and sufficient condition)

$$\sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} |h(m, n)| < \infty$$



The Fourier transform

■ Definition

❖ 1-D Fourier transform

$$f(x) = \int_{-\infty}^{\infty} F(u) \exp(j2\pi ux) du$$

$$\Leftrightarrow F(u) = \int_{-\infty}^{\infty} f(x) \exp(-j2\pi ux) dx$$

❖ 2-D Fourier transform

$$f(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} F(u, v) \exp(j2\pi(xu + yv)) dudv$$

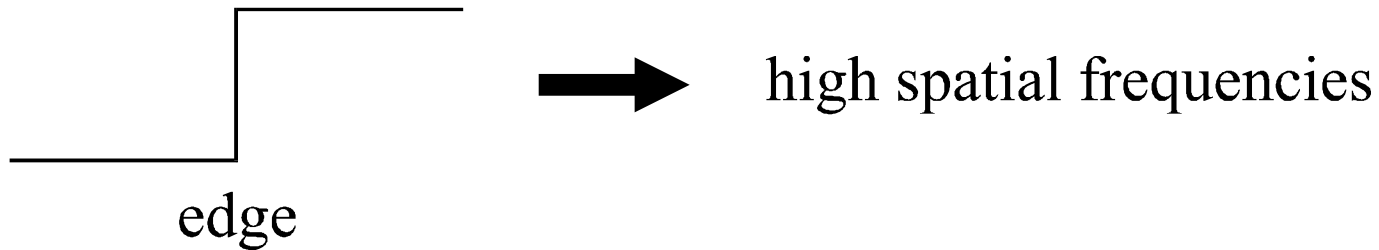
$$\Leftrightarrow F(u, v) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \exp(-j2\pi(ux + vy)) dx dy$$



Frequency domain

■ Properties

- ❖ $f(t) \rightarrow F(\omega)$; ω = angular frequency
- ❖ $f(x,y) \rightarrow F(u,v)$; u,v = spatial frequencies that represent the luminance change with respect to spatial distance



Properties of Fourier transform

❖ Uniqueness

- $f(x, y)$ and $F(u, v)$ are unique with respect to one another

❖ Separability

$$F(u, v) = \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} f(x, y) \exp(-j2\pi ux) dx \right] \exp(-j2\pi vy) dy$$

❖ Convolution theorem

$$g(x, y) = h(x, y) * f(x, y) \iff G(u, v) = H(u, v)F(u, v)$$



❖ Inner product preservation

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) h^*(x, y) dx dy = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} F(u, v) H^*(u, v) du dv$$

Setting $h=f$, Parseval energy conservation formula

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |f(x, y)|^2 dx dy = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |F(u, v)|^2 du dv$$

❖ Hankel transform : polar coordinate form of FT

$$F_p(\xi, \phi) \equiv F(\xi \cos \phi, \xi \sin \phi)$$

$$= \int_0^{2\pi} \int_0^{\infty} f_p(r, \theta) \exp[-j2\pi r \xi \cos(\theta - \phi)] r dr d\theta$$

where $f_p(r, \theta) = f(r \cos \theta, r \sin \theta)$



Fourier series

■ 1-D case

$$x(n) = \int_{-0.5}^{0.5} X(u) \exp(-j2\pi nu) du$$

$$\Leftrightarrow X(u) = \sum_{n=-\infty}^{\infty} x(n) \exp(-j2\pi nu), \quad -0.5 \leq u < 0.5$$



2D Fourier series

■ 2-D case

$$x(m, n) = \int_{-0.5}^{0.5} \int_{-0.5}^{0.5} X(u, v) \exp(j2\pi(mu_1 + nv)) du dv$$

$$\Leftrightarrow X(u, v) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} x(m, n) \exp(-j2\pi(mu + nv)), \quad -0.5 \leq u, v < 0.5$$

❖ $X(u, v)$ is periodic : period = 1

$$X(u, v) = X(u \pm k, v \pm l), \quad k, l = 0, 1, 2, \dots$$

❖ Sufficient condition for existence of $X(u, v)$

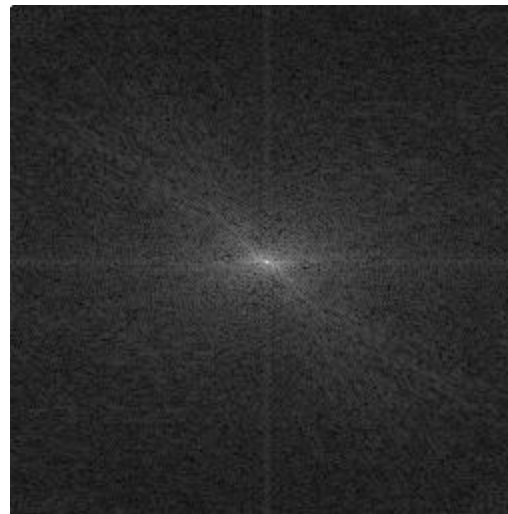
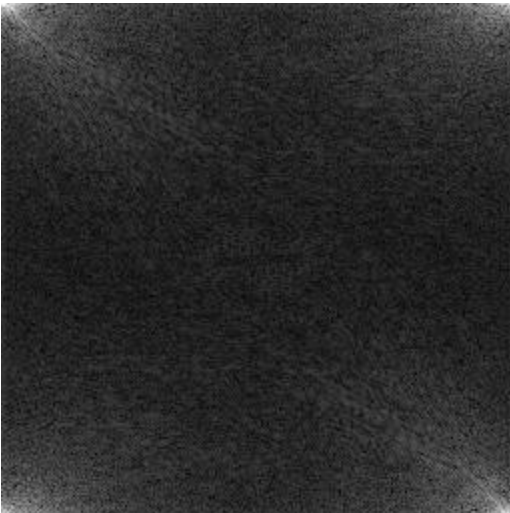
$$\begin{aligned} |X(u, v)| &= \left| \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} x(m, n) \exp(-j2\pi(mu + nv)) \right| \\ &\leq \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} |x(m, n)| |\exp(-j2\pi(mu + nv))| \leq \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} |x(m, n)| < \infty \end{aligned}$$



Eg. 2D Fourier transform



original 256x256 lena



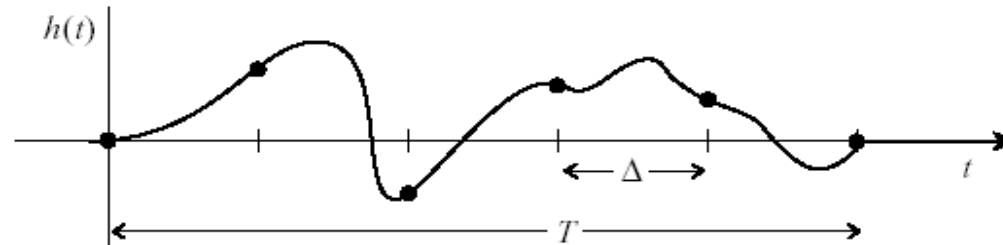
normalized spectrum
(log-scale)

TABLE 2.4 Properties and Examples of Fourier Transform of Two-Dimensional Sequences

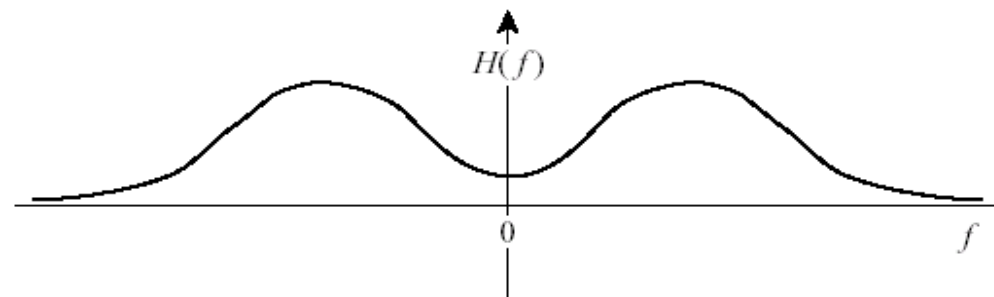
Property	Sequence	Transform
	$x(m, n), y(m, n), h(m, n), \dots$	$X(\omega_1, \omega_2), Y(\omega_1, \omega_2), H(\omega_1, \omega_2), \dots$
Linearity	$a_1 x_1(m, n) + a_2 x_2(m, n)$	$a_1 X_1(\omega_1, \omega_2) + a_2 X_2(\omega_1, \omega_2)$
Conjugation	$x^*(m, n)$	$X^*(-\omega_1, -\omega_2)$
Separability	$x_1(m) x_2(n)$	$X_1(\omega_1) X_2(\omega_2)$
Shifting	$x(m \pm m_0, n \pm n_0)$	$\exp[\pm j(m_0 \omega_1 + n_0 \omega_2)] X(\omega_1, \omega_2)$
Modulation	$\exp[\pm j(\omega_{01} m + \omega_{02} n)] x(m, n)$	$X(\omega_1 \mp \omega_{01}, \omega_2 \mp \omega_{02})$
Convolution	$y(m, n) = h(m, n) \circledast x(m, n)$	$Y(\omega_1, \omega_2) = H(\omega_1, \omega_2) X(\omega_1, \omega_2)$
Multiplication	$h(m, n) x(m, n)$	$\left(\frac{1}{4\pi^2}\right) H(\omega_1, \omega_2) \circledast X(\omega_1, \omega_2)$
Spatial correlation	$c(m, n) = h(m, n) \star x(m, n)$	$C(\omega_1, \omega_2) = H(-\omega_1, -\omega_2) X(\omega_1, \omega_2)$
Inner product	$I = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} x(m, n) y^*(m, n)$	$I = \frac{1}{4\pi^2} \int_{-\pi}^{\pi} \int_{-\pi}^{\pi} X(\omega_1, \omega_2) Y^*(\omega_1, \omega_2) d\omega_1 d\omega_2$
Energy conservation	$\mathcal{E} = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} x(m, n) ^2$	$\mathcal{E} = \frac{1}{4\pi^2} \int_{-\pi}^{\pi} \int_{-\pi}^{\pi} X(\omega_1, \omega_2) ^2 d\omega_1 d\omega_2$
	$\sum_{m, n=-\infty}^{\infty} \exp[j(m\omega_{01} + n\omega_{02})]$	$4\pi^2 \delta(\omega_1 - \omega_{01}, \omega_2 - \omega_{02})$
	$\delta(m, n)$	$\frac{1}{4\pi^2} \int_{-\pi}^{\pi} \int_{-\pi}^{\pi} \exp[-j(\omega_1 m + \omega_2 n)] d\omega_1 d\omega_2$



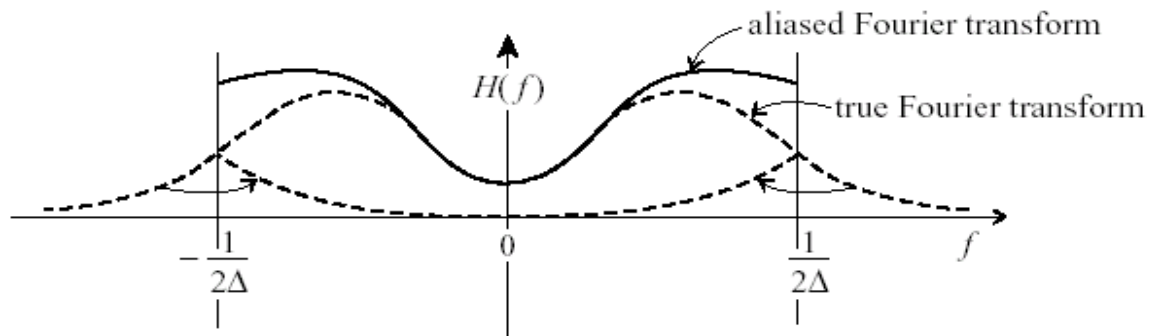
Sampling and aliasing



(a)



(b)

