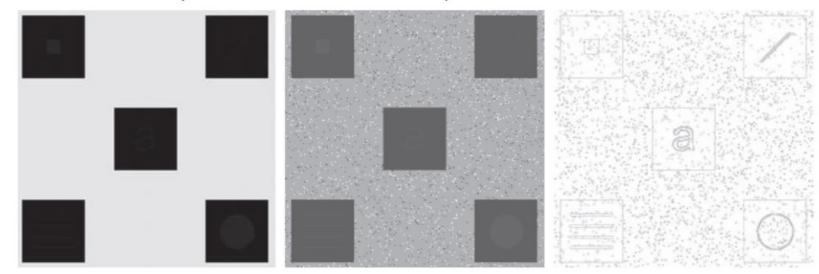




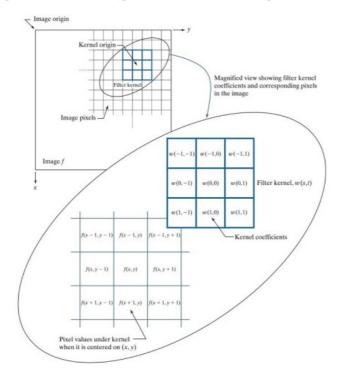
Local Processing

- Local processing is very effective approach in image processing (Natural images are Non-stationary)
 - -Local histogram equalization
 - -Local and adaptive intensity transform
 - Local statistics (mean and variance)





- \rightarrow For $n \times n$ window,
 - -Filtering/Mask/Kernel/Window/Template Processing





Spatial Domain Process

Smoothing Linear Filtering (Correlation and/or Convolution)

$$g(x,y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) f(x-s,y-t)$$

$$g(x,y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) f(x+s,y+t)$$



Spatial Domain Process

> Correlation/Convolution, valid (center) and same (right)

ightharpoonup Initial position for w				Cor	rela	tio	n re	esult	Ful	ll co	orre	lati	ion	res	ult			
11	2	3!	0	0	0	0						0	0	0	0	0	0	0
14	5	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	8	9	0	0	0	0	0	9	8	7	0	0	0	9	8	7	0	0
0	0	0	1	0	0	0	0	6	5	4	0	0	0	6	5	4	0	0
0	0	0	0	0	0	0	0	3	2	1	0	0	0	3	2	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0						0	0	0	0	0	0	0

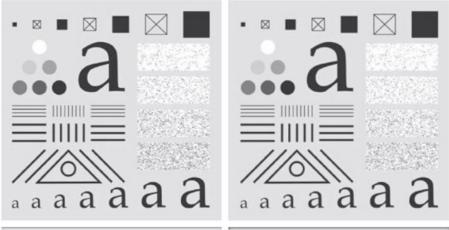
$\mathbf{Rotated}\ w$							Con	vol	utio	n r	esult	Ful	l co	nve	olut	tion	re	sult
19	8	7	0	0	0	0						0	0	0	0	0	0	0
6	5	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	2	1	0	0	0	0	0	1	2	3	0	0	0	1	2	3	0	0
0	0	0	1	0	0	0	0	4	5	6	0	0	0	4	5	6	0	0
0	0	0	0	0	0	0	0	7	8	9	0	0	0	7	8	9	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0						0	0	0	0	0	0	0

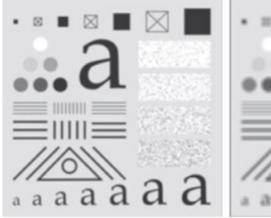


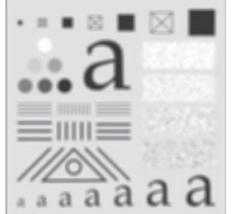
- > Blurring Effect:
- > Boxcar windows:

	1	1	1
$\frac{1}{9} \times$	1	1	1
	1	1	1

1 × 1	3 × 3
11 × 11	21 × 21









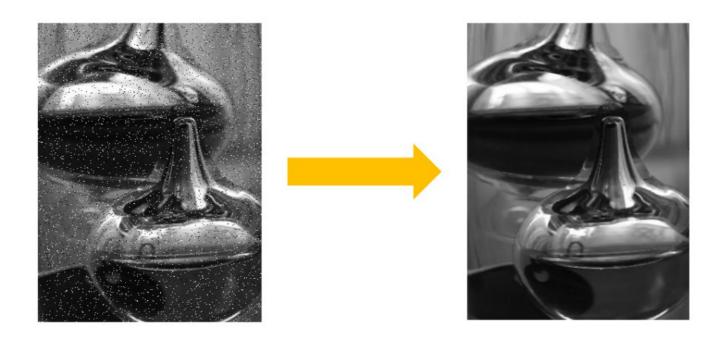
- > Most Common Spatial Filter:
 - -Gaussian Kernel:

$$G_{\sigma}(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \xrightarrow{kernel\ limited\ size} G_{\sigma}(x,y) = Ke^{-\frac{x^2+y^2}{2\sigma^2}}$$

- -Kernel/Windows size: $\approx ([6\sigma] \times [6\sigma])$
- -K: Normalization factor $(\sum_{x} \sum_{y} G_{\sigma}(x, y) = 1)$
- -Less blurring



- > Order statistics filter:
 - -Median (Best simple choice for salt & pepper noise)
 - $-g(x,y) = \sum_{(s,t)\in S(x,y)} median\{f(s,t)\}\$





Spatial Domain Process

- > Image Sharpening:
 - Highlight edges using *first* or *second* derivative:
- > Laplacian of image

$$\pm \left(\frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial Y^2} \right) = \pm \nabla^2 f$$

> Discrete Implementation with + sign (left) and - sign (right):

0	1	0	1	1	1	0	-1	0	-1	-1	-1
1	-4	1	1	-8	1	-1	4	-1	-1	8	-1
0	1	0	1	1	1	0	-1	0	-1	-1	-1



Spatial Domain Process

> Image enhancement:

$$g(x,y) = f(x,y) + c\nabla^2 f(x,y)$$

> Kernel formulation:

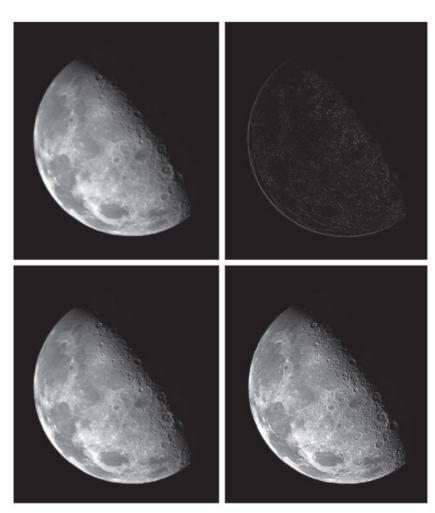
$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 00 \end{bmatrix} + c \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$



Spatial Domain Process

> Example:

(a) Blurred image of the North Pole of the moon. (b) Laplacian image obtained using the kernel in Fig. 3.45(a). (c) Image sharpened using Eq. (3-54) with c = -1. (d) Image sharpened using the same procedure, but with the kernel in Fig. 3.45(b).





Spatial Domain Process

> Noise suppression in Laplacian processing:

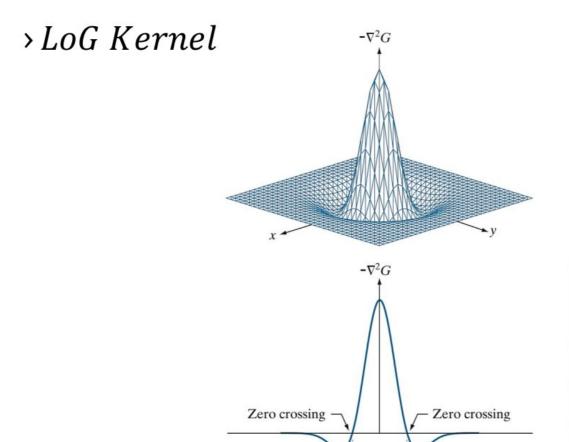
$$-\left(\frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial Y^2}\right) = -\nabla^2 f$$

