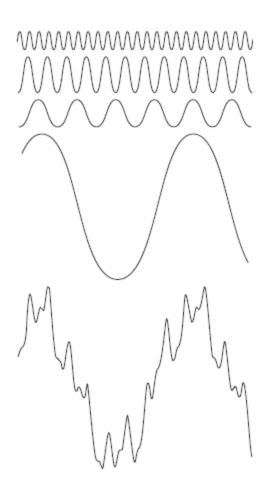
EE610 – Image Processing

Amit Sethi asethi, 7483

Periodic signal of arbitrary shape can be constructed by summing up sinusoids



Revision of complex numbers

- Real and imaginary
- Complex conjugate
- Euler's formula for e^{jθ}
- Magnitude and phase

Revision of Fourier series

$$f(t) = \sum_{n=-\infty}^{\infty} c_n e^{j\frac{2\pi n}{T}t}$$

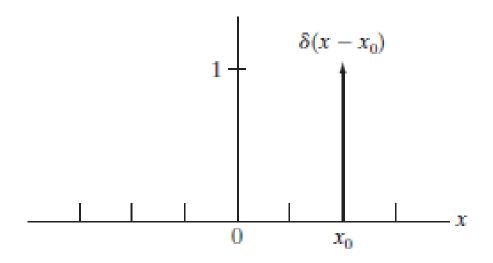
$$c_n = \frac{1}{T} \int_{-T/2}^{T/2} f(t) e^{-j\frac{2\pi n}{T}t} dt$$
 for $n = 0, \pm 1, \pm 2, \dots$

Fourier transform pair

$$F(\mu) = \int_{-\infty}^{\infty} f(t) e^{-j2\pi\mu t} dt$$

$$f(t) = \int_{-\infty}^{\infty} F(\mu) e^{j2\pi\mu t} d\mu$$

Impulse and shifted impulse



- Definition of an impulse function
- Sifting property of impulse and shifted impulse
- Same in discrete domain

Fourier transform of Dirac delta

$$F(\mu) = \int_{-\infty}^{\infty} \delta(t) e^{-j2\pi\mu t} dt \qquad F(\mu) = \int_{-\infty}^{\infty} \delta(t - t_0) e^{-j2\pi\mu t} dt$$

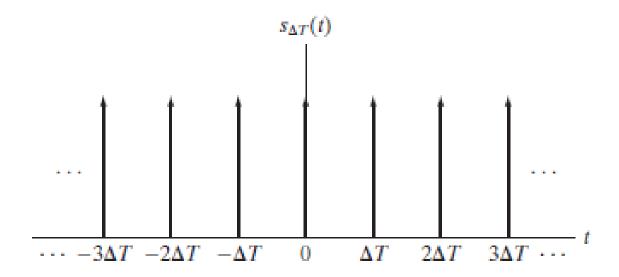
$$= \int_{-\infty}^{\infty} e^{-j2\pi\mu t} \delta(t) dt \qquad = \int_{-\infty}^{\infty} e^{-j2\pi\mu t} \delta(t - t_0) dt$$

$$= e^{-j2\pi\mu 0} = e^{0} \qquad = e^{-j2\pi\mu t_0}$$

$$= 1 \qquad = \cos(2\pi\mu t_0) - j\sin(2\pi\mu t_0)$$

$$e^{-j2\pi\mu t_0}$$

Impulse train



$$s_{\Delta T}(t) = \sum_{n=-\infty}^{\infty} \delta(t - n\Delta T)$$

Fourier transform of an impulse train

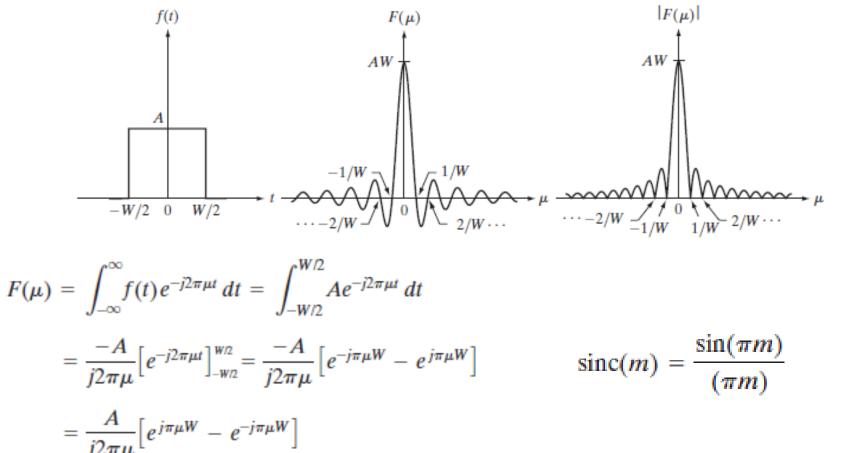
$$S(\mu) = \Im \left\{ s_{\Delta T}(t) \right\}$$

$$= \Im \left\{ \frac{1}{\Delta T} \sum_{n=-\infty}^{\infty} e^{j\frac{2\pi n}{\Delta T}t} \right\}$$

$$= \frac{1}{\Delta T} \Im \left\{ \sum_{n=-\infty}^{\infty} e^{j\frac{2\pi n}{\Delta T}t} \right\}$$

$$= \frac{1}{\Delta T} \sum_{n=-\infty}^{\infty} \delta \left(\mu - \frac{n}{\Delta T} \right)$$

Fourier transform of a box function



 $=AW\frac{\sin(\pi\mu W)}{(\pi\mu W)}$

Convolution and multiplication

$$f(t) \star h(t) = \int_{-\infty}^{\infty} f(\tau) h(t - \tau) d\tau$$

$$\Im\{f(t) \star h(t)\} = \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} f(\tau) h(t - \tau) d\tau \right] e^{-j2\pi\mu t} dt$$

$$= \int_{-\infty}^{\infty} f(\tau) \left[\int_{-\infty}^{\infty} h(t - \tau) e^{-j2\pi\mu t} dt \right] d\tau$$

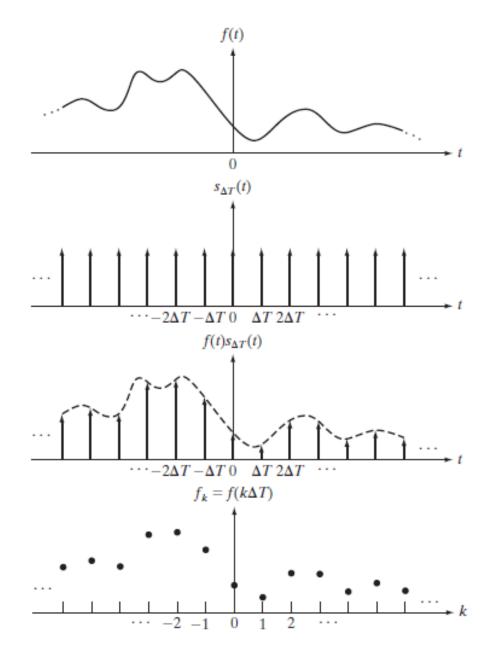
$$\Im\{f(t) \star h(t)\} = \int_{-\infty}^{\infty} f(\tau) \left[H(\mu) e^{-j2\pi\mu \tau} \right] d\tau$$

$$= H(\mu) \int_{-\infty}^{\infty} f(\tau) e^{-j2\pi\mu \tau} d\tau$$

$$= H(\mu) F(\mu)$$

Source: Digital Image Processing, Gonzalez and Woods, Prentice Hall

Sampling of a function



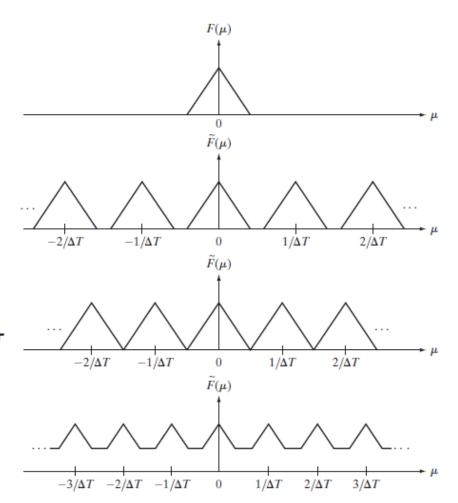
Frequency spectrum of sampled function

$$\begin{split} \widetilde{F}(\mu) &= F(\mu) \bigstar S(\mu) \\ &= \int_{-\infty}^{\infty} F(\tau) S(\mu - \tau) d\tau \\ &= \frac{1}{\Delta T} \int_{-\infty}^{\infty} F(\tau) \sum_{n = -\infty}^{\infty} \delta \left(\mu - \tau - \frac{n}{\Delta T}\right) d\tau \end{split}$$

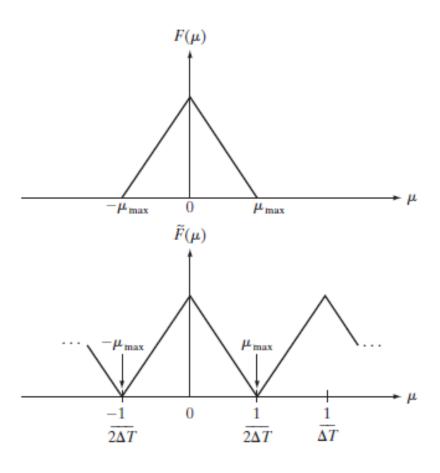
$$= \frac{1}{\Delta T} \sum_{n = -\infty}^{\infty} \int_{-\infty}^{\infty} F(\tau) \delta \left(\mu - \tau - \frac{n}{\Delta T}\right) d\tau$$

$$= \frac{1}{\Delta T} \sum_{n = -\infty}^{\infty} F\left(\mu - \frac{n}{\Delta T}\right) d\tau$$

$$= \frac{1}{\Delta T} \sum_{n = -\infty}^{\infty} F\left(\mu - \frac{n}{\Delta T}\right)$$