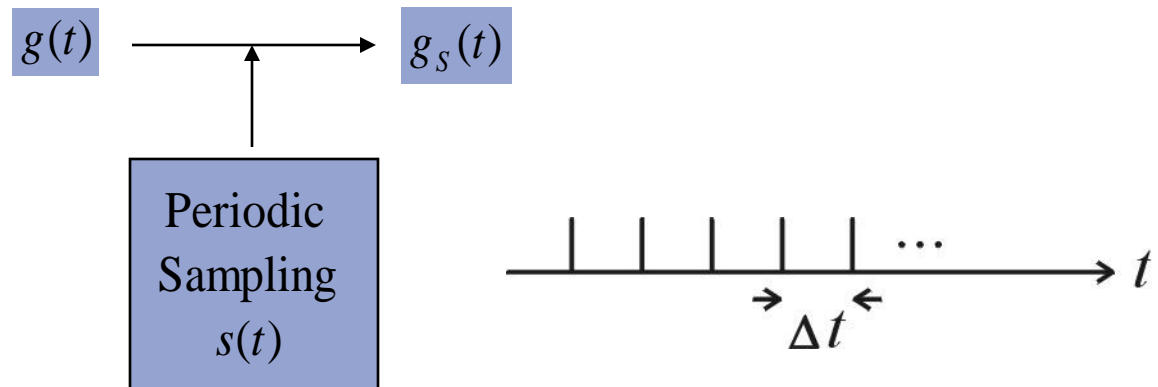


(c)



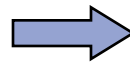
Sampling Theory

■ For One-Dimensional Signal



$$g_s(t) = g(t) \bullet s(t)$$

$$\text{where } s(t) = \sum_m \delta(t - m\Delta t)$$



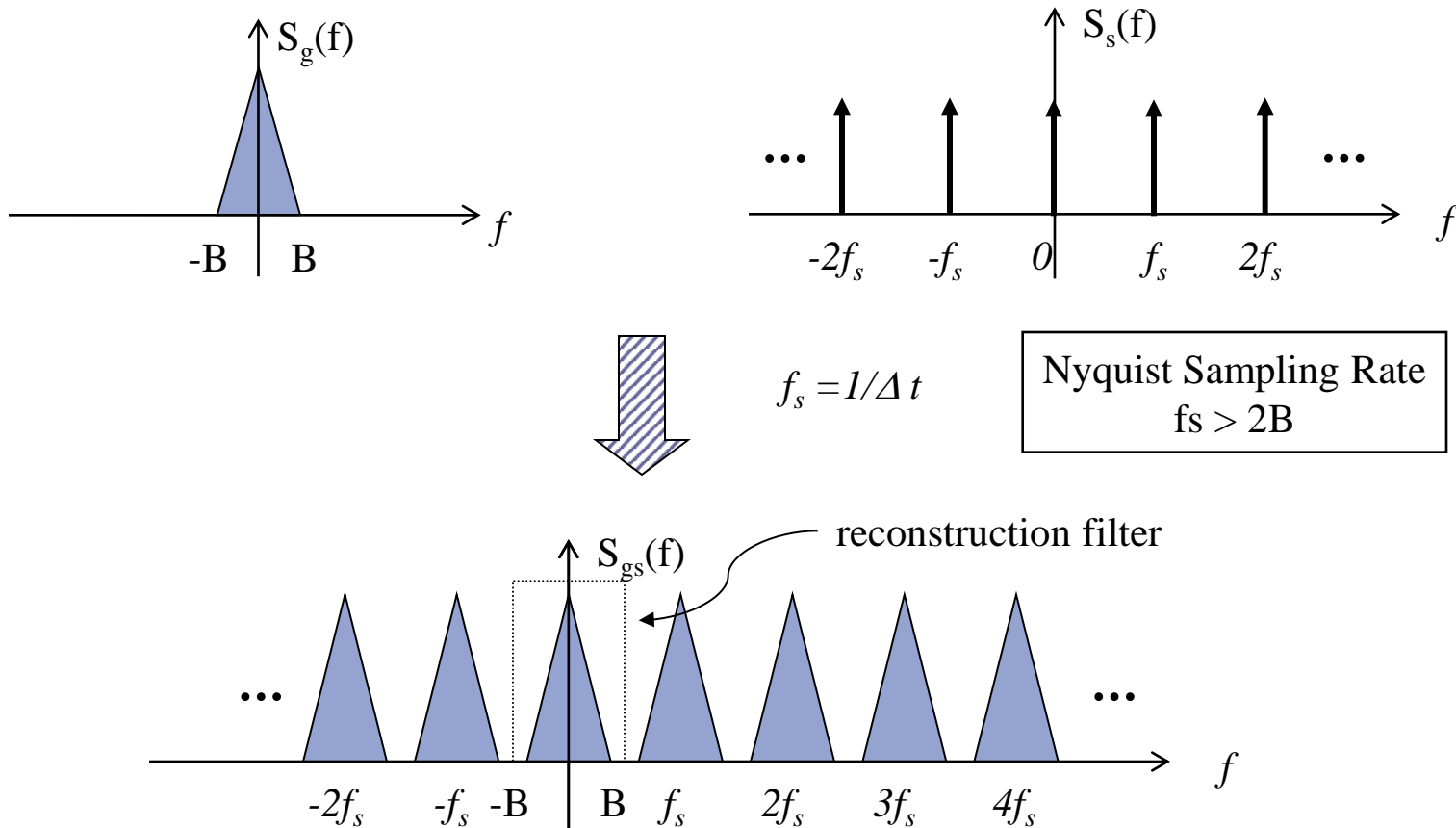
$$S_{g_s}(f) = S_g(f) \otimes S_s(f)$$

(Fourier Transform)



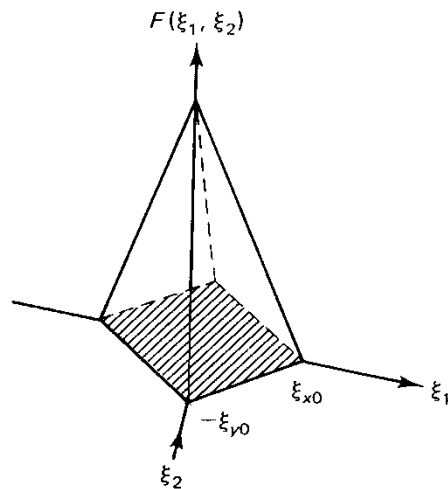
Sampling Theory (cont.)

■ For One-Dimensional Signal (cont.)

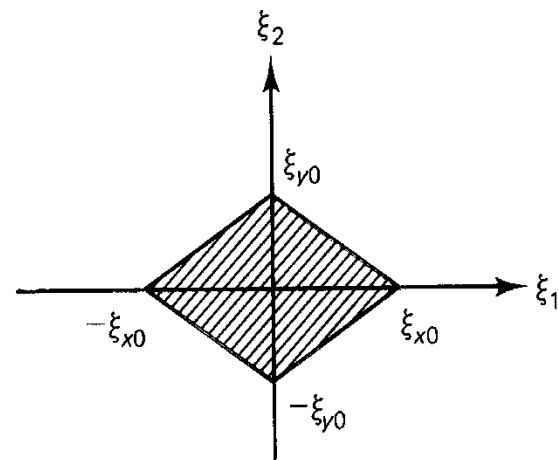


Sampling Theory(cont.)

- For Two-Dimensional Signal
 - ❖ Band-limited Image



Fourier Transform of
a bandlimited function



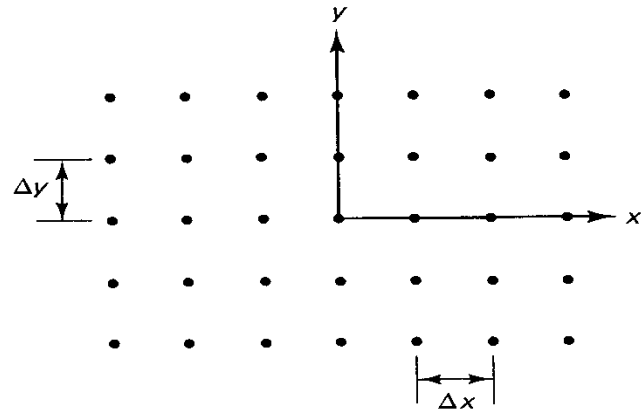
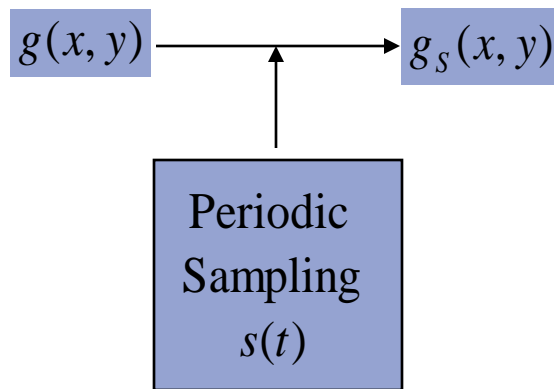
Its region of support

Sampling Theory (cont.)

■ For Two-Dimensional Signal (cont.)

❖ Structure

- Orthogonal Structure (Rectangular Tessellation)
- Field Quincunx Structure (Triangular Tessellation)



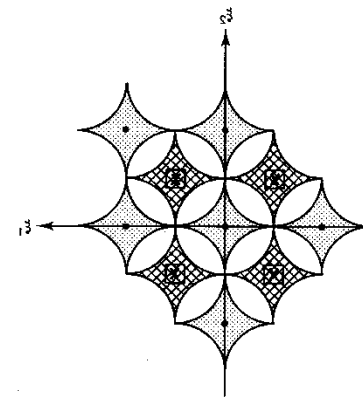
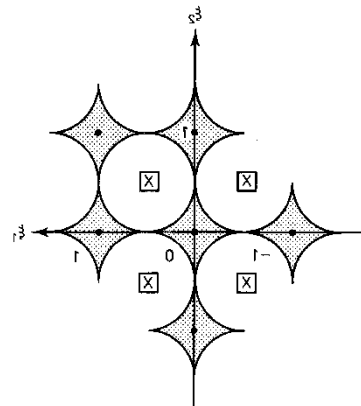
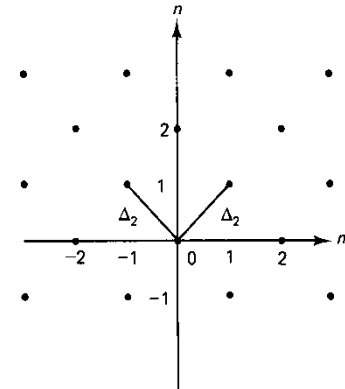
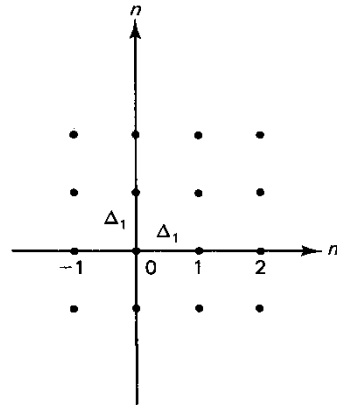
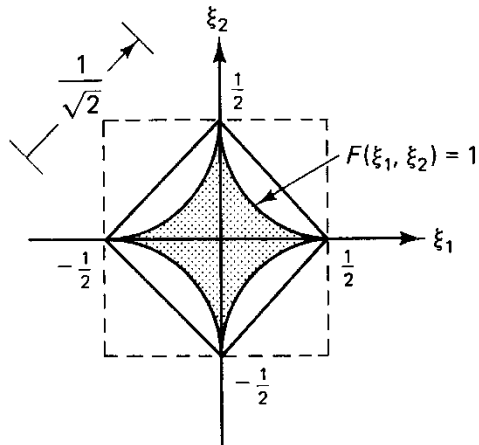
$$g_s(x, y) = g(x, y) \bullet s(x, y) \quad \Rightarrow \quad S_{g_s}(u, v) = S_g(u, v) \otimes S_s(u, v)$$

(Fourier Transform)



Sampling Theory(cont.)

- For Two-Dimensional Signal(cont.)
 - ❖ Structure(cont.)