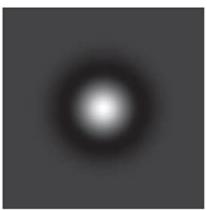
> Laplacian of Gaussian (LoG) of image:

$$LoG(f) = -\nabla^{2}(G_{\sigma} * f) = (-\nabla^{2}G_{\sigma}) * f$$

$$\nabla^{2}G_{\sigma} = \left(\frac{2\sigma^{2} - x^{2} - y^{2}}{\sigma^{4}}\right) e^{-\frac{x^{2} + y^{2}}{2\sigma^{2}}}$$







0	0	-1	0	0
0	-1	-2	-1	0
-1	-2	16	-2	-1
0	-1	-2	-1	0
0	0	-1	0	0



Spatial Domain Process

 \rightarrow LoG approximation via DoG (Difference of Gaussian)

$$G_D(x,y) = \frac{1}{2\pi\sigma_1^2} e^{-\frac{x^2+y^2}{2\sigma_1^2}} - \frac{1}{2\pi\sigma_2^2} e^{-\frac{x^2+y^2}{2\sigma_2^2}}$$



Spatial Domain Process

> Image Sharpening using image gradient:

$$\nabla f = \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x}, & \frac{\partial f}{\partial y} \end{bmatrix}^T \Rightarrow M(x, y) = \|\nabla f\|, \widehat{M}(x, y, y) = \left| \frac{\partial f}{\partial x} \right| + \left| \frac{\partial f}{\partial y} \right|$$

 \rightarrow Discrete implementation of g_x and g_y (Sobel Mask):

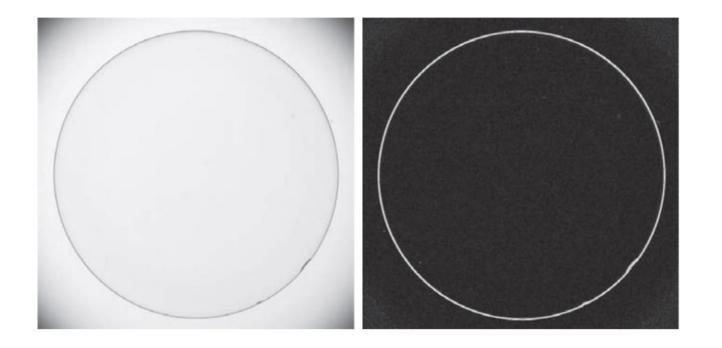
-1	-2	-1
0	0	0
1	2	1

-1	0	1
-2	0	2
-1	0	1



Spatial Domain Process

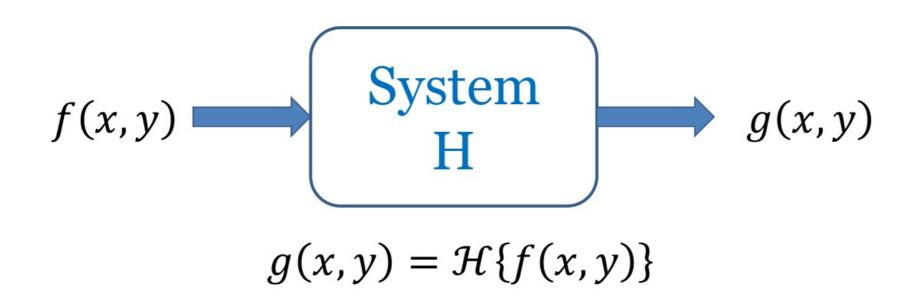
> Image Sharpening using image gradient, M(x, y):





Two Dimensional Systems:

> General Definition:





System Properties:

> Linearity:

$$\mathcal{H}\{af_1(x,y) + bf_2(x,y)\} = a\mathcal{H}\{f_1(x,y)\} + b\mathcal{H}\{f_2(x,y)\}$$

> Spatial Invariant:

$$\mathcal{H}\{f(x-x_0,y-y_0)\} = g(x-x_0,y-y_0)$$

- > Causality: We do not care about it!
- > Stability: Same as before.