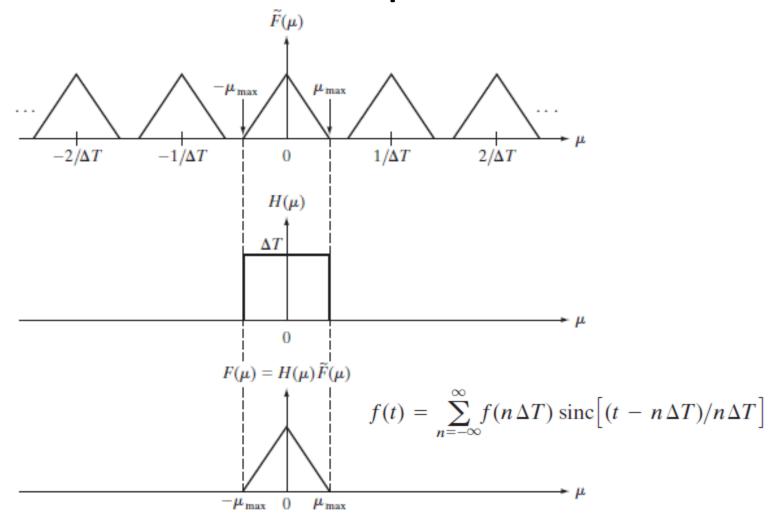


Nyquist criterion

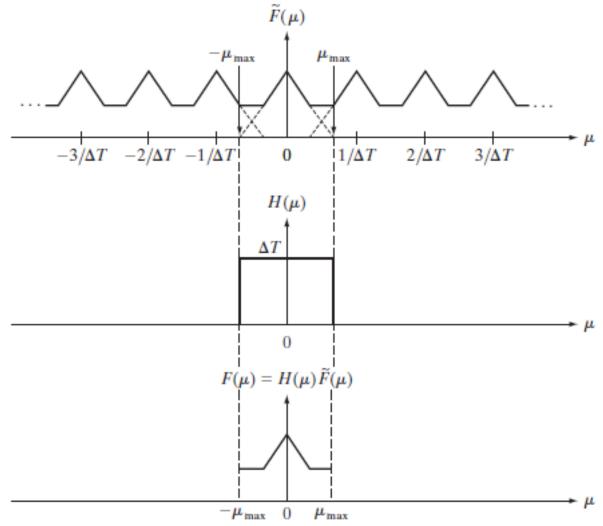


$$\frac{1}{\Delta T} > 2\mu_{\text{max}}$$

Convolving samples with a sinc function for interpolation

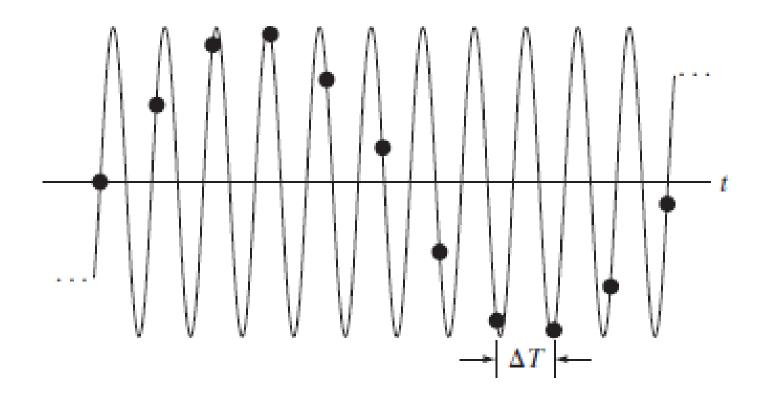


Aliasing is a consequence of violating Nyquist limit during interpolation

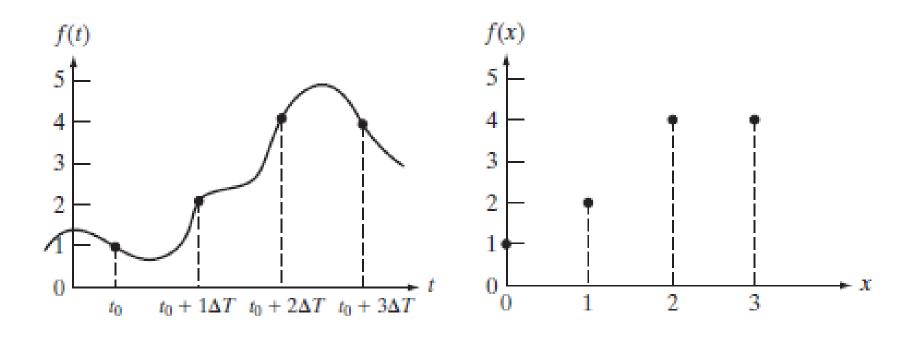


Source: Digital Image Processing, Gonzalez and Woods, Prentice Hall

Aliasing in spatial (time) domain



Making space (or time) discrete



Discrete Fourier Transform

$$\begin{split} \widetilde{F}(\mu) &= \int_{-\infty}^{\infty} \widetilde{f}(t) \, e^{-j2\pi\mu t} \, dt \\ &= \int_{-\infty}^{\infty} \sum_{n=-\infty}^{\infty} f(t) \, \delta(t-n \, \Delta T) e^{-j2\pi\mu t} \, dt \\ &= \sum_{n=-\infty}^{\infty} \int_{-\infty}^{\infty} f(t) \, \delta(t-n \, \Delta T) e^{-j2\pi\mu t} \, dt \\ &= \sum_{n=-\infty}^{\infty} f_n \, e^{-j2\pi\mu n \, \Delta T} \end{split}$$

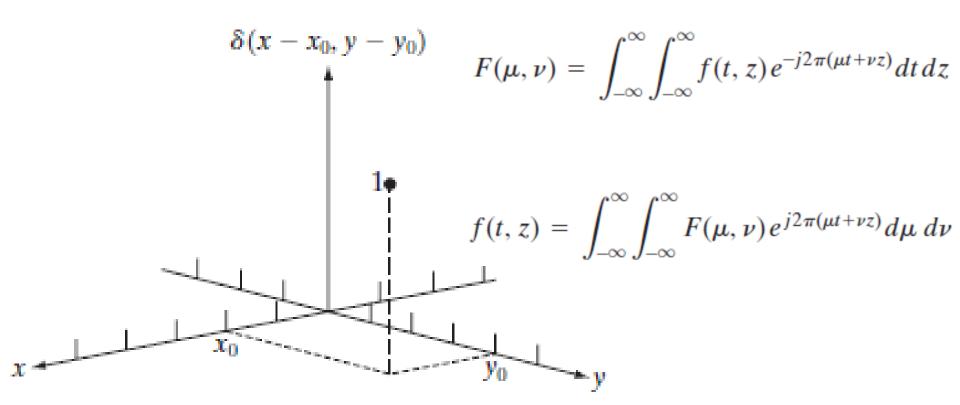
$$\mu = \frac{m}{M\Delta T}$$

$$F_m = \sum_{n=0}^{M-1} f_n e^{-j2\pi mn/M}$$

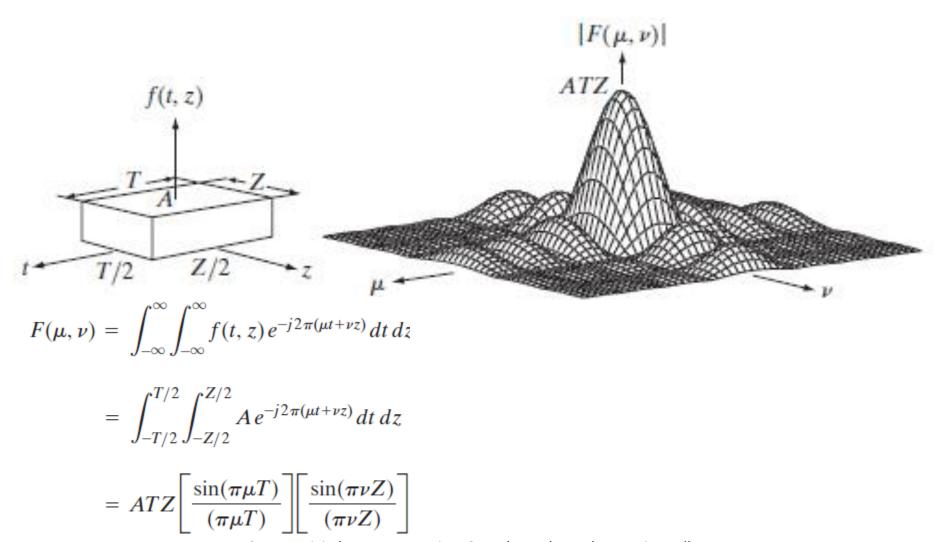
$$f_n = \frac{1}{M} \sum_{m=0}^{M-1} F_m e^{j2\pi mn/M}$$