2D sampling

- For Two-Dimensional Signal (cont.)
 - ❖ Orthogonal Structure (Rectangular Tessellation)

$$g_s(x, y) = g(x, y) \bullet s(x, y) \implies S_{g_s}(u, v) = S_g(u, v) \otimes S_s(u, v)$$

(Fourier Transform)

- Sampling Function

$$s(x, y) = \sum_n \sum_m \delta(x - m\Delta x, y - n\Delta y)$$

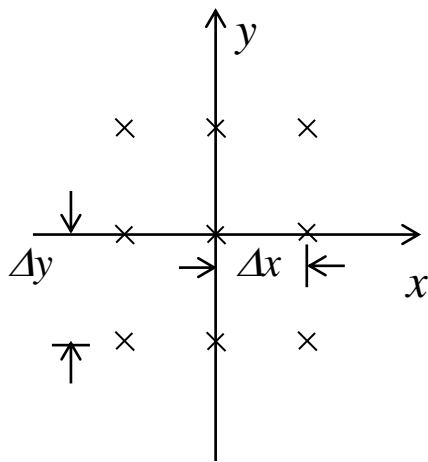
$$S_s(u, v) = \Delta u \Delta v \sum_k \sum_l \delta(u - k\Delta u, v - l\Delta v)$$

$$\text{where } \Delta u = \frac{1}{\Delta x}, \quad \Delta v = \frac{1}{\Delta y}$$

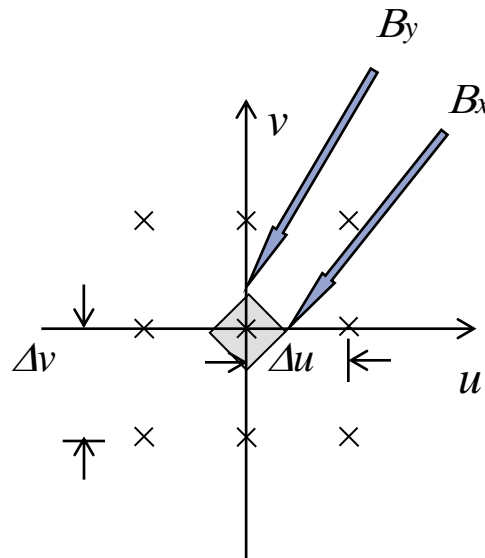


2D sampling - Spectrum

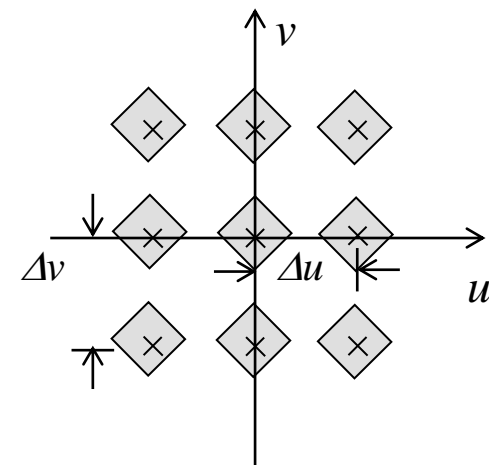
- For Two-Dimensional Signal (cont.)
 - ❖ Orthogonal Structure (cont.)
 - Spectrum of sampled signals



(a) sampling function



(b) spectrum of sampling function and signal



(c) spectrum of sampled signal

2D sampling - Reconstruction

■ For Two-Dimensional Signal(cont.)

❖ Orthogonal Structure(cont.)

- Reconstruction of the original image from its samples

If $2B_x < \Delta u$ and $2B_y < \Delta v$, then

$$H(u, v) = \begin{cases} \Delta x \Delta y = \frac{1}{\Delta u \Delta v}, & (u, v) \in \mathfrak{R} \\ 0, & \text{otherwise} \end{cases}$$

$$g(x, y) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} g_s(m, n) \left(\frac{\sin(x\Delta u - m)\pi}{(x\Delta u - m)\pi} \right) \left(\frac{\sin(y\Delta v - n)\pi}{(y\Delta v - n)\pi} \right)$$

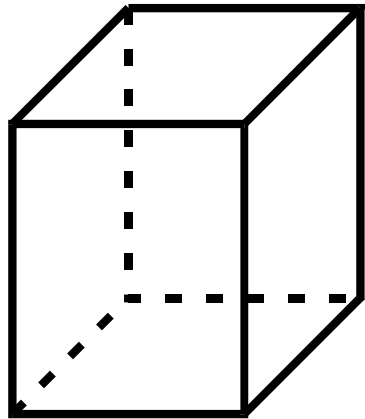
- Nyquist Sampling Rate(or Frequency) and Nyquist Interval

$$\Delta u_{\text{Nyquist}} = 2B_x, \Delta v_{\text{Nyquist}} = 2B_y, \\ \Delta x_{\text{Nyquist}} = \frac{1}{\Delta u_{\text{Nyquist}}} = \frac{1}{2B_x}, \Delta y_{\text{Nyquist}} = \frac{1}{\Delta v_{\text{Nyquist}}} = \frac{1}{2B_y},$$

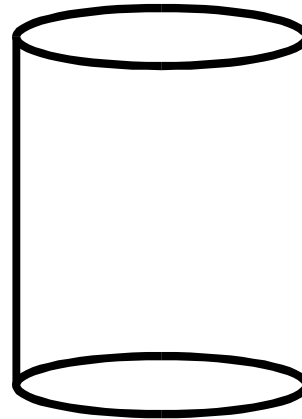


Reconstruction Filter

rectangular filter



cylindrical filter



$$h_r(x, y) = K \left(\frac{\sin \omega_x x}{\omega_x x} \right) \left(\frac{\sin \omega_y y}{\omega_y y} \right)$$

$$h_c(x, y) = \frac{2\pi\omega_0 J_1(\omega_0 \sqrt{x^2 + y^2})}{\sqrt{x^2 + y^2}}$$

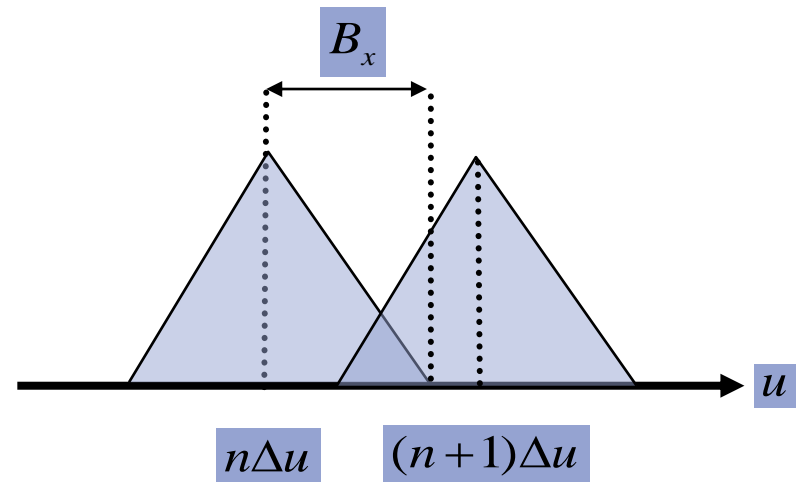
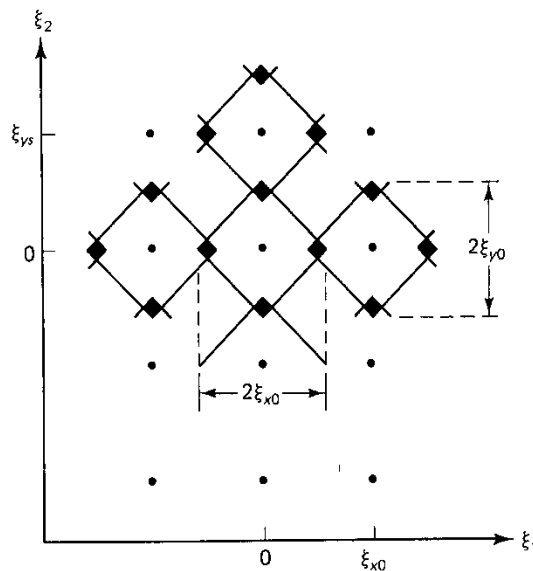
where $J_1(\cdot)$ is a first-order Bessel function

Aliasing effect

- For Two-Dimensional Signal(cont.)
 - ❖ Orthogonal Structure(cont.)
 - Aliasing Effect

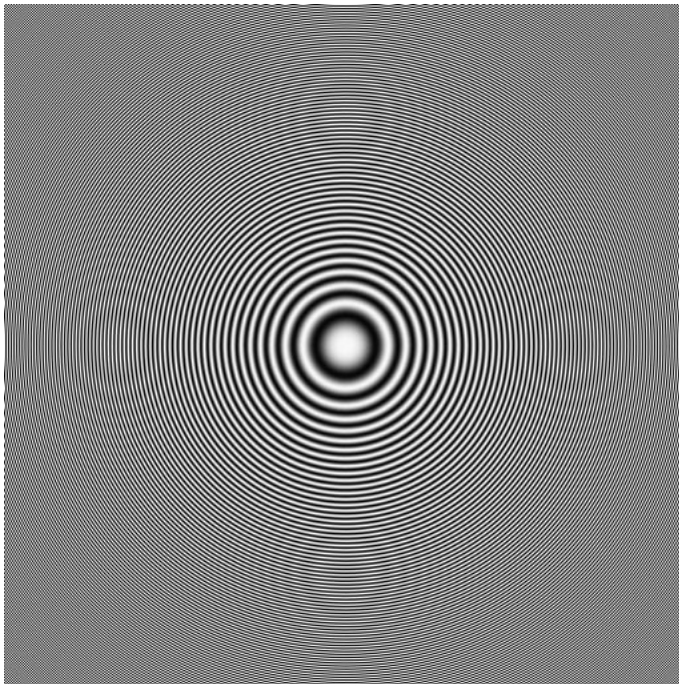
If $\Delta u < \Delta u_{Nyquist}$ or $\Delta v < \Delta v_{Nyquist}$, then

the original image cannot be reconstructed from its samples.

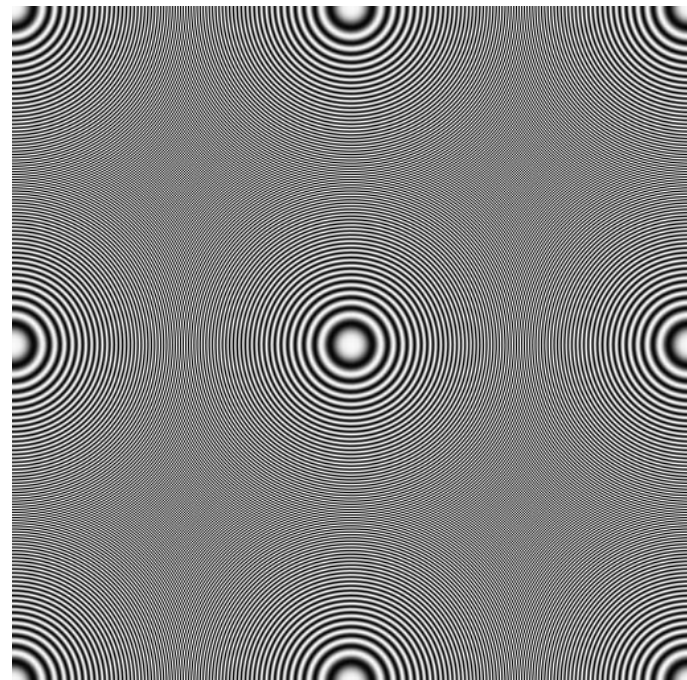


Eg. Aliasing

- For Two-Dimensional Signal (cont.)
 - ❖ Orthogonal Structure (cont.)
 - Aliasing Effect (cont.)



Zone Plate image ($\alpha = 1$)



Aliasing ($\alpha = 2$)

Eg. Aliasing

■ Examples



Little aliasing due to an effective antialiasing filter



Noticeable aliasing

Practical limitations in sampling

■ Practical Limitations

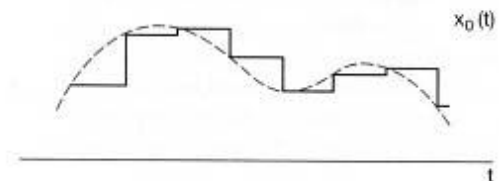
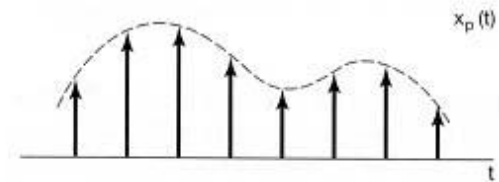
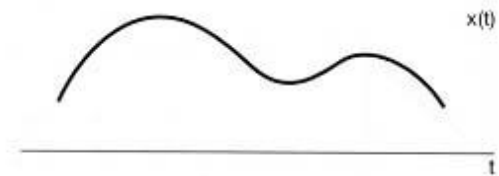
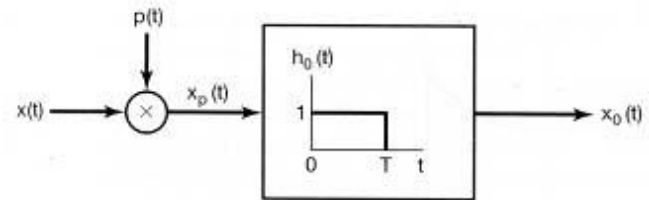
- ❖ Real-world images are not band-limited.
 - aliasing errors
 - can be reduced by LPF before sampling
 - LPF attenuate higher spatial frequencies
 - Resolution loss
 - blurring
- ❖ No ideal LPF at reconstruction stage.



Sampling aperture

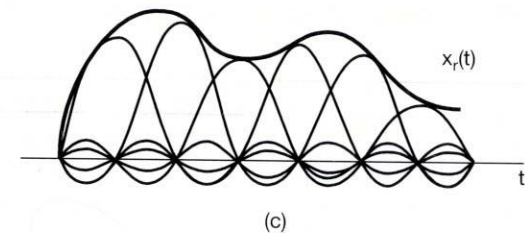
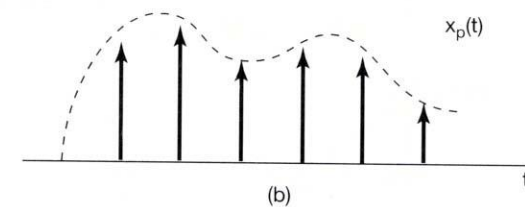
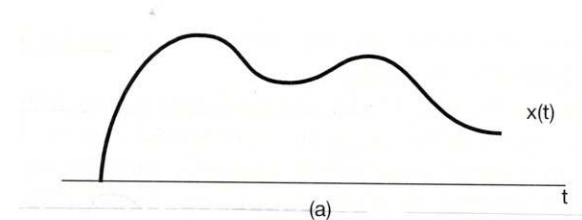
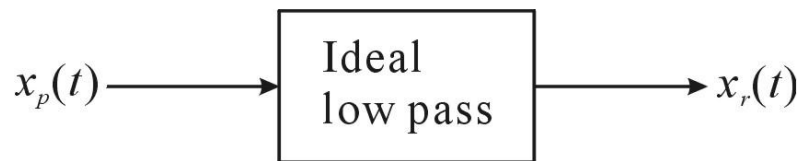
- Finite aperture (finite duration pulse)

$$H_0(\omega) = e^{-j\omega T/2} \left[\frac{2 \sin(\omega T/2)}{\omega} \right]$$



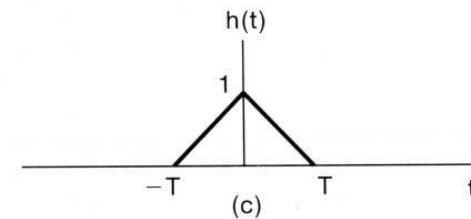
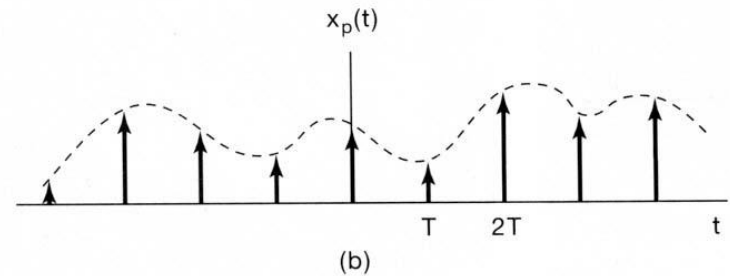
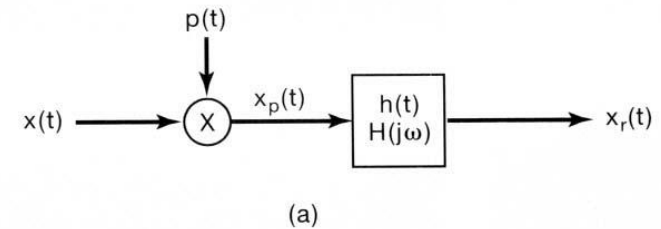
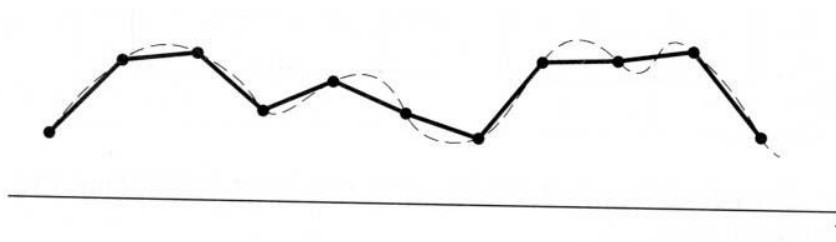
Reconstruction

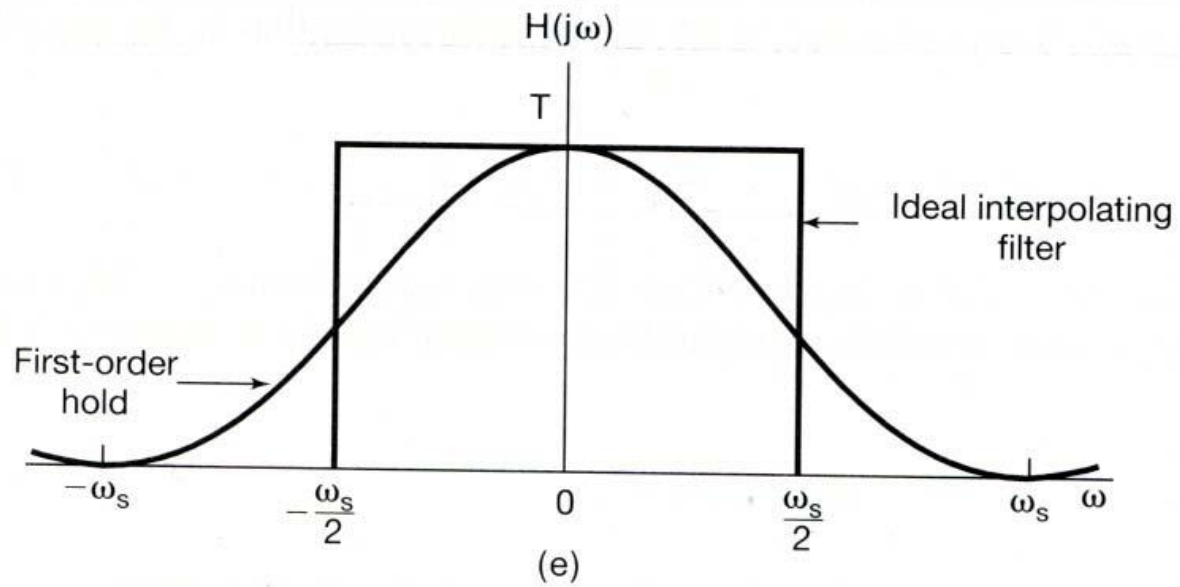
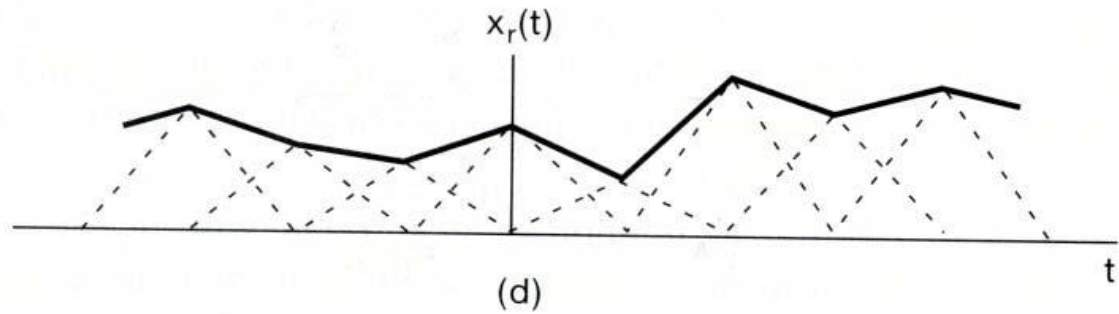
- Reconstruction of a signal from its sample using interpolation



Linear interpolation

■ linear interpolation





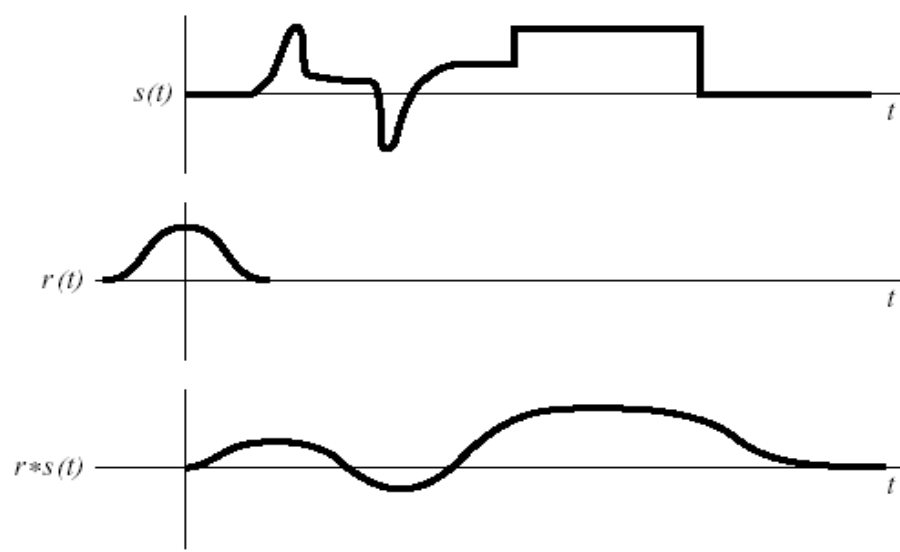
Sampling Theory(cont.)

One-dimensional interpolation function	Diagram	Definition $p(x)$	Two-dimensional interpolation function $p_d(x, y) = p(x)p(y)$	Frequency response $P_d(\xi_1, \xi_2)$	$P_d(\xi_1, 0)$
Rectangle (zero-order hold) ZOH $p_0(x)$		$\frac{1}{\Delta x} \text{rect}\left(\frac{x}{\Delta x}\right)$	$p_0(x)p_0(y)$	$\text{sinc}\left(\frac{\xi_1}{2\xi_{x0}}\right)\text{sinc}\left(\frac{\xi_2}{2\xi_{y0}}\right)$	
Triangle (first-order hold) FOH $p_1(x)$		$\frac{1}{\Delta x} \text{tri}\left(\frac{x}{\Delta x}\right)$ $p_0(x) \odot p_0(x)$	$p_1(x)p_1(y)$	$\left[\text{sinc}\left(\frac{\xi_1}{2\xi_{x0}}\right)\text{sinc}\left(\frac{\xi_2}{2\xi_{y0}}\right)\right]^2$	
nth-order hold $n = 2$, quadratic $n = 3$, cubic splines $p_n(x)$		$p_0(x) \odot \dots \odot p_0(x)$ n convolutions	$p_n(x)p_n(y)$	$\left[\text{sinc}\left(\frac{\xi_1}{\xi_{x0}}\right)\text{sinc}\left(\frac{\xi_2}{\xi_{y0}}\right)\right]^{n+1}$	
Gaussian $p_g(x)$		$\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{x^2}{2\sigma^2}\right]$	$\frac{1}{2\pi\sigma^2} \exp\left[-\frac{(x^2 + y^2)}{2\sigma^2}\right]$	$\exp[-2\pi^2\sigma^2(\xi_1^2 + \xi_2^2)]$	
Sinc		$\frac{1}{\Delta x} \text{sinc}\left(\frac{x}{\Delta x}\right)$	$\frac{1}{\Delta x \Delta y} \text{sinc}\left(\frac{x}{\Delta x}\right)\text{sinc}\left(\frac{y}{\Delta y}\right)$	$\text{rect}\left(\frac{\xi_1}{2\xi_{x0}}\right)\text{rect}\left(\frac{\xi_2}{2\xi_{y0}}\right)$	

Convolution(I)

■ Def.

$$g * h \equiv \int_{-\infty}^{\infty} g(\tau) h(t - \tau) d\tau$$



Convolution(II)

■ Convolution theorem

$$g * h \iff G(f)H(f)$$

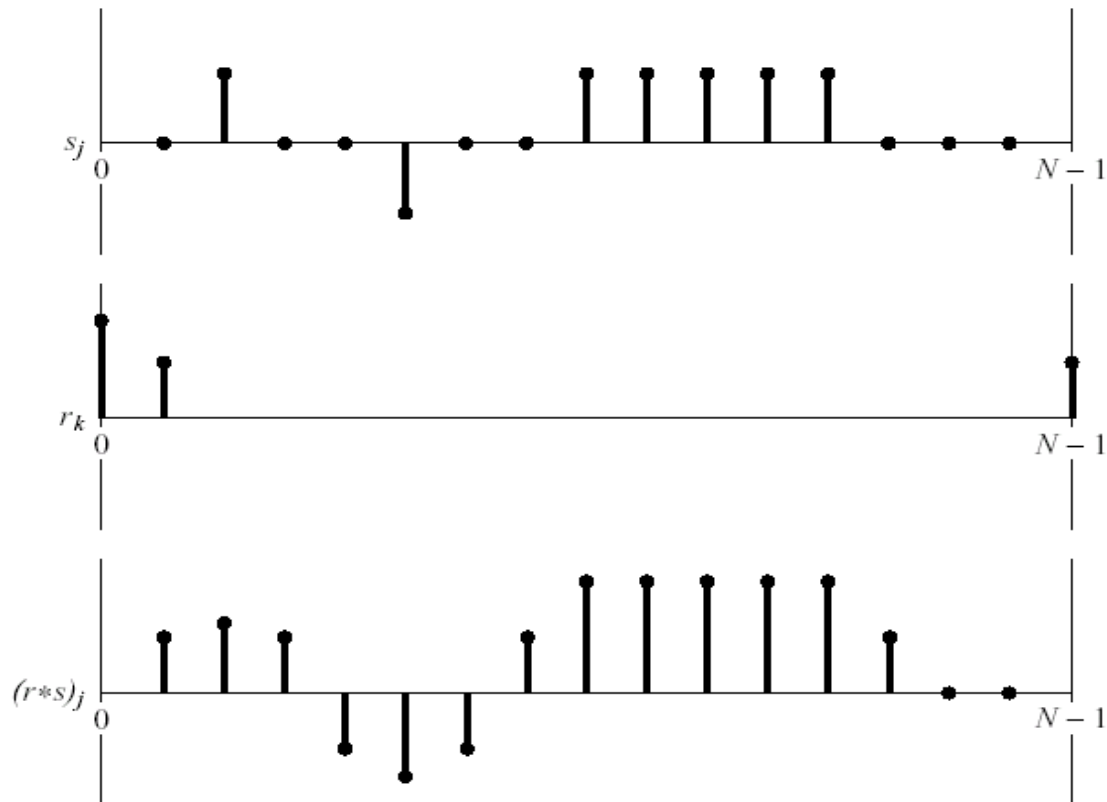
- o direct convolution → complex computation
- o FFT and multiplication → less computation



Convolution(III)

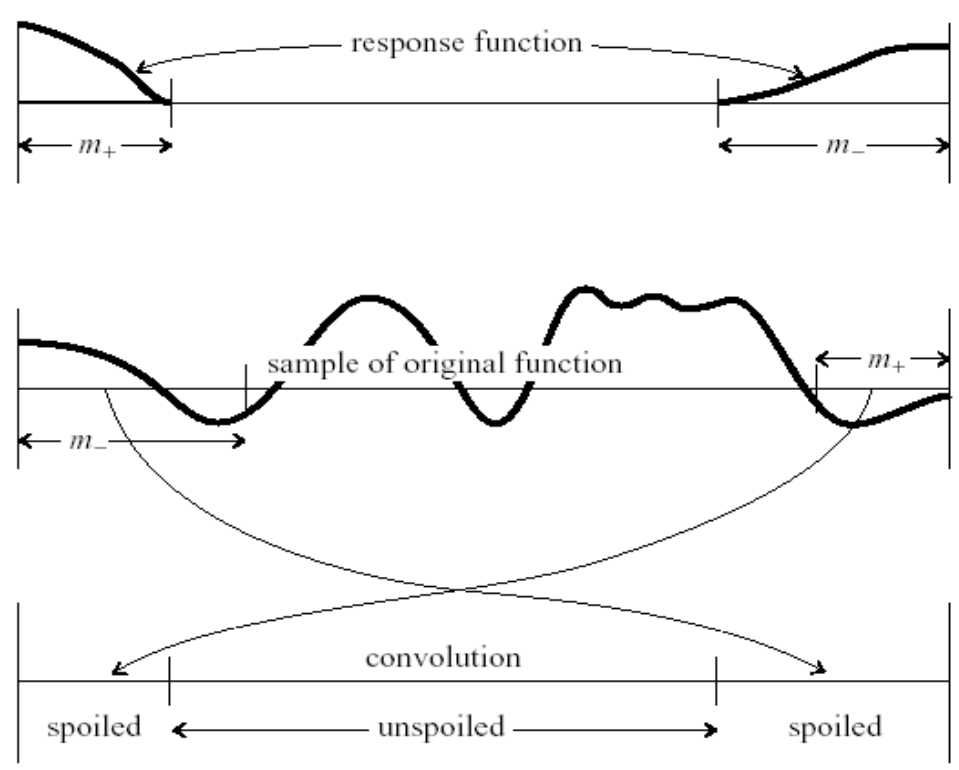
■ Convolution of discrete sampled function

$$(r * s)_j \equiv \sum_{k=-M/2+1}^{M/2} s_{j-k} r_k$$



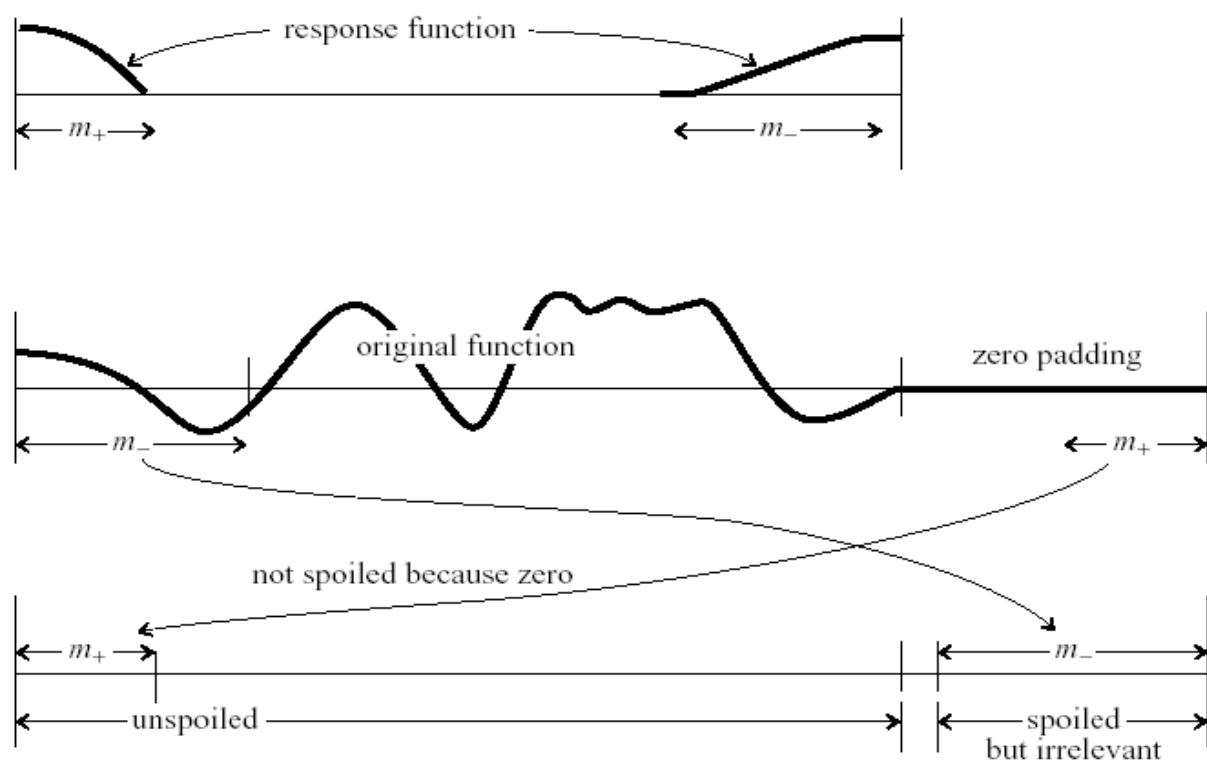
Convolution(IV)

- Trouble in using DFT of finite duration
 - ➔ End effects
 - ➔ Treated by zero padding
- End effect



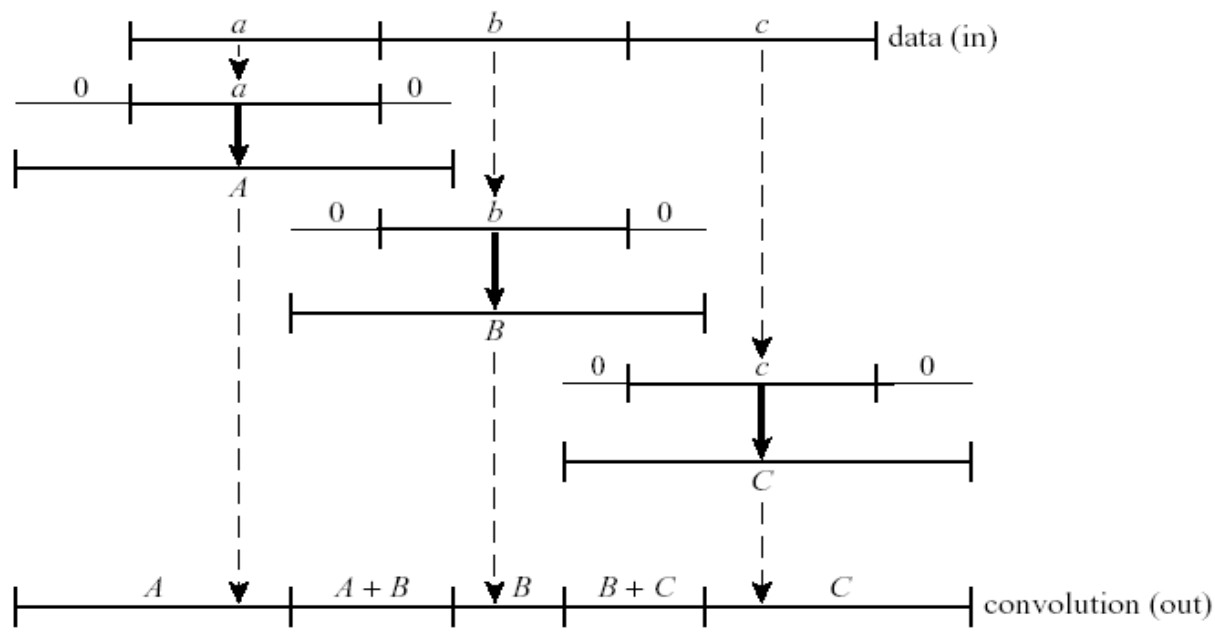
Convolution(V)

■ Zero padding



Convolution(VI)

- Convolving very large data sets



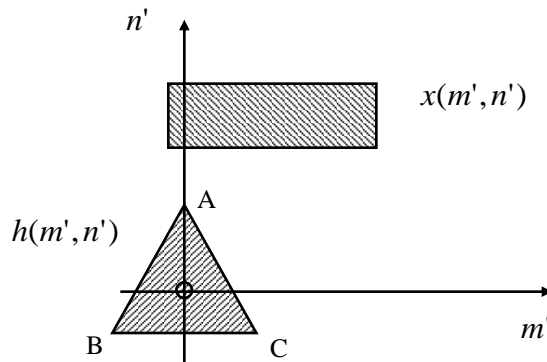
<Overlap-add method>



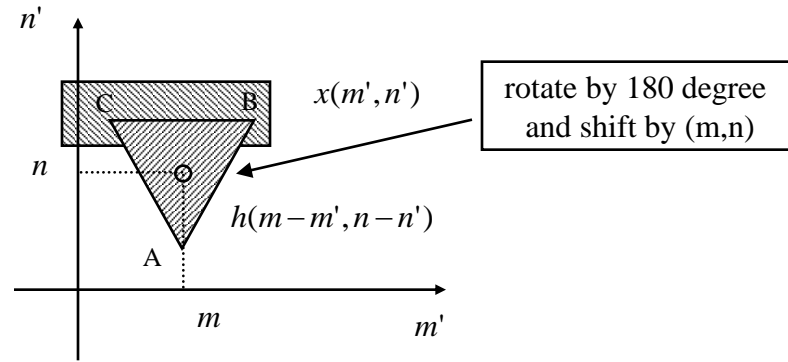
2D convolution

2-D convolution

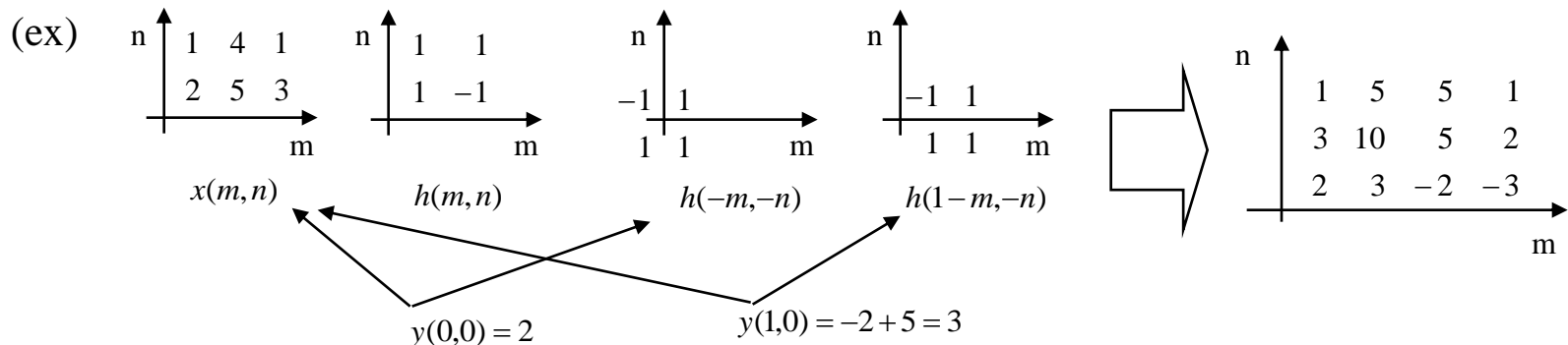
$$y(m,n) = h(m,n) * x(m,n) = \sum_{m'} \sum_{n'} x(m',n') h(m-m',n-n')$$



(a) impulse response



(b) output at location (m,n) is the sum of product of quantities in the area of overlap



Discrete Fourier Transform

■ Fourier Transform

$$H(f) = \int_{-\infty}^{\infty} h(t) e^{2\pi i f t} dt$$
$$h(t) = \int_{-\infty}^{\infty} H(f) e^{-2\pi i f t} df$$

■ Discrete Fourier Transform

$$H(f_n) = \int_{-\infty}^{\infty} h(t) e^{2\pi i f_n t} dt \approx \sum_{k=0}^{N-1} h_k e^{2\pi i f_n t_k} \Delta = \Delta \sum_{k=0}^{N-1} h_k e^{2\pi i k n / N}$$

DFT:

$$H_n \equiv \sum_{k=0}^{N-1} h_k e^{2\pi i k n / N}$$

IDFT:

$$h_k = \frac{1}{N} \sum_{n=0}^{N-1} H_n e^{-2\pi i k n / N}$$



Fast Fourier Transform(FFT)

$$H_n = \sum_{k=0}^{N-1} W^{nk} h_k \quad W \equiv e^{2\pi i/N}$$

[Danielson&Lanczos][Cooley&Tukey]

$$\begin{aligned} F_k &= \sum_{j=0}^{N-1} e^{2\pi i j k / N} f_j \\ &= \sum_{j=0}^{N/2-1} e^{2\pi i k (2j) / N} f_{2j} + \sum_{j=0}^{N/2-1} e^{2\pi i k (2j+1) / N} f_{2j+1} \\ &= \sum_{j=0}^{N/2-1} e^{2\pi i k j / (N/2)} f_{2j} + W^k \sum_{j=0}^{N/2-1} e^{2\pi i k j / (N/2)} f_{2j+1} \\ &= F_k^e + W^k F_k^o \end{aligned}$$

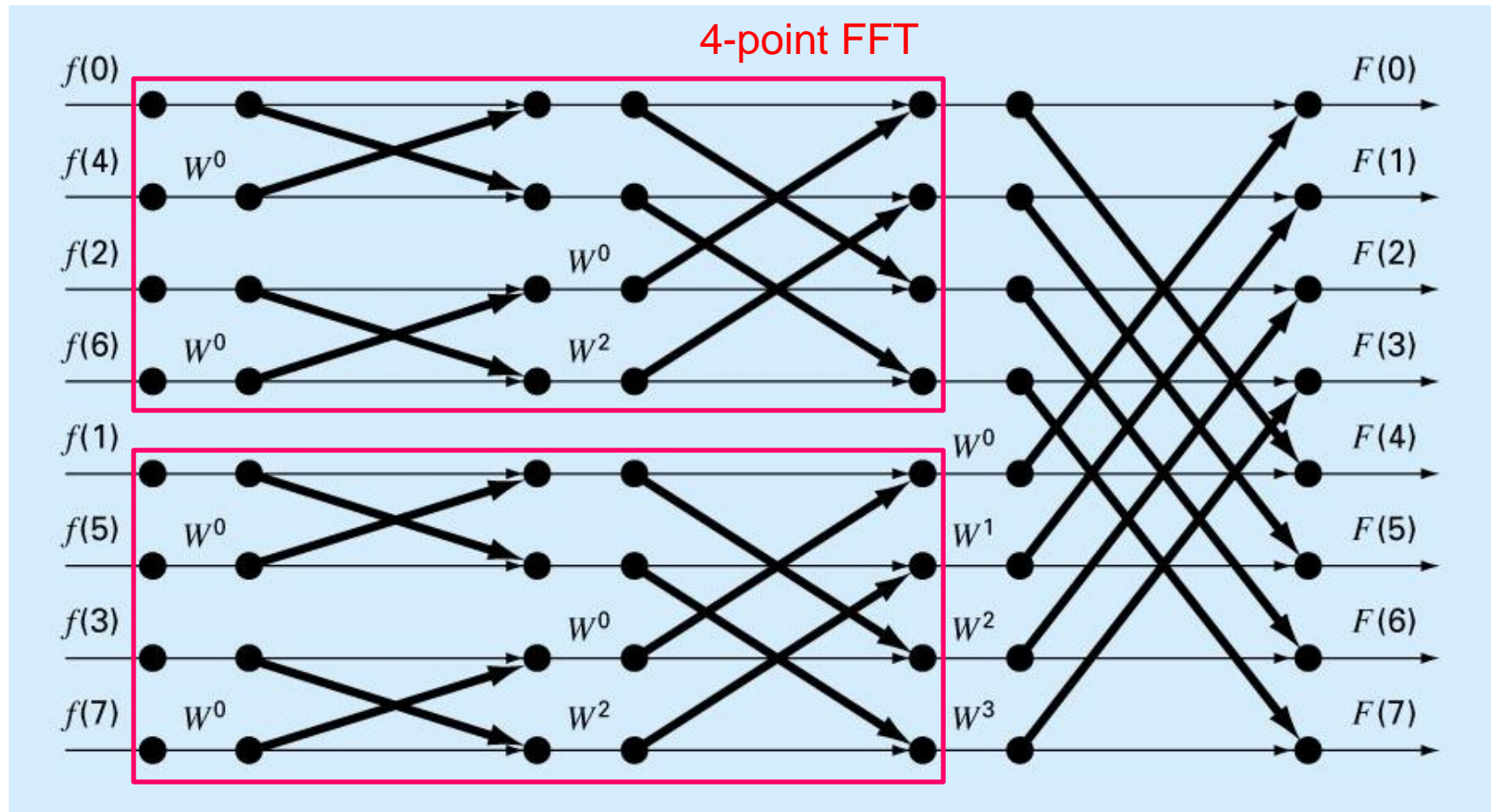
Diagram illustrating the decomposition of the FFT sum into even and odd components:

- The term $e^{2\pi i k (2j) / N} f_{2j}$ is labeled **even**.
- The term $e^{2\pi i k (2j+1) / N} f_{2j+1}$ is labeled **odd**.



Decimation-in-time FFT

Cooley-Tukey Algorithm



Sande-Tukey Algorithm

Power of 2 Sampling

$$N = 2^M$$

Exponential Power Formulation

$$\begin{aligned} F_j &= \sum_{k=0}^{N-1} f_k e^{-i2\pi jk/N}, \quad k = 0, 1, \dots, N-1 \\ &= \sum_{k=0}^{N-1} f_k w^{jk}, \quad k = 0, 1, \dots, N-1 \end{aligned}$$

$$w = e^{-i2\pi/N}$$

Transform Splitting

$$\begin{aligned} F_j &= \sum_{k=0}^{N/2-1} f_k e^{-i2\pi jk/N} + \sum_{k=N/2}^{N-1} f_k e^{-i2\pi jk/N} \\ &= \sum_{k=0}^{N/2-1} f_k e^{-i2\pi jk/N} + \sum_{m=0}^{N/2-1} f_{m+N/2} e^{-i2\pi j(m+N/2)/N} \\ &= \sum_{k=0}^{N/2-1} (f_k + e^{-i\pi j} f_{k+N/2}) e^{-i2\pi jk/N} \end{aligned}$$

$$e^{-i\pi j} = (-1)^j$$

Even Frequency Numbers

$$\begin{aligned} F_{2j} &= \sum_{k=0}^{N/2-1} (f_k + f_{k+N/2}) e^{-i2\pi 2jk/N} \\ &= \sum_{k=0}^{N/2-1} (f_k + f_{k+N/2}) e^{-i2\pi jk/(N/2)} \\ &= \sum_{k=0}^{N/2-1} (f_k + f_{k+N/2}) w^{2jk} \end{aligned}$$

Odd Frequency Numbers

$$\begin{aligned} F_{2j+1} &= \sum_{k=0}^{N/2-1} (f_k - f_{k+N/2}) e^{-i2\pi (2j+1)k/N} \\ &= \sum_{k=0}^{N/2-1} (f_k - f_{k+N/2}) e^{-i2\pi k/N} e^{-i2\pi jk/(N/2)} \\ &= \sum_{k=0}^{N/2-1} (f_k - f_{k+N/2}) w^k w^{2jk} \end{aligned}$$

Half-size Sequences

$$g_k = f_k + f_{k+N/2}$$

$$h_k = (f_k - f_{k+N/2}) w^k$$

Half-size Transforms

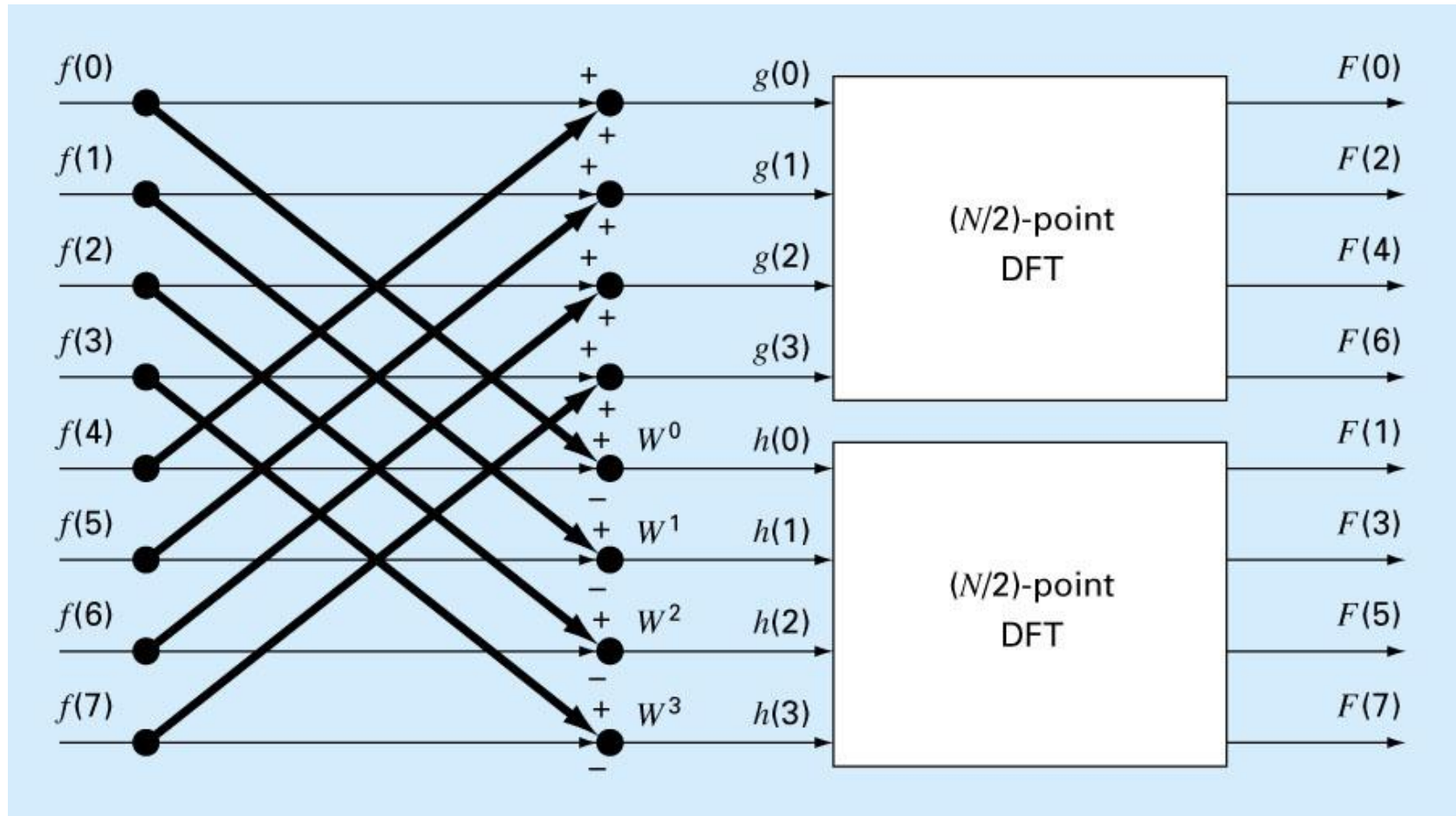
$$F_{2j} = G_j$$

$$F_{2j+1} = H_j$$

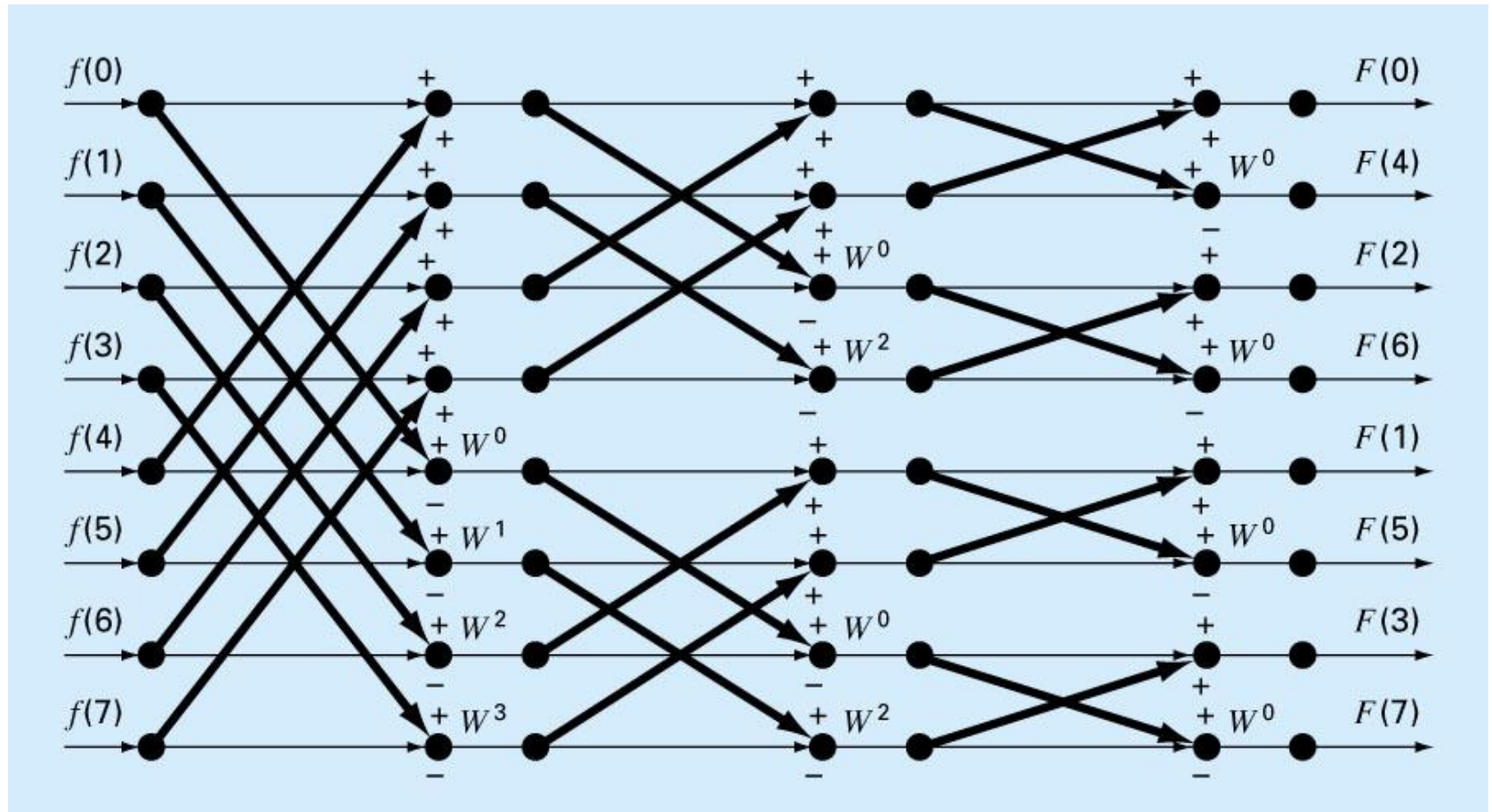


Decimation-in-frequency FFT(I)

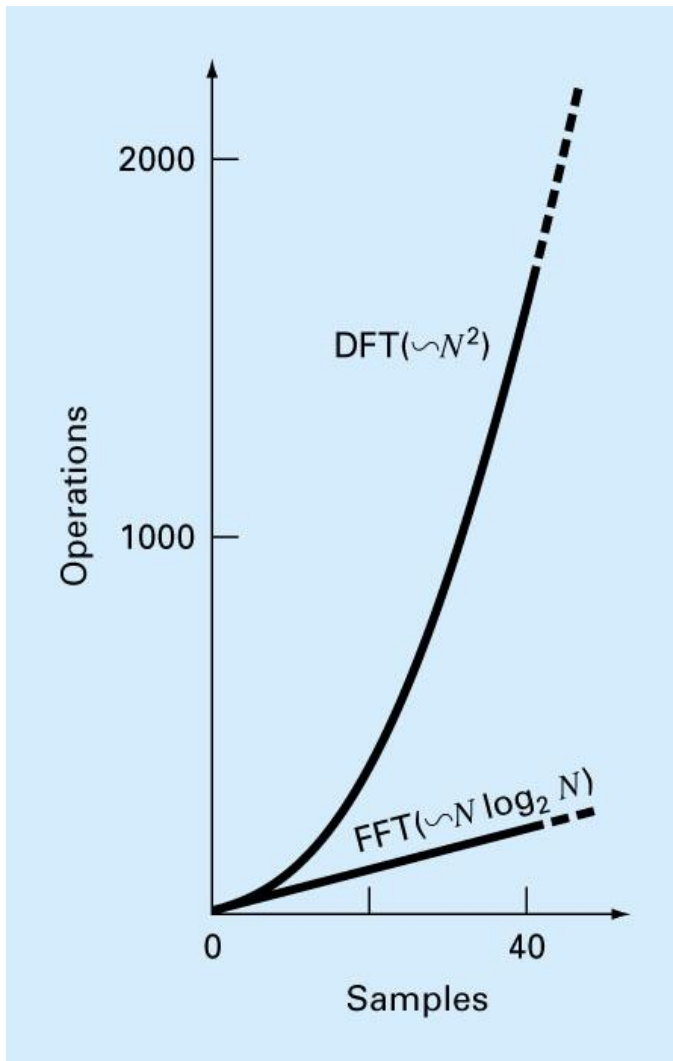
Sand-Tukey Algorithm



Decimation-in-frequency FFT (II)



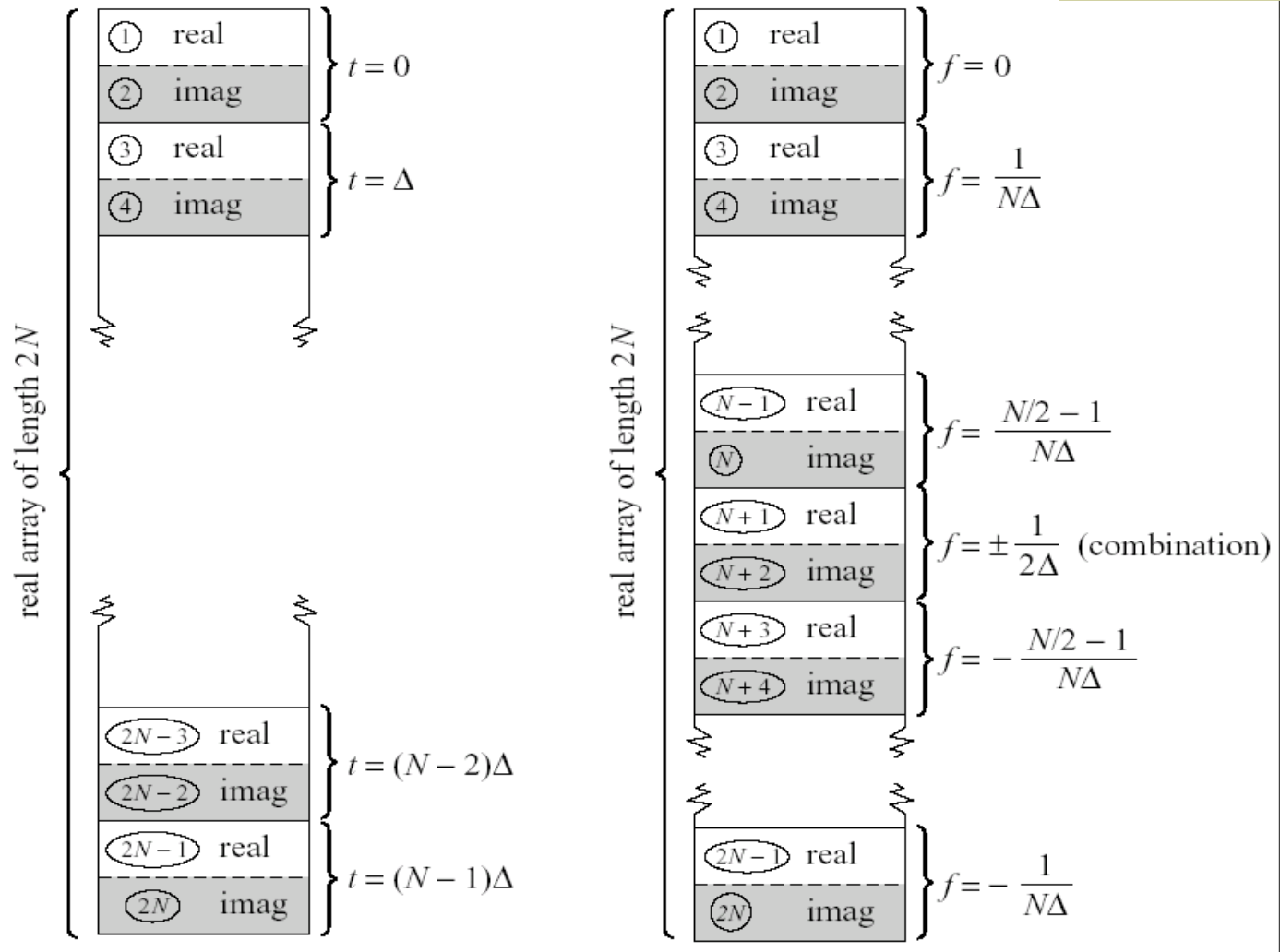
Why FFT?



Further reading: http://en.wikipedia.org/wiki/Cooley-Tukey_FFT_algorithm



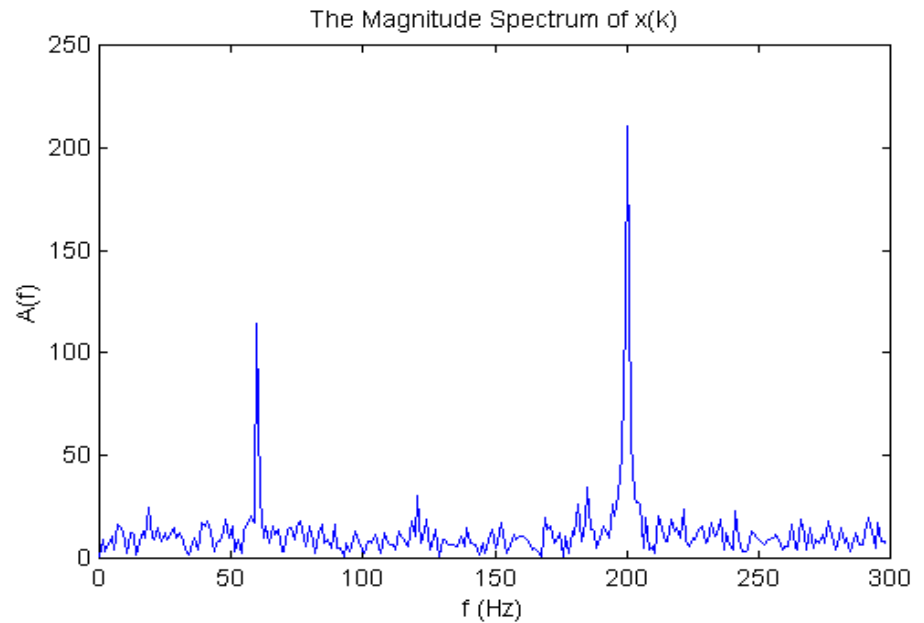
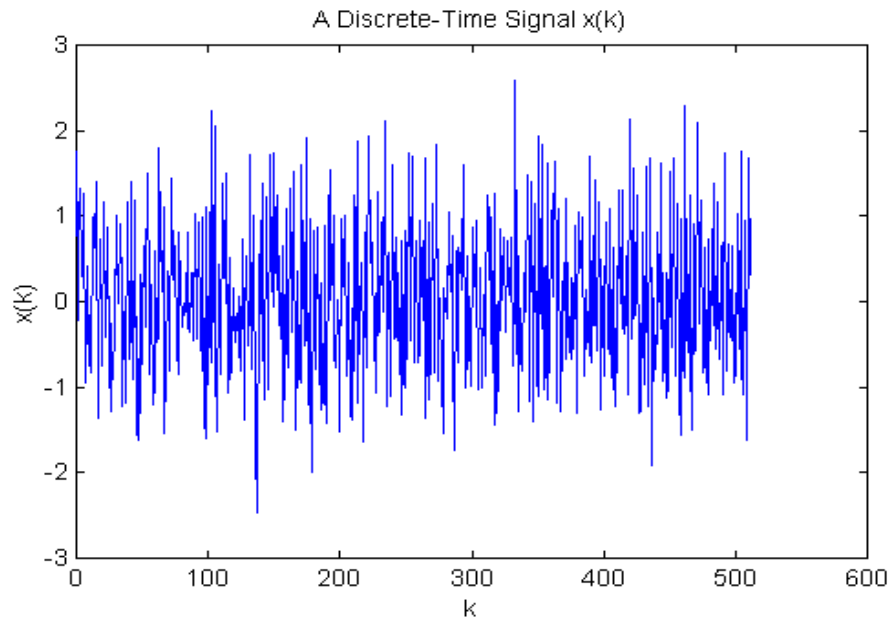
Computation of FFT(I)



input and output of four1() in NR in C

Computation of FFT(II)

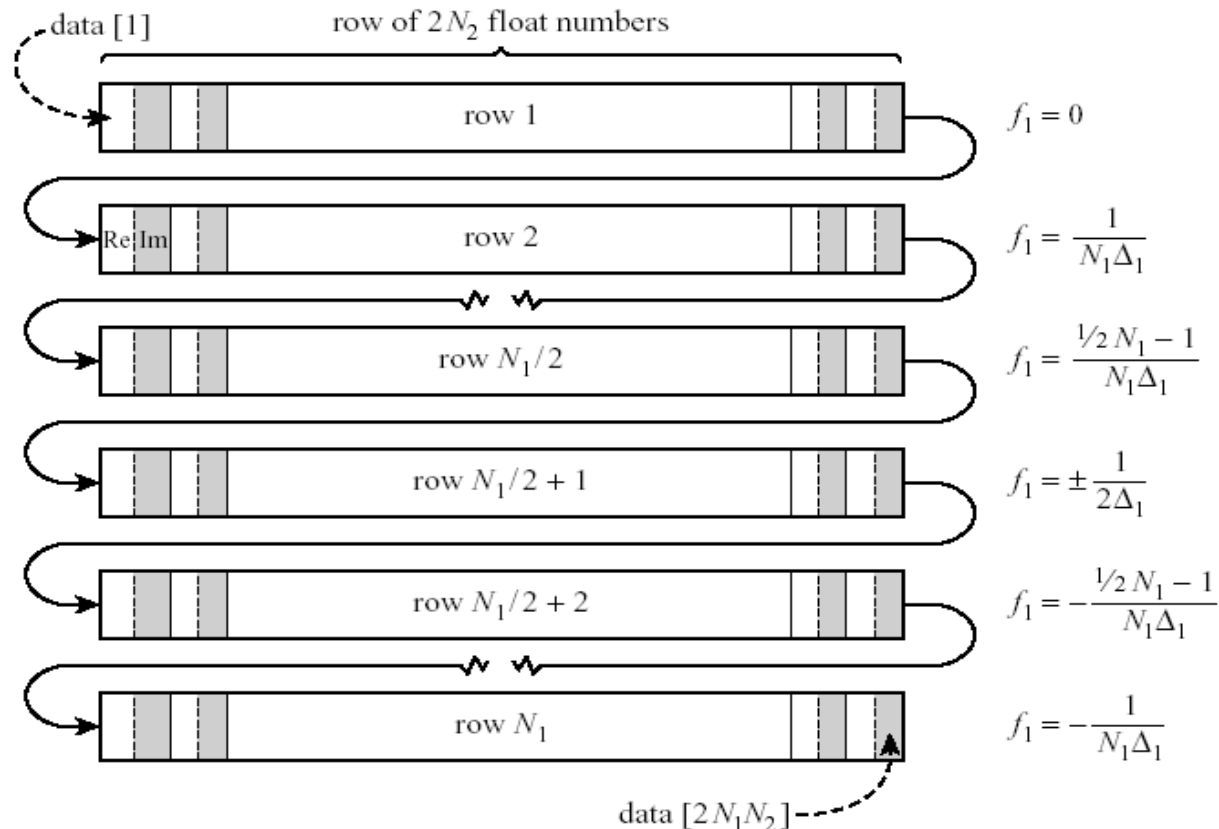
■ Eg. FFT



2D FFT(I)

$$H(n_1, n_2) \equiv \sum_{k_2=0}^{N_2-1} \sum_{k_1=0}^{N_1-1} \exp(2\pi i k_2 n_2 / N_2) \exp(2\pi i k_1 n_1 / N_1) h(k_1, k_2)$$

$$\begin{aligned} H(n_1, n_2) &= \text{FFT-on-index-1} (\text{FFT-on-index-2} [h(k_1, k_2)]) \\ &= \text{FFT-on-index-2} (\text{FFT-on-index-1} [h(k_1, k_2)]) \end{aligned}$$



2D FFT(II)

* Generalization to L-dimension

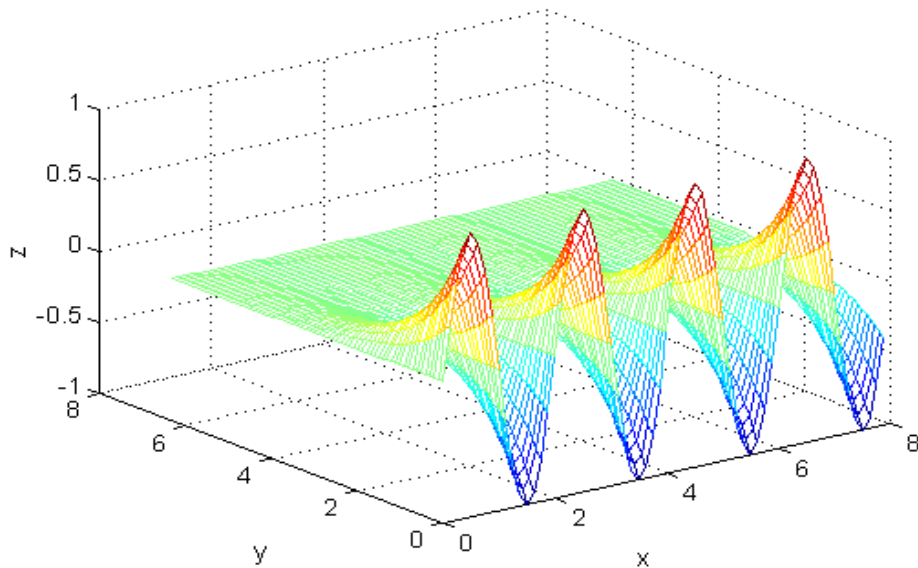
$$H(n_1, \dots, n_L) \equiv \sum_{k_L=0}^{N_L-1} \cdots \sum_{k_1=0}^{N_1-1} \exp(2\pi i k_L n_L / N_L) \times \cdots \\ \times \exp(2\pi i k_1 n_1 / N_1) h(k_1, \dots, k_L)$$



2D FFT(III)

■ Eg. 2D FFT

A Two-Dimensional Signal $z(k,l)$



Two-Dimensional Magnitude Spectrum $A(m,n)$