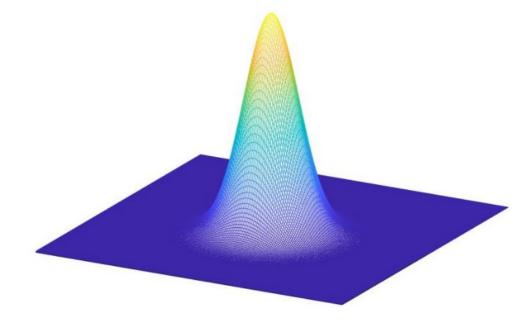
Unit Impulse (pinhole)

> Mathematical Definition:

$$\delta(x,y) = \begin{cases} 0, & (x,y) \neq (0,0) \\ \infty, & (x,y) = (0,0) \end{cases}$$

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \delta(x, y) dx dy = 1$$

> Approximation:





Point Spread Function (PSF)

> Definition:

$$H(x, y; x_0, y_0) = \mathcal{H}\{\delta(x - x_0, y - y_0)\}\$$

> Linear Shift Invariant (LSI):

$$H(x, y; x_0, y_0) = \mathcal{H}\{\delta(x - x_0, y - y_0)\} = H(x - x_0, y - y_0)$$

$$H(x, y) = \mathcal{H}\{\delta(x, y)\}$$



Convolution and Correlation

> Discrete Convolution:

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

> Discrete Correlation:

$$(f \approx h)(x,y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m,n)h(x+m,y+n)$$



Discrete Fourier Transform (DFT):

> Forward Transform

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

> Inverse Transform:

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



DFT (Definitions)

> Useful definitions:

	Name	Expression(s)
1)	Discrete Fourier transform (DFT) of $f(x,y)$	$F(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) e^{-j2\pi(ux/M + vy/N)}$
2)	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)	Spectrum	$ F(u,v) = [R^2(u,v) + I^2(u,v)]^{1/2}$ $R = \text{Real}(F); I = \text{Imag}(F)$
4)	Phase angle	$\phi(u,v) = \tan^{-1} \left[\frac{I(u,v)}{R(u,v)} \right]$
5)	Polar representation	$F(u,v) = F(u,v) e^{j\phi(u,v)}$
6)	Power spectrum	$P(u,v) = F(u,v) ^2$
7)	Average value	$\overline{f} = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) = \frac{1}{MN} F(0, 0)$
8)	Periodicity (k_1 and k_2 are integers)	$F(u,v) = F(u + k_1 M, v) = F(u, v + k_2 N)$ $= F(u + k_1, v + k_2 N)$ $f(x,y) = f(x + k_1 M, y) = f(x, y + k_2 N)$ $= f(x + k_1 M, y + k_2 N)$



DFT Pairs

> Useful Pairs:

	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)	$f(x,y)e^{j2\pi(u_0x/M+v_0y/N)} \Leftrightarrow F(u-u_0,v-v_0)$ $f(x-x_0,y-y_0) \Leftrightarrow F(u,v)e^{-j2\pi(ux_0/M+vy_0/N)}$
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	$f(r, \theta + \theta_0) \Leftrightarrow F(\omega, \varphi + \theta_0)$ $r = \sqrt{x^2 + y^2} \qquad \theta = \tan^{-1}(y/x) \qquad \omega = \sqrt{u^2 + v^2} \qquad \varphi = \tan^{-1}(v/u)$
6)	Convolution theorem [†]	$f \star h)(x,y) \Leftrightarrow (F \cdot H)(u,v)$ $(f \cdot h)(x,y) \Leftrightarrow (1/MN)[(F \star H)(u,v)]$
7)	Correlation theorem [†]	$(f \stackrel{.}{\sim} h)(x,y) \Leftrightarrow (F^* \bullet H)(u,v)$ $(f^* \bullet h)(x,y) \Leftrightarrow (1/MN)[(F \stackrel{.}{\sim} H)(u,v)]$



DFT Pairs

> Useful Pairs:

- 8) Discrete unit $\delta(x,y) \Leftrightarrow 1$ impulse $1 \Leftrightarrow MN\delta(u,v)$
- 9) Rectangle $\operatorname{rec}[a,b] \Leftrightarrow ab \frac{\sin(\pi ua)}{(\pi ua)} \frac{\sin(\pi vb)}{(\pi vb)} e^{-j\pi(ua+vb)}$
- 10) Sine $\sin(2\pi u_0 x/M + 2\pi v_0 y/N) \Leftrightarrow \frac{jMN}{2} \left[\delta(u + u_0, v + v_0) \delta(u u_0, v v_0) \right]$
- 11) Cosine $\cos(2\pi u_0 x/M + 2\pi v_0 y/N) \Leftrightarrow \frac{1}{2} [\delta(u + u_0, v + v_0) + \delta(u u_0, v v_0)]$