$$f(x) \star h(x) = \sum_{m=0}^{M-1} f(m)h(x-m)$$

Extension to two variables

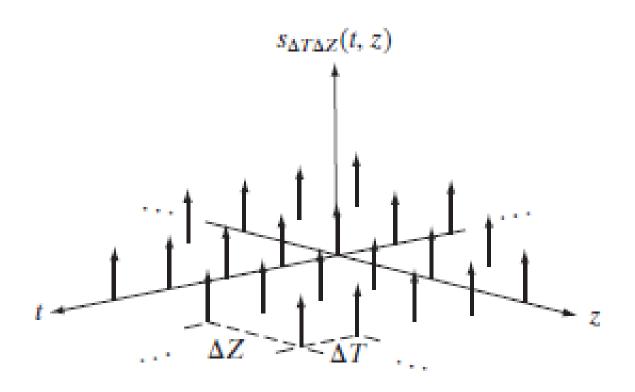


Box and Sinc in 2-D

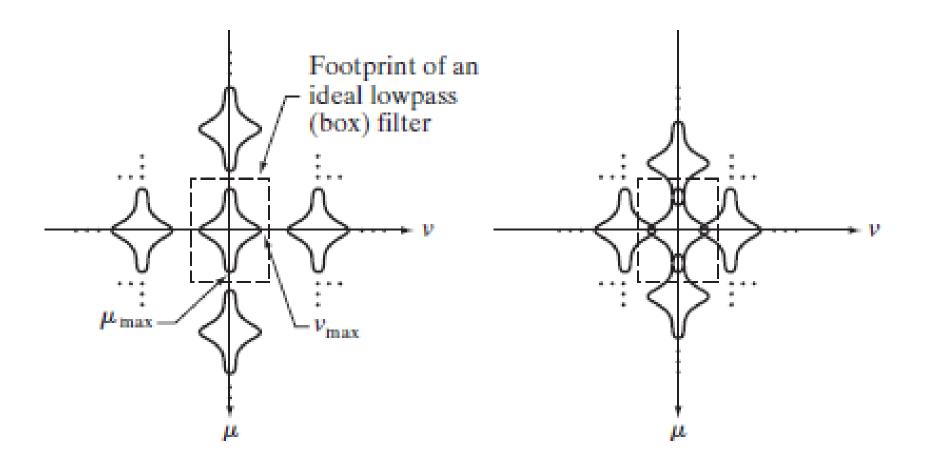


Source: Digital Image Processing, Gonzalez and Woods, Prentice Hall

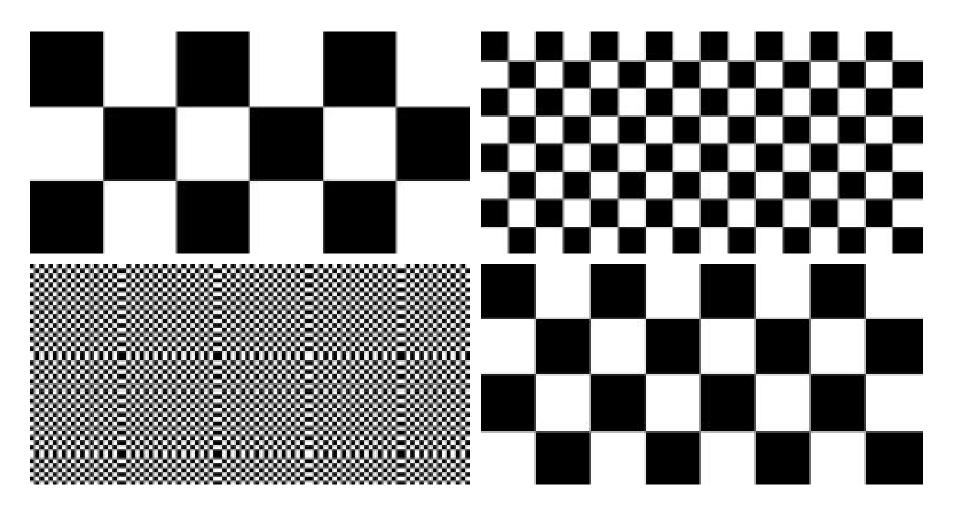
Impulse train in 2-D



Aliasing in 2-D



Spatial examples of aliasing



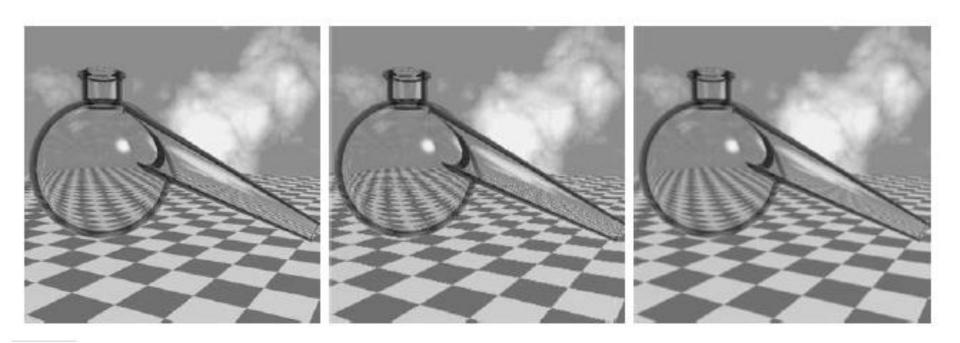
Aliasing due to reduction of image resolution and anti-aliasing using smoothing



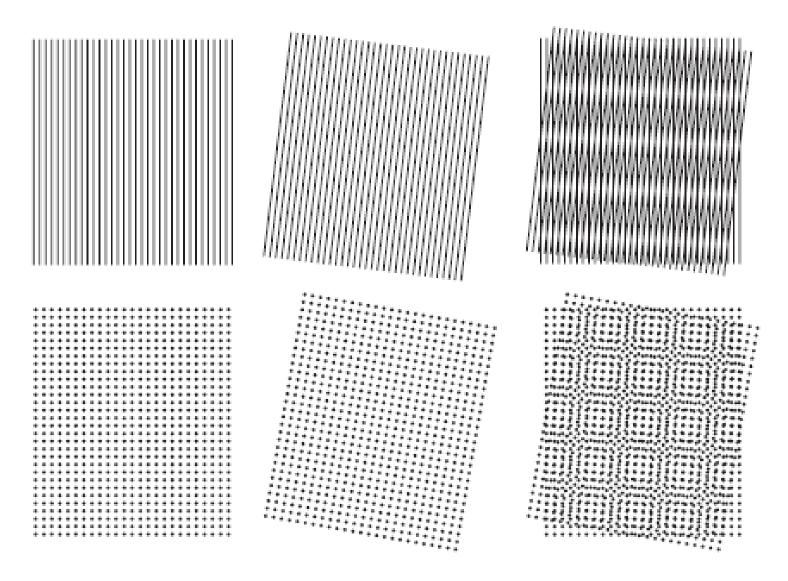




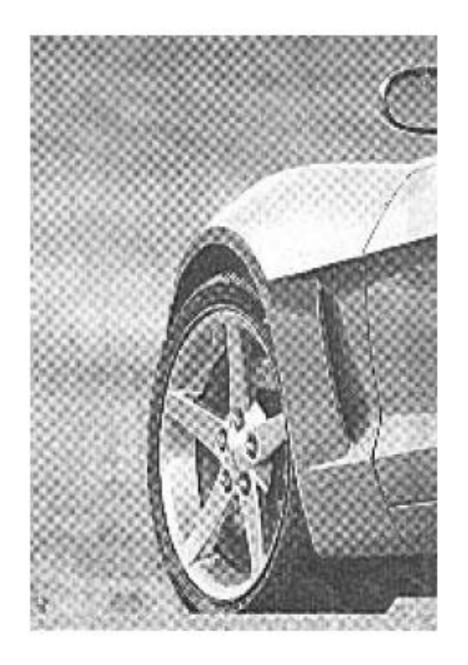
Jaggies due to aliasing, and antialiasing using smoothing



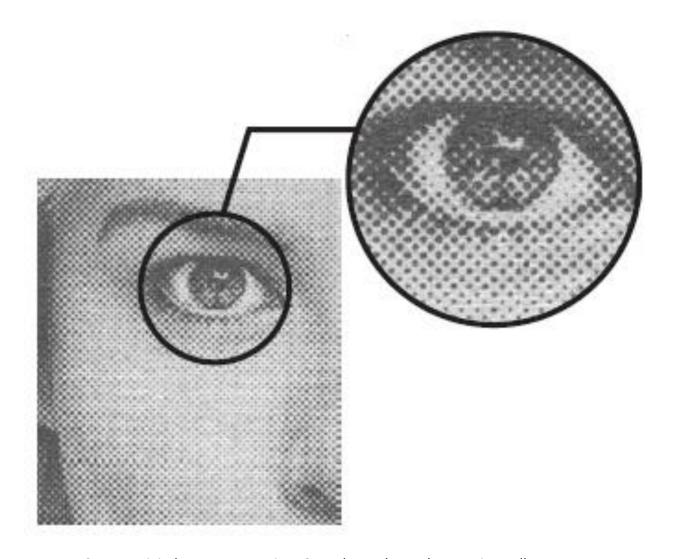
Moiré effect



Oriented dots and Cartesian grid create Moiré patterns



Close up of newspaper printing



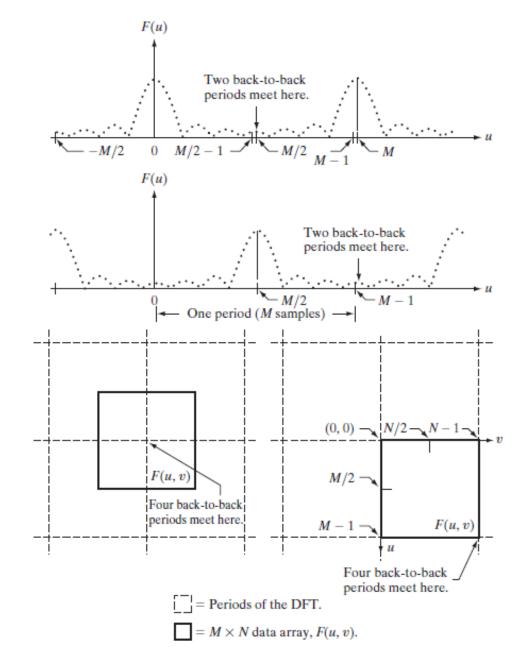
Source: Digital Image Processing, Gonzalez and Woods, Prentice Hall

DFT in 2-D

$$F(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) e^{-j2\pi(ux/M + vy/N)}$$

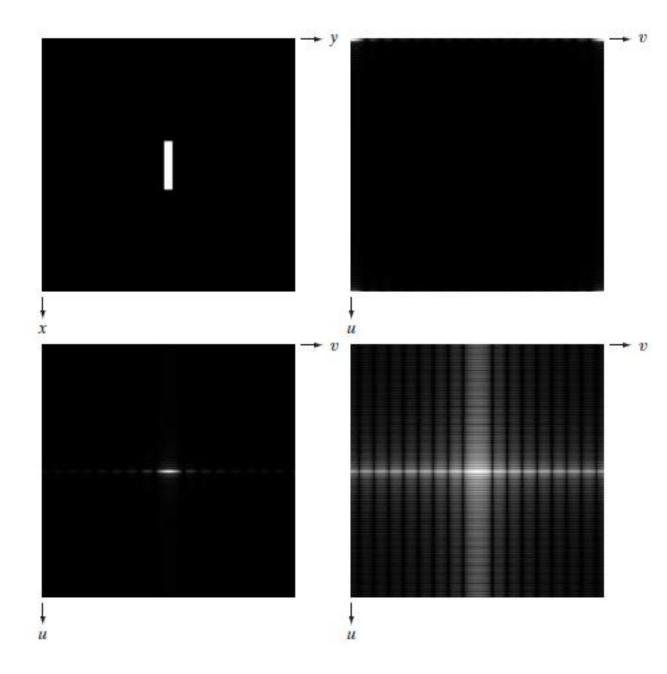
$$f(x, y) = \frac{1}{MN} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u, v) e^{j2\pi(ux/M + vy/N)}$$

Representation of DFT



	Spatial Domain [†]		Frequency Domain [†]
1)	f(x, y) real	\Leftrightarrow	$F^*(u,v) = F(-u,-v)$
2)	f(x, y) imaginary	\Leftrightarrow	$F^*(-u,-v) = -F(u,v)$
3)	f(x, y) real	\Leftrightarrow	R(u, v) even; $I(u, v)$ odd
4)	f(x, y) imaginary	\Leftrightarrow	R(u, v) odd; $I(u, v)$ even
5)	f(-x, -y) real	\Leftrightarrow	$F^*(u, v)$ complex
6)	f(-x, -y) complex	\Leftrightarrow	F(-u, -v) complex
7)	$f^*(x, y)$ complex	\Leftrightarrow	$F^*(-u-v)$ complex
8)	f(x, y) real and even	\Leftrightarrow	F(u, v) real and even
9)	f(x, y) real and odd	\Leftrightarrow	F(u, v) imaginary and odd
10)	f(x, y) imaginary and even	\Leftrightarrow	F(u, v) imaginary and even
11)	f(x, y) imaginary and odd	\Leftrightarrow	F(u, v) real and odd
12)	f(x, y) complex and even	\Leftrightarrow	F(u, v) complex and even
13)	f(x, y) complex and odd	\Leftrightarrow	F(u, v) complex and odd

DFT of a bar: Original, **DFT** not centered, centered, log Xform

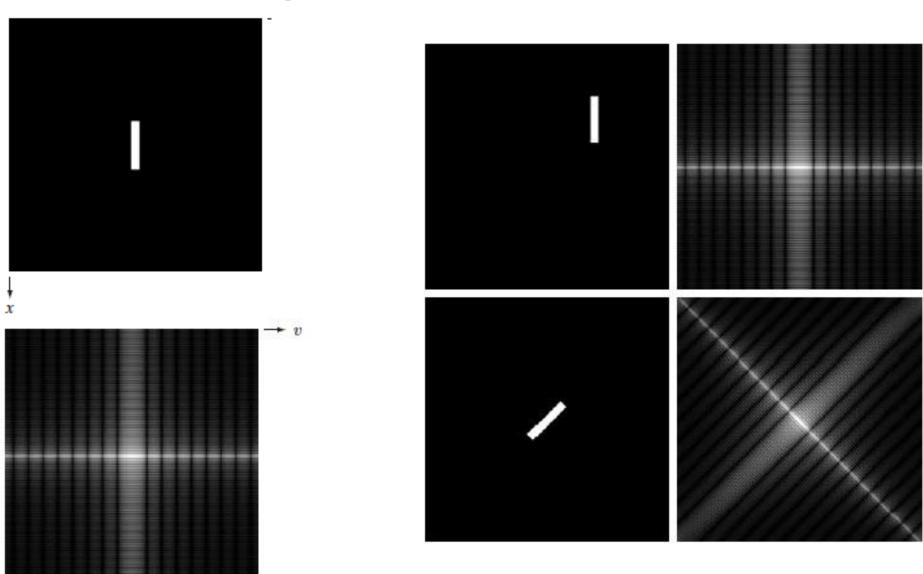


Rotation and phase shift

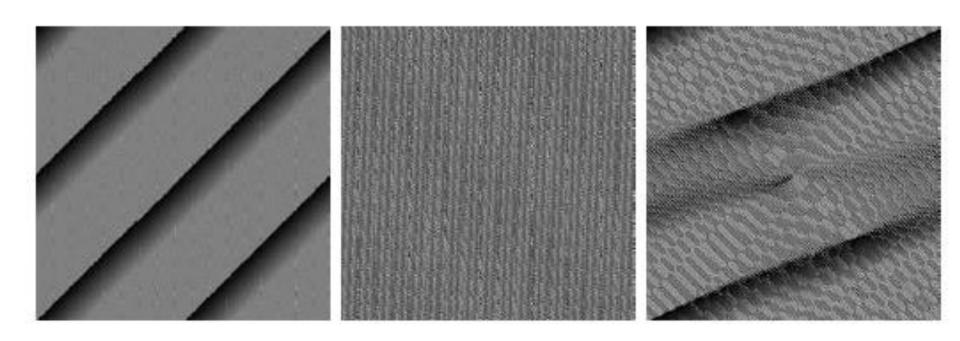
$$f(x, y)e^{j2\pi(u_0x/M+v_0y/N)} \Leftrightarrow F(u-u_0, v-v_0)$$

$$f(x - x_0, y - y_0) \Leftrightarrow F(u, v) e^{-j2\pi(x_0u/M + y_0v/N)}$$

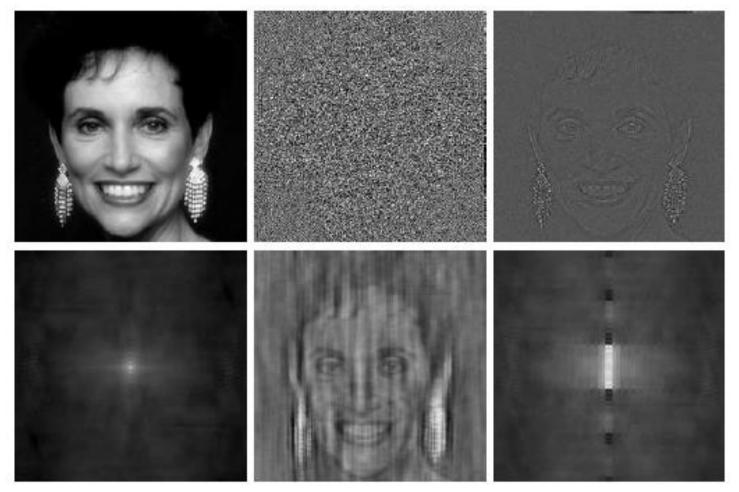
Visualizing rotation and translation



Phase of original bar, translated, rotated

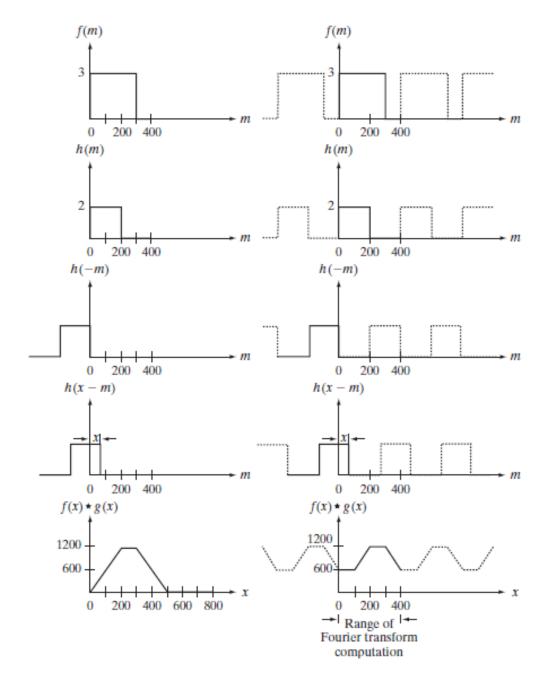


Importance of phase: Original, phase, reconstruction based on: phase, magnitude, some other image's magnitude, some other image's phase



Source: Digital Image Processing, Gonzalez and Woods, Prentice Hall

Implicit periodicity leads to wraparound



Name	Expression(s)		
Discrete Fourier transform (DFT) of $f(x, y)$	$F(u, v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) e^{-j2\pi(ux/M + vy/N)}$		
Inverse discrete Fourier transform (IDFT) of F(u, v)	$f(x, y) = \frac{1}{MN} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u, v) e^{j2\pi(ux/M + vy/N)}$		
3) Polar representation	$F(u,v) = F(u,v) e^{j\phi(u,v)}$		
4) Spectrum	$ F(u,v) = [R^2(u,v) + I^2(u,v)]^{1/2}$		
	R = Real(F); I = Imag(F)		
5) Phase angle	$\phi(u, v) = \tan^{-1} \left[\frac{I(u, v)}{R(u, v)} \right]$		
6) Power spectrum	$P(u, v) = F(u, v) ^2$		
7) Average value	$\overline{f}(x, y) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) = \frac{1}{MN} F(0, 0)$		

(Continued)

Name	Expression(s)			
8) Periodicity (k ₁ and k ₂ are integers)	$F(u, v) = F(u + k_1 M, v) = F(u, v + k_2 N)$ = $F(u + k_1 M, v + k_2 N)$			
	$f(x, y) = f(x + k_1 M, y) + k_2 N $ $f(x, y) = f(x + k_1 M, y) = f(x, y + k_2 N)$			
	$= f(x + k_1 M, y + k_2 N)$ $M - 1 N - 1$			
9) Convolution	$f(x, y) \star h(x, y) = \sum_{m=0}^{\infty} \sum_{n=0}^{\infty} f(m, n)h(x - m, y - n)$			
10) Correlation	$f(x, y) \approx h(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f^{*}(m, n) h(x + m, y + n)$			
11) Separability	The 2-D DFT can be computed by computing 1-D DFT transforms along the rows (columns) of the image, followed by 1-D transforms along the columns (rows) of the result. See Section 4.11.1.			
12) Obtaining the inverse Fourier transform using a forward transform algorithm.	$MNf^*(x, y) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F^*(u, v) e^{-j2\pi(ux/M + vy/N)}$ This equation indicates that inputting $F^*(u, v)$ into an algorithm that computes the forward transform (right side of above equation) yields $MNf^*(x, y)$. Taking the complex conjugate and dividing by MN gives the desired inverse. See Section 4.11.2.			

Source: Digital Image Processing, Gonzalez and Woods, Prentice Hall

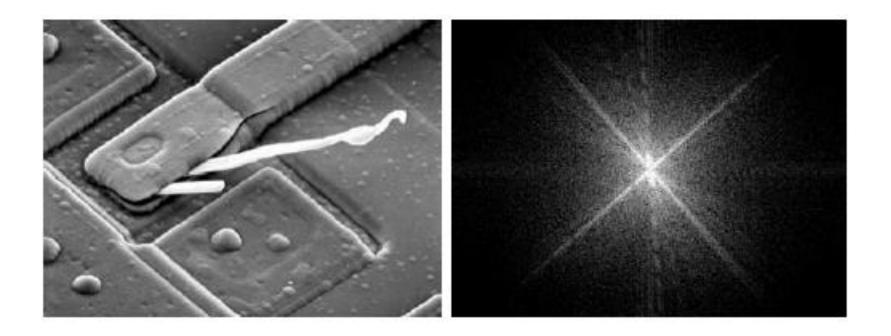
Name	DFT Pairs
1) Symmetry properties	See Table 4.1
2) Linearity	$af_1(x, y) + bf_2(x, y) \Leftrightarrow aF_1(u, v) + bF_2(u, v)$
3) Translation (general)	$f(x, y) e^{j2\pi(u_0x/M + v_0y/N)} \iff F(u - u_0, v - v_0)$ $f(x - x_0, y - y_0) \iff F(u, v) e^{-j2\pi(ux_0/M + vy_0/N)}$
4) Translation to center of the frequency rectangle, (M/2, N/2)	$f(x, y)(-1)^{x+y} \Leftrightarrow F(u - M/2, v - N/2)$ $f(x - M/2, y - N/2) \Leftrightarrow F(u, v)(-1)^{u+v}$
5) Rotation	$f(r, \theta + \theta_0) \Leftrightarrow F(\omega, \varphi + \theta_0)$ $x = r \cos \theta y = r \sin \theta u = \omega \cos \varphi v = \omega \sin \varphi$
6) Convolution theorem [†]	$f(x, y) \star h(x, y) \Leftrightarrow F(u, v)H(u, v)$ $f(x, y)h(x, y) \Leftrightarrow F(u, v) \star H(u, v)$

(Continued)

Name		DFT Pairs		
7)	Correlation theorem [†]	$f(x, y) \stackrel{\wedge}{\approx} h(x, y) \Leftrightarrow F^*(u, v) H(u, v)$ $f^*(x, y)h(x, y) \Leftrightarrow F(u, v) \stackrel{\wedge}{\approx} H(u, v)$		
8)	Discrete unit impulse	$\delta(x, y) \Leftrightarrow 1$		
9)	Rectangle	$rect[a, b] \Leftrightarrow ab \frac{\sin(\pi ua)}{(\pi ua)} \frac{\sin(\pi vb)}{(\pi vb)} e^{-j\pi(ua+vb)}$		
10)	Sine	$\sin(2\pi u_0 x + 2\pi v_0 y) \Leftrightarrow$		
		$j\frac{1}{2}[\delta(u+Mu_0,v+Nv_0)-\delta(u-Mu_0,v-Nv_0)]$		
11)	Cosine	$\cos(2\pi u_0 x + 2\pi v_0 y) \Leftrightarrow$		
		$\frac{1}{2} \left[\delta(u + Mu_0, v + Nv_0) + \delta(u - Mu_0, v - Nv_0) \right]$		
The following Fourier transform pairs are derivable only for continuous variables, denoted as before by t and z for spatial variables and by μ and ν for frequency variables. These results can be used for DFT work by sampling the continuous forms.				
12) Differentiation (The expressions on the right assume that $f(\pm \infty, \pm \infty) = 0.$) $f(t, z) \Leftrightarrow (j2\pi\mu)^m (j2\pi\nu)^n F(\mu, \nu)$ $\frac{\partial^m f(t, z)}{\partial t^m} \Leftrightarrow (j2\pi\mu)^m F(\mu, \nu); \frac{\partial^n f(t, z)}{\partial z^n} \Leftrightarrow (j2\pi\nu)^n F(\mu, \nu)$				
13) (Gaussian	$A2\pi\sigma^2 e^{-2\pi^2\sigma^2(t^2+z^2)} \Leftrightarrow Ae^{-(\mu^2+\nu^2)/2\sigma^2}$ (A is a constant)		

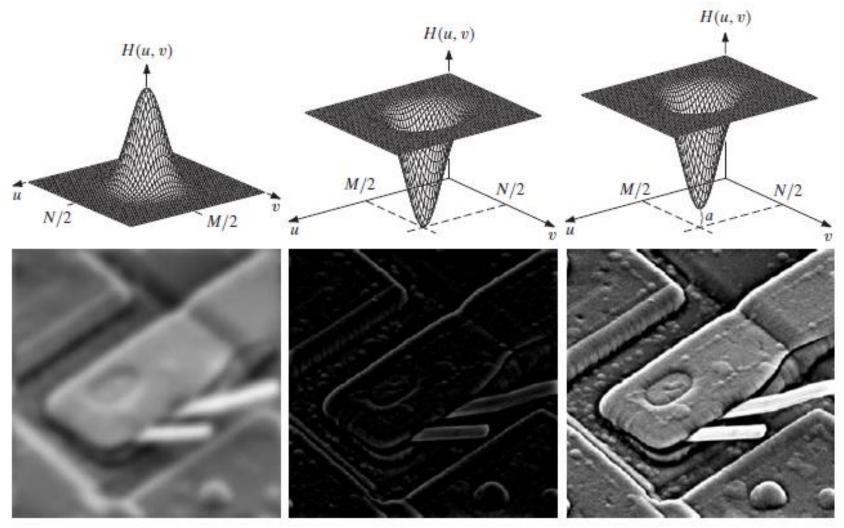
[†]Assumes that the functions have been extended by zero padding. Convolution and correlation are associative, commutative, and distributive.

Source: Digital Image Processing, Gonzalez and Woods, Prentice Hall



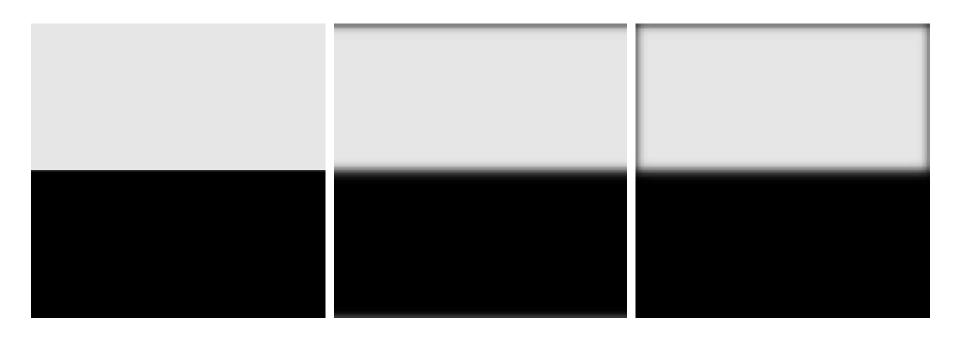
Filtering in frequency domain

$$g(x, y) = \mathfrak{I}^{-1}[H(u, v)F(u, v)]$$

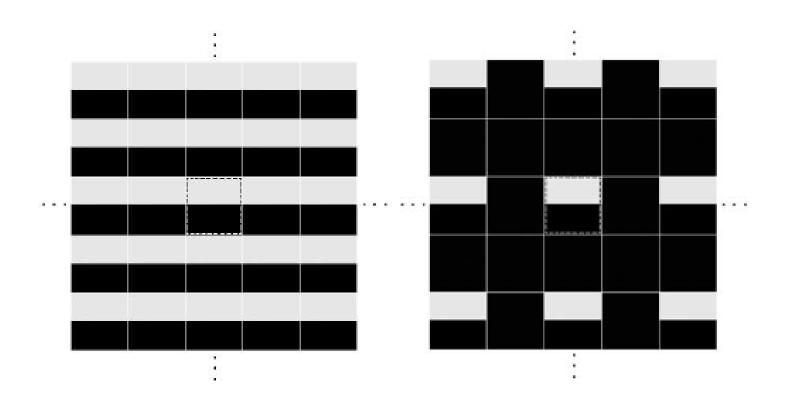


Source: Digital Image Processing, Gonzalez and Woods, Prentice Hall

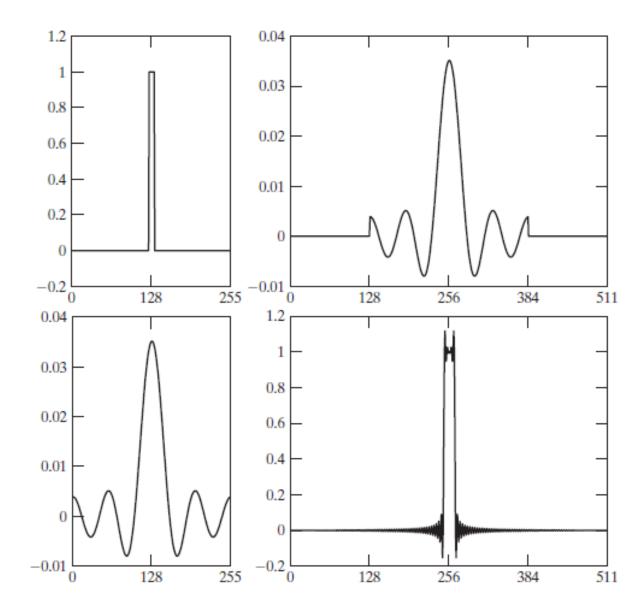
Effect of wraparound and zero padding



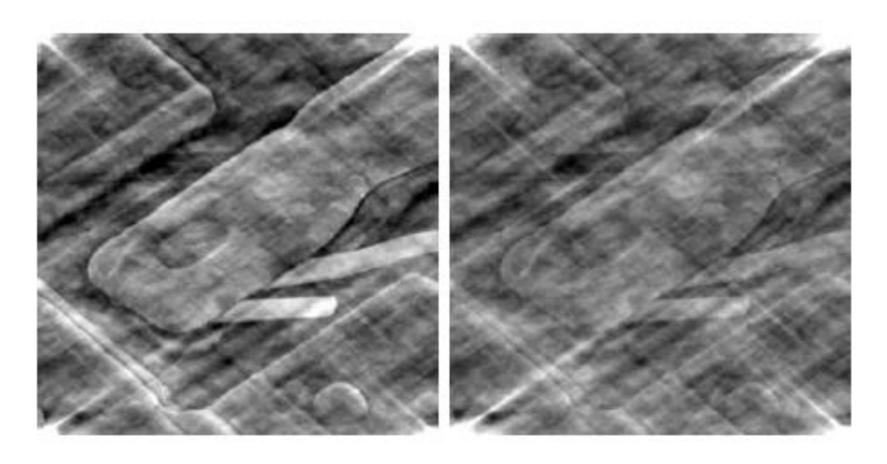
Implicit periodicity without and with zero padding



One cannot work with ideal frequency cut-offs and avoiding wraparound errors



Importance of phase – Multiplying phase with 0.5 and 0.25; and zero phase shift filters



$$g(x, y) = \Im^{-1} [H(u, v)R(u, v) + jH(u, v)I(u, v)]$$

Source: Digital Image Processing, Gonzalez and Woods, Prentice Hall

Summary of frequency filtering

- Given an input image f(x, y) of size M × N, obtain the padding parameters P and Q from Eqs. (4.6-31) and (4.6-32). Typically, we select P = 2M and Q = 2N.
- 2. Form a padded image, $f_p(x, y)$, of size $P \times Q$ by appending the necessary number of zeros to f(x, y).
- 3. Multiply $f_p(x, y)$ by $(-1)^{x+y}$ to center its transform.
- **4.** Compute the DFT, F(u, v), of the image from step 3.
- 5. Generate a real, symmetric filter function, H(u, v), of size $P \times Q$ with center at coordinates (P/2, Q/2). Form the product G(u, v) = H(u, v)F(u, v) using array multiplication; that is, G(i, k) = H(i, k)F(i, k).
- Obtain the processed image:

$$g_p(x, y) = \{ \text{real} [\Im^{-1}[G(u, v)]] \} (-1)^{x+y}$$

where the real part is selected in order to ignore parasitic complex components resulting from computational inaccuracies, and the subscript p indicates that we are dealing with padded arrays.

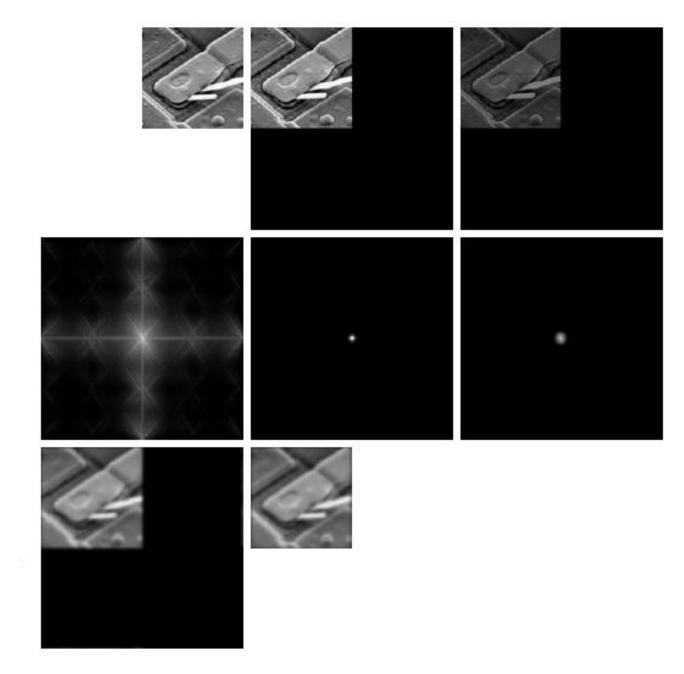
7. Obtain the final processed result, g(x, y), by extracting the $M \times N$ region from the top, left quadrant of $g_p(x, y)$.

Example

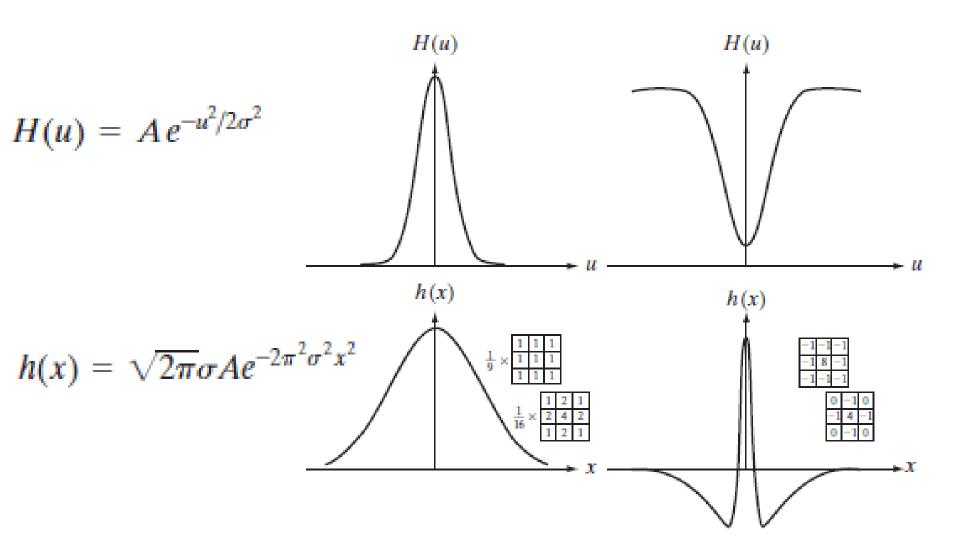
FIGURE 4.36

- (a) An $M \times N$ image, f.
- (b) Padded image, f_p of size P × Q.
- (c) Result of multiplying f_p by $(-1)^{x+y}$.
- (d) Spectrum of F_p . (e) Centered Gaussian lowpass filter, H, of size $P \times Q$.
- (f) Spectrum of the product HF_p .
- (g) g_p , the product of $(-1)^{x+y}$ and the real part of the IDFT of HF_p .
- (h) Final result, g, obtained by

cropping the first M rows and N columns of g_p .

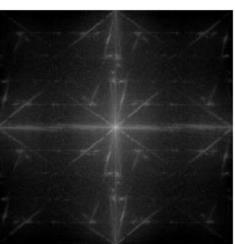


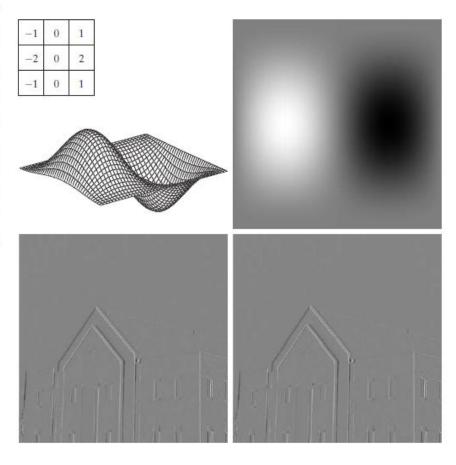
Filtering using Gaussian filters



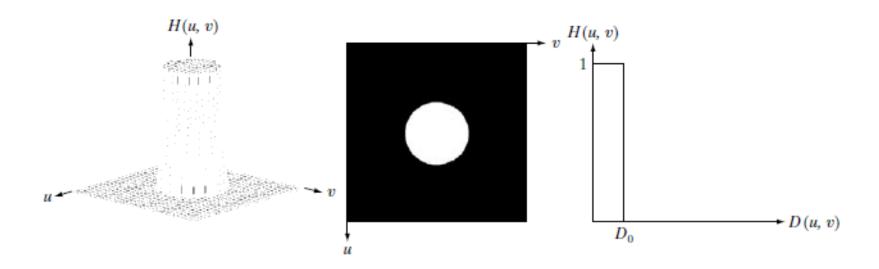
Equivalence of spatial and frequency filtering





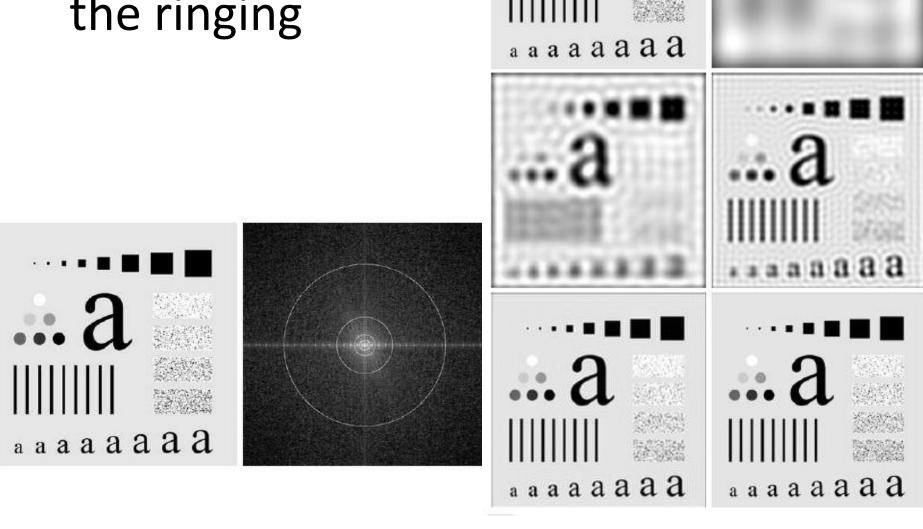


An ideal low pass filter

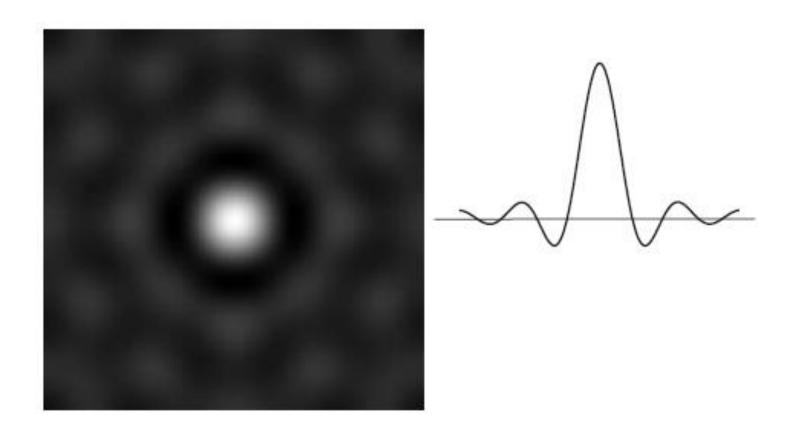


$$H(u,v) = \begin{cases} 1 & \text{if } D(u,v) \leq D_0 \\ 0 & \text{if } D(u,v) > D_0 \end{cases} \qquad D(u,v) = \left[(u-P/2)^2 + (v-Q/2)^2 \right]^{1/2}$$

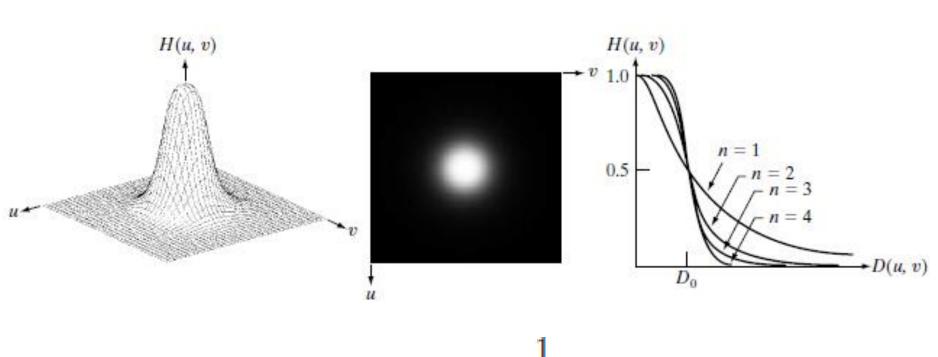
Results of ILPF; notice the ringing



Spatial domain ILPF shows where ringing comes from



Butterworth filters reduce ringing

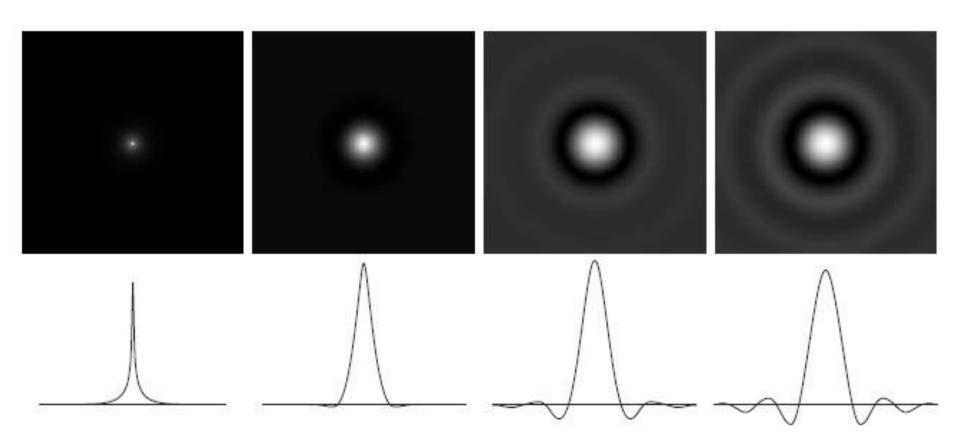


$$H(u, v) = \frac{1}{1 + [D(u, v)/D_0]^{2n}}$$

Ringing is impercepti ble in Butterwort h filters of order 2 of various D₀

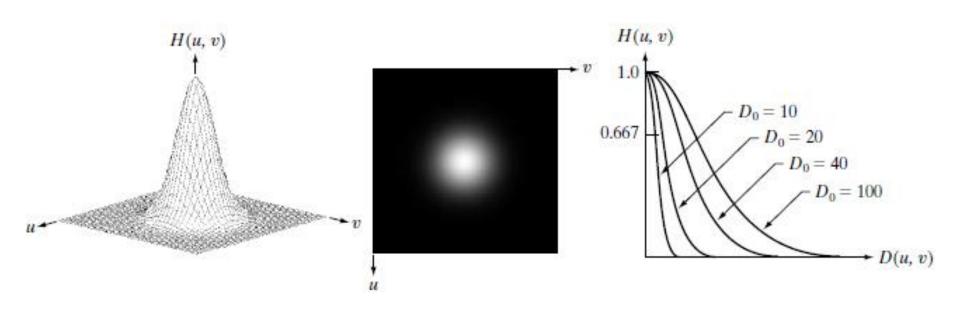


Ringing increases in BLPFs with order (1, 2, 5, 20)

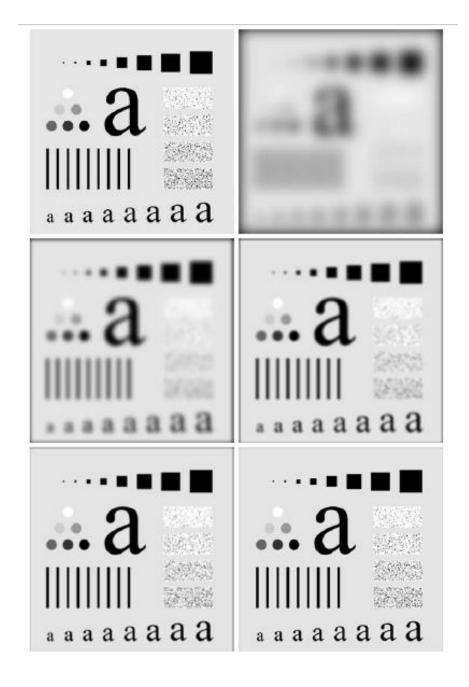


Another option is GLPF

$$H(u, v) = e^{-D^2(u, v)/2D_0^2}$$



Use of different cut-offs in GLPFs



Summary of the three LPFs

Lowpass filters. D_0 is the cutoff frequency and n is the order of the Butterworth filter.

Ideal	Butterworth	Gaussian
$H(u,v) = \begin{cases} 1 & \text{if } D(u,v) \le D_0 \\ 0 & \text{if } D(u,v) > D_0 \end{cases}$	$H(u,v) = \frac{1}{1 + [D(u,v)/D_0]^{2n}}$	$H(u, v) = e^{-D^2(u,v)/2D_0^2}$

Blurring with GLPF for continuity

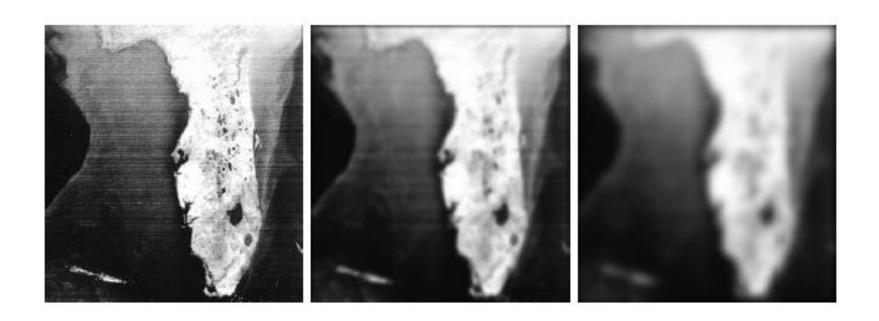
Historically, certain computer programs were written using only two digits rather than four to define the applicable year. Accordingly, the company's software may recognize a date using "00" as 1900 rather than the year 2000.

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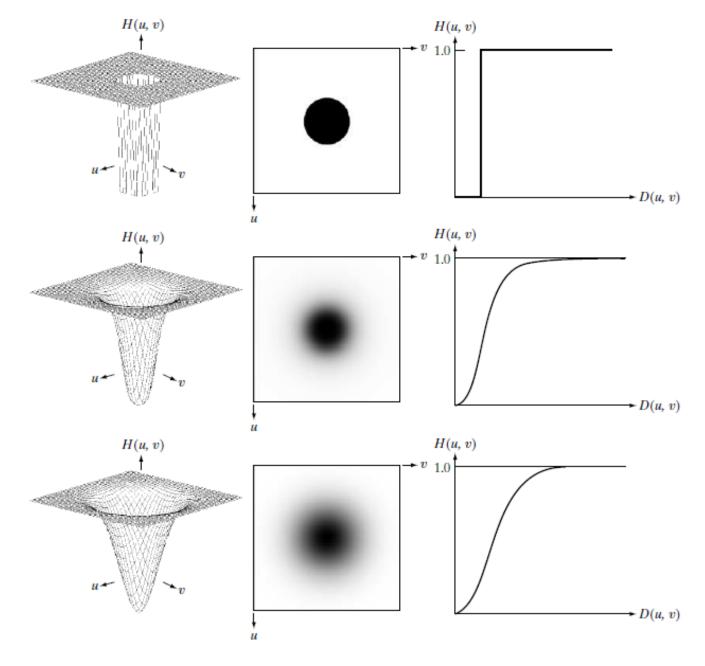
Anti-wrinkle cream or smoothening with GLPFs



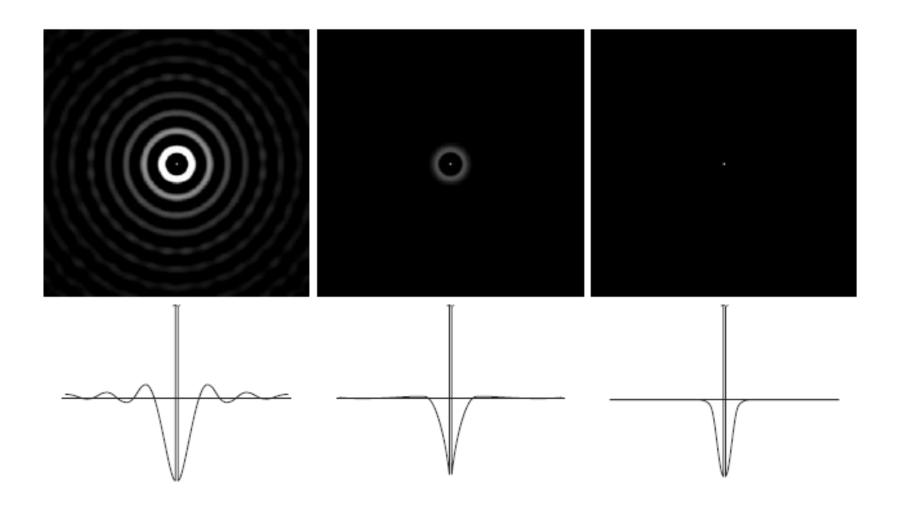
Removal of scan lines using GLPF



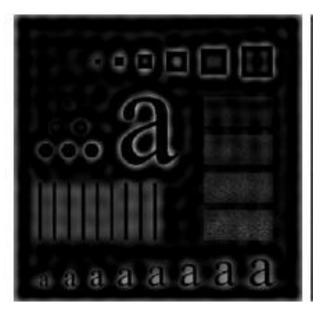
High pass filters



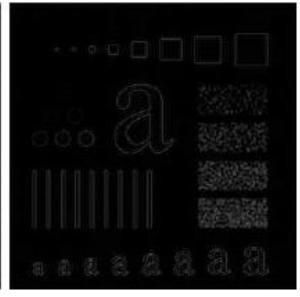
Ideal, Butterworth, and Gaussian HPFs in spatial domain



IHPF with different radii



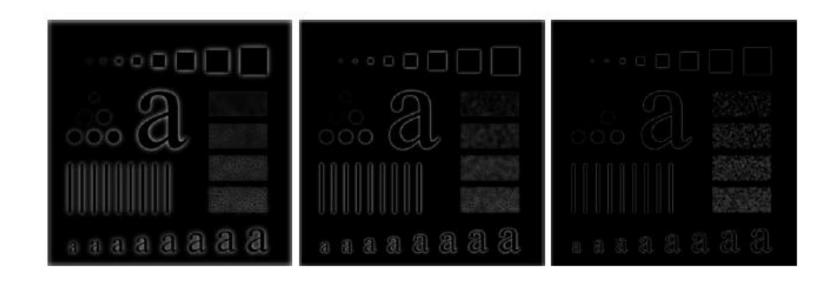








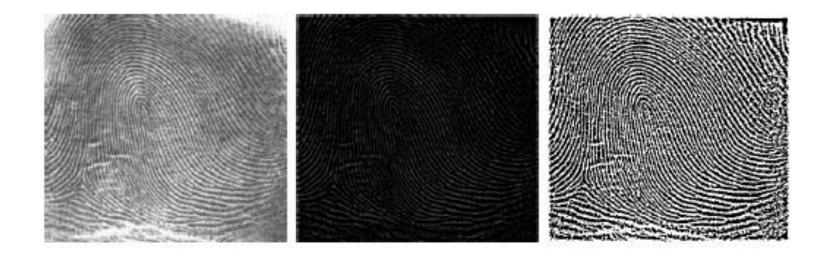




Highpass filters. D_0 is the cutoff frequency and n is the order of the Butterworth filter.

Ideal	Butterworth	Gaussian
$H(u,v) = \begin{cases} 1 & \text{if } D(u,v) \leq D_0 \\ 0 & \text{if } D(u,v) > D_0 \end{cases}$	$H(u,v) = \frac{1}{1 + [D_0/D(u,v)]^{2n}}$	$H(u,v) = 1 - e^{-D^2(u,v)/2D_0^2}$

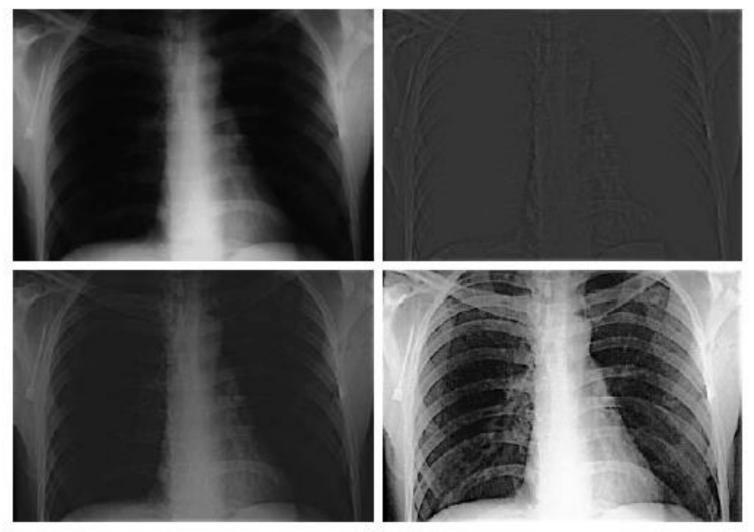
HPF and thresholding



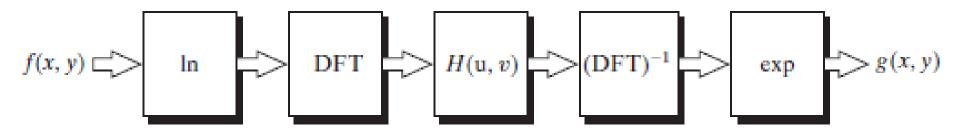
Enhancement using Laplacian



Original, GHPF, Adding the two, equalizing histogram



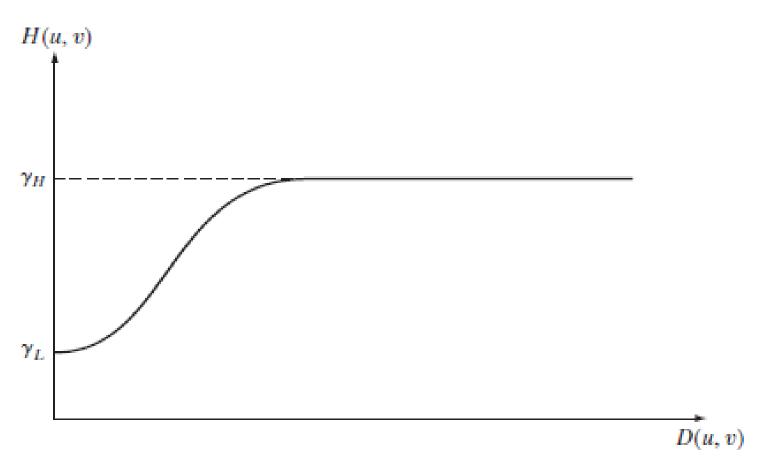
Homomorphic filtering



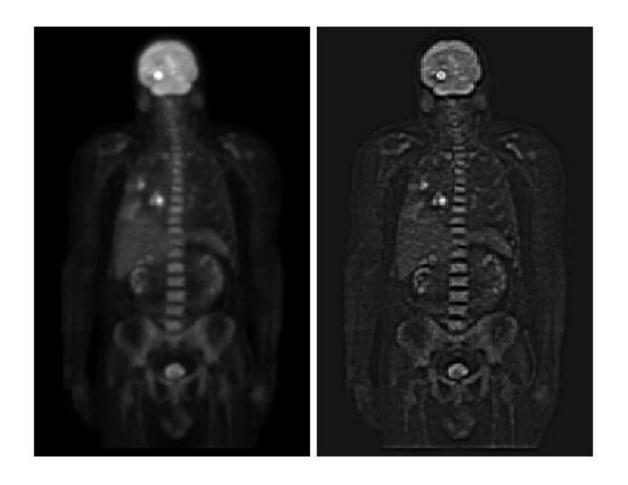
- Taking log of illumination × reflectance
- Filter is precisely designed to affect illumination and reflectance separately, assuming low frequency illumination and high frequency reflectance

Example radial cross section of a filter

$$H(u,v) = (\gamma_H - \gamma_L) \left[1 - e^{-c[D^2(u,v)/D_0^2]} \right] + \gamma_L$$
 (4.9-29)



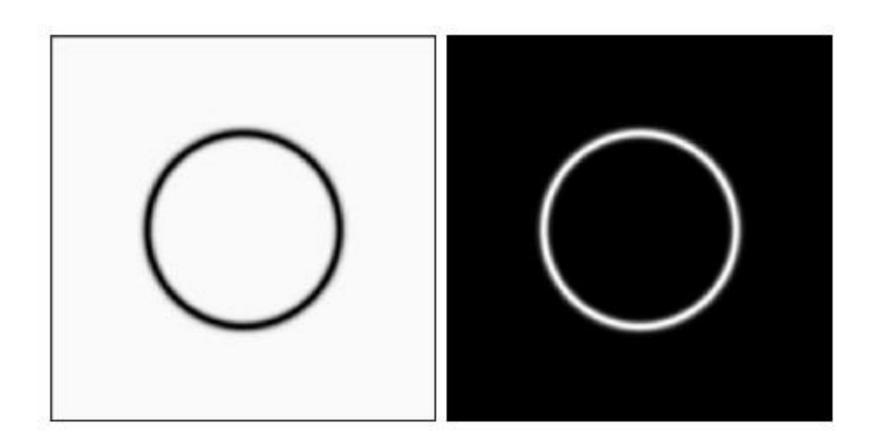
Example enhancement of tumors in PET scan using homomorphic filtering



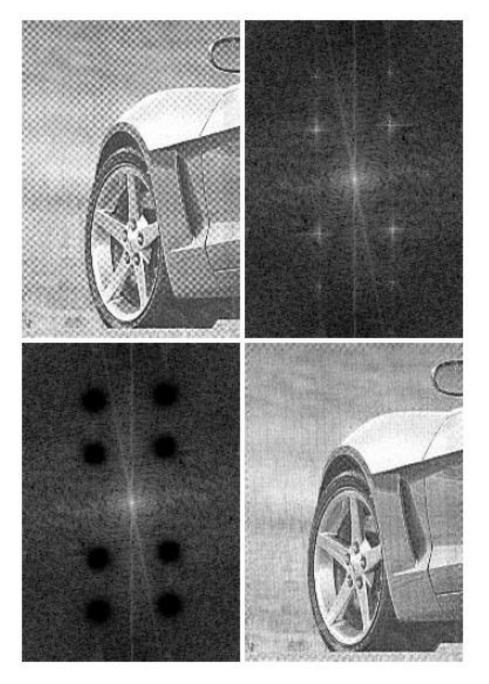
Examples of band reject filters

Similarly, bandpass filters can be defined

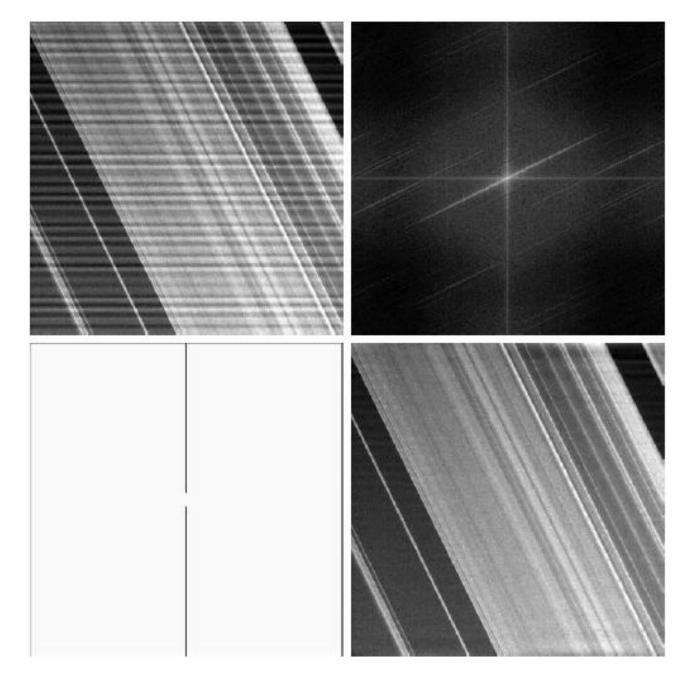
Band reject vs. bandpass



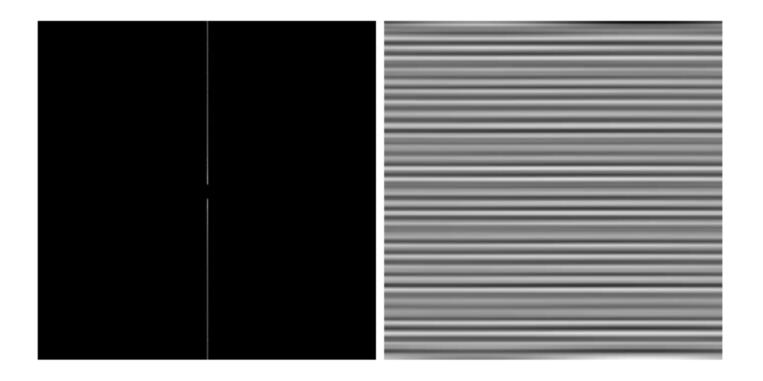
Original, DFT Butterworth notch-reject multiplied, result



Saturn rings, DFT, Vertical notchreject, result



Notch-pass filter shows interference pattern



Separability of 2-D DFT and IDFT

$$F(u,v) = \sum_{x=0}^{M-1} e^{-j2\pi ux/M} \sum_{y=0}^{N-1} f(x,y) e^{-j2\pi vy/N}$$

$$= \sum_{x=0}^{M-1} F(x, v) e^{-j2\pi ux/M}$$

$$m(n) = \frac{1}{2}M\log_2 M$$

$$a(n) = M \log_2 M$$

$$F(x, v) = \sum_{y=0}^{N-1} f(x, y) e^{-j2\pi vy/N}$$

$$MNf^*(x, y) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F^*(u, v) e^{-j2\pi(ux/M + vy/N)}$$

FFT algorithm for DFT

$$F(u) = \sum_{x=0}^{M-1} f(x) W_M^{ux} \qquad M = 2^n$$

$$W_M = e^{-j2\pi/M} \qquad M = 2K$$

$$F(u) = \sum_{x=0}^{2K-1} f(x) W_{2K}^{ux}$$

$$= \sum_{x=0}^{K-1} f(2x) W_{2K}^{u(2x)} + \sum_{x=0}^{K-1} f(2x+1) W_{2K}^{u(2x+1)}$$

$$F(u) = \sum_{x=0}^{K-1} f(2x) W_K^{ux} + \sum_{x=0}^{K-1} f(2x+1) W_K^{ux} W_{2K}^{u}$$

$$F(u) = F_{\text{even}}(u) + F_{\text{odd}}(u)W_{2K}^{u}$$

Savings of FFT over DFT 2ⁿ/n