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
$$f(\pm \infty, \pm \infty) = 0$$
.
$$\frac{\partial}{\partial t} \int_{0}^{m} \left(\frac{\partial}{\partial z}\right)^{n} f(t, z) \Leftrightarrow (j2\pi\mu)^{m} (j2\pi\nu)^{n} F(\mu, \nu)$$

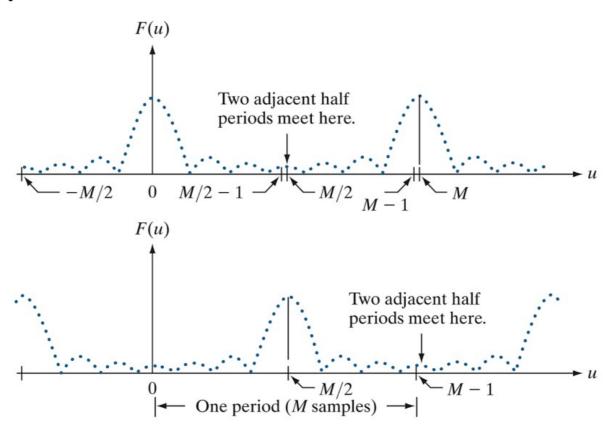
$$\frac{\partial^{m} f(t, z)}{\partial t^{m}} \Leftrightarrow (j2\pi\mu)^{m} F(\mu, \nu); \frac{\partial^{n} f(t, z)}{\partial z^{m}} \Leftrightarrow (j2\pi\nu)^{n} F(\mu, \nu)$$

13) Gaussian
$$A2\pi\sigma^2 e^{-2\pi^2\sigma^2(t^2+z^2)} \Leftrightarrow Ae^{-(\mu^2+\nu^2)/2\sigma^2} \quad (A \text{ is a constant})$$



DFT Centering

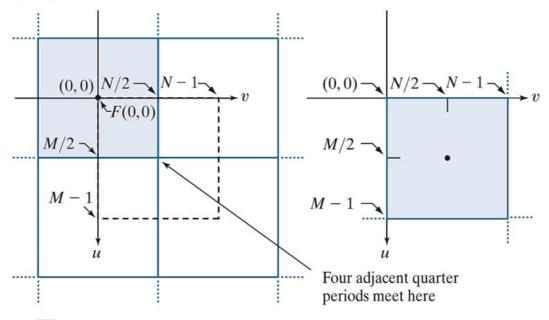
> From DSP:





DFT Centering

For DIP (*fftshift*):



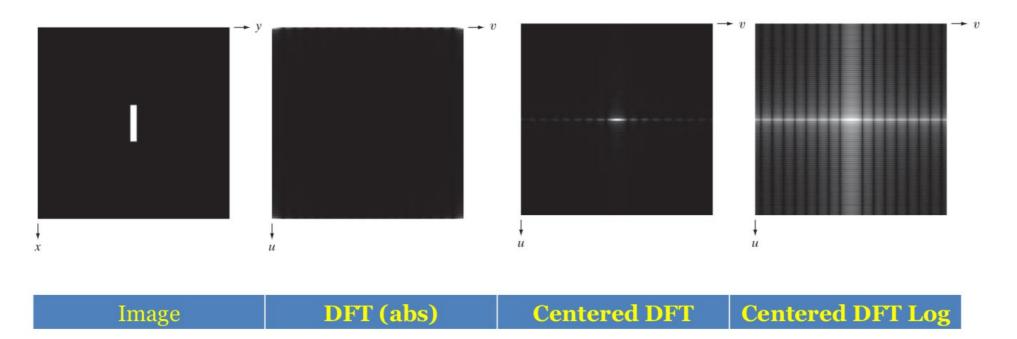
- $= M \times N$ data array computed by the DFT with f(x, y) as input
- $= M \times N$ data array computed by the DFT with $f(x, y)(-1)^{x+y}$ as input

····· = Periods of the DFT



DFT Centering

> Example:





The Importance of Phase

> Let swap phase and magnitude of DFT of two images:





The Importance of Phase

> Let swap phase and magnitude of DFT of two images:

