

Arithmetical and Logic Operations

- Arithmetic/logic operations are performed on a pixel by pixel basis between two or more images.
- •Basic arithmetic operations are: Gray-value point operations are used including the following functions

Operation	Definition	preferred data type
ADD	c = a + b	integer
SUB	c = a - b	integer
MUL	c = a * b	integer or floating point
DIV	c = a / b	floating point
LOG	c = log(a)	floating point
EXP	c = exp(a)	floating point
SQRT	c = sqrt(a)	floating point
TRIG.	$c = \sin/\cos/\tan(a)$	floating point
INVERT	$c = (2^B - 1) - a$	integer



Arithmetical and Logic Operations

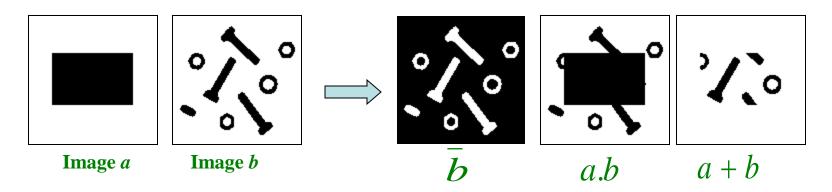
Basic logic operations are: Binary operations are used including the following functions

$$NOT$$
 $c = \bar{a}$

$$OR$$
 $c = a + b$

$$AND$$
 $c = a \cdot b$

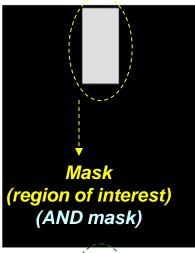
$$XOR$$
 $c = a \oplus b = a \cdot \overline{b} + \overline{a} \cdot b$

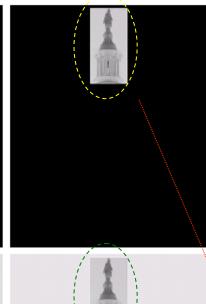


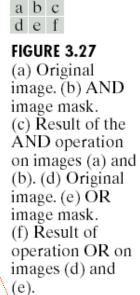
Note: The images can be binary (bi-level) images. Each pixel is 1 (True-white) or 0 (False-black).

Arithmetical and Logic Operations















Note: The images can be *gray-level* images. Each pixel is an 8-bit binary number. Bit by bit operation is used.

Image Subtraction

The difference image between two images f(x,y) and h(x,y) can be expressed by: g(x,y) = f(x,y) - h(x,y)

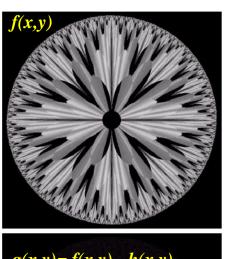


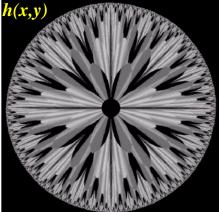
FIGURE 3.28

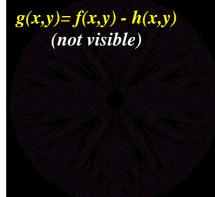
(a) Original fractal image. (b) Result of setting the four lower-order bit planes to zero. (c) Difference between (a) and (b). (d) Histogram-equalized difference image. (Original image courtesy of Ms. Melissa D. Binde, Swarthmore

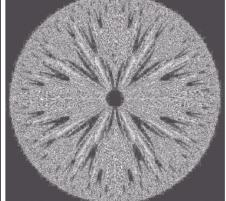
College,

Swarthmore, PA).







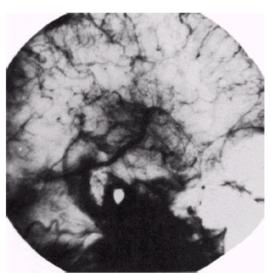


 \bigcirc Contrast stretched g(x,y)

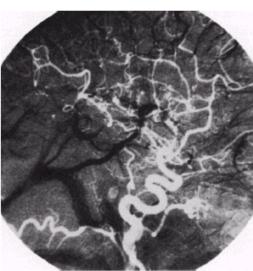
(visible after Contrast Streaching)

Image Subtraction

- Image subtraction is used in medical imaging called mask mode radiography.
- The initial image is captured and used as the mask image, h(x,y). Then after injecting a contrast material into the bloodstream the mask image is subtracted from the resulting image f(x,y) to give an enhanced output image g(x,y).



h(x,y)



g(x,y) = f(x,y) - h(x,y)

(Result after Subtraction)

a b

FIGURE 3.29

Enhancement by image subtraction.

- (a) Mask image.
- (b) An image (taken after injection of a contrast medium into the bloodstream) with mask subtracted out.



Image Averaging

• Consider a noisy image, g(x, y), formed by the addition of noise $\eta(x, y)$ to an original image f(x, y):

$$g(x, y) = f(x, y) + \eta(x, y)$$

- •Consider an uncorrelated noise with zero average value.
- •An enhanced image, $\overline{g}(x, y)$, can be formed by adding K different noisy images.

$$\overline{g}(x,y) = \frac{1}{K} \sum_{i=1}^{K} g_i(x,y)$$

•The expected value of \overline{g} :

$$E\{\overline{g}(x, y)\} = f(x, y)$$



Image Averaging

•Then/variances:

$$\sigma^{2}_{\overline{g}(x,y)} = \frac{1}{K} \sigma^{2}_{\eta(x,y)}$$
Variance is dictated by noise

•Standard deviations in the average image:

$$\sigma_{\bar{g}(x,y)} = \frac{1}{\sqrt{K}} \sigma_{\eta(x,y)}$$

- •As K increases the variability (noise) of the pixel values at each location (x,y) decreases.
- In other words, the average image, $\overline{g}(x, y)$, approaches the input image f(x,y) as the number of noisy images used in the averaging operation increases.

Image Averaging

FIGURE 3.30 (a) Image of Galaxy Pair NGC 3314. (b) Image corrupted by additive Gaussian noise with zero mean and a standard deviation of 64 gray levels. (c)-(f) Results of averaging K = 8, 16, 64, and 128 noisy images. (Original image courtesy of NASA.)

Original im.





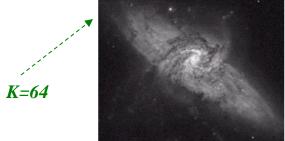
One of the noisy images







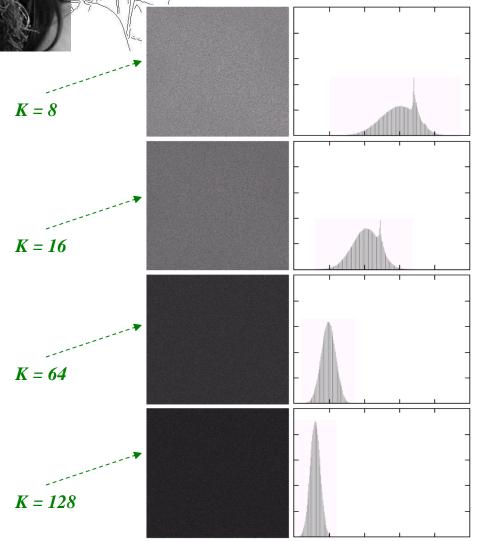
Average of K=16 noisy images





Average of K=128 noisy images

Image Averaging



a b

FIGURE 3.31 (a) From top to bottom: Difference images between Fig. 3.30(a) and the four images in Figs. 3.30(c) through (f), respectively. (b) Corresponding histograms.

difference = original - averaged $d(x, y) = f(x, y) - \overline{g}(x, y)$



Spatial Filtering

- •Spatial filtering refers to some neighborhood operations working with the values of the image pixels in the neighborhood and the corresponding values of a subimage that has the same dimensions as the neighborhood.
- •This subimage is called, a <u>filter</u>, mask, kernel, template or a window. The values in a filter is referred to as <u>coefficients</u>.
- •The filtering can be performed in
 - spatial domain.
 - frequency domain (we will study later) and
- •There are two main types of spatial domain filtering
 - •linear spatial filtering (convolution filter/mask/kernel) and
 - •nonlinear spatial filtering.

Spatial Filtering

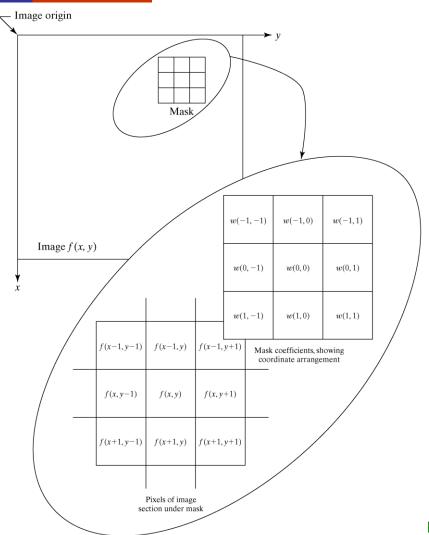
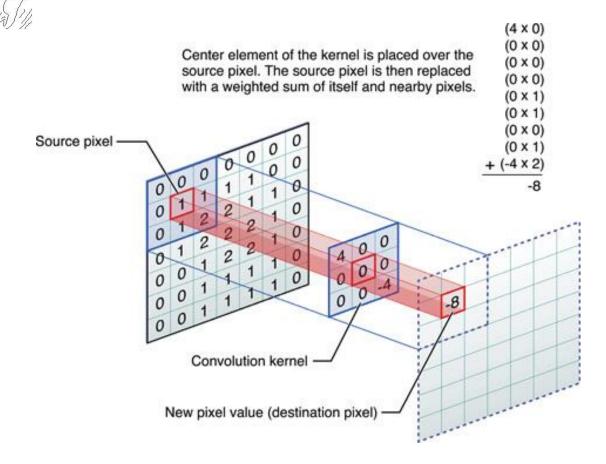


FIGURE 3.12 The mechanics of linear spatial filtering. The magnified drawing shows a 3×3 mask and the corresponding image neighborhood directly under it. The neighborhood is shown displaced out from under the mask for ease of readability.

Linear Spatial Filtering





Linear Spatial Filtering

• Using a 3×3 mask shown in the previous slide the response, R, of a linear filtering with the filter mask at point (x,y) in the image is:

$$R = \omega(-1, -1)f(x-1, y-1) + \omega(-1, 0)f(x-1, y) + \dots$$
$$+ \omega(0, 0)f(x, y) + \dots + \omega(1, 0)f(x+1, y) + \omega(1, 1)f(x+1, y+1)$$

•In general, linear filtering of an image of size $M \times N$ with a filter mask of size $m \times n$ is given by:

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

• where a = (m - 1)/2, b = (n - 1)/2





Inear Spatial Filtering

•Linear spatial filtering is often called convolution operation and the filter mask is also referred to as convolution mask.

•Response, R, of a $m \times n$ mask at any point (x,y) in the image can be formulated by:

$$R = \omega_1 z_1 + \omega_2 z_2 + \dots + \omega_{mn} z_{mn}$$
$$= \sum_{i=1}^{mn} \omega_i z_i$$

•Where, ω 's are the mask coefficients and **Z**'s are the image pixel values.

•Given a 3×3 mask below the response at any point (x,y) is:

FIGURE 3.33
Another
representation of a general 3 × 3
spatial filter mask.

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

$$R = \sum_{i=1}^{9} \omega_i z_i$$



Smoothing Spatial Filters

- •Smoothing filters are used for noise reduction and blurring operations. Blurring can be used as a preprocessing step for other image processing operations.
- There are two main types of Smoothing filters:
 - •Smoothing Linear Filters
 - •Smoothing Nonlinear Filters

Smoothing Linear Filters/ Averaging Filters

- •The response of a smoothing linear spatial filter is simply the average of the pixels contained in the neighborhood of the filter mask.
- •These kind of filters are called averaging filters or lowpass filters.



Convolution and Correlation

•Convolution involves calculating the weighted sum of a neighborhood of pixels. The weights are taken from a convolution kernel. Each value from the neighborhood of pixels is multiplied with its opposite on the matrix. For example, the top-left of the neighbor is multiplied by the bottom-right of the kernel. All these values are summed up to calculate the result of the convolution.

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

Consider a 3x3 neighborhood. Given a convolution kernel (mask) ω , you need to rotate the mask with 180° as follows,

Convolution operation

Convolution kernel, ω

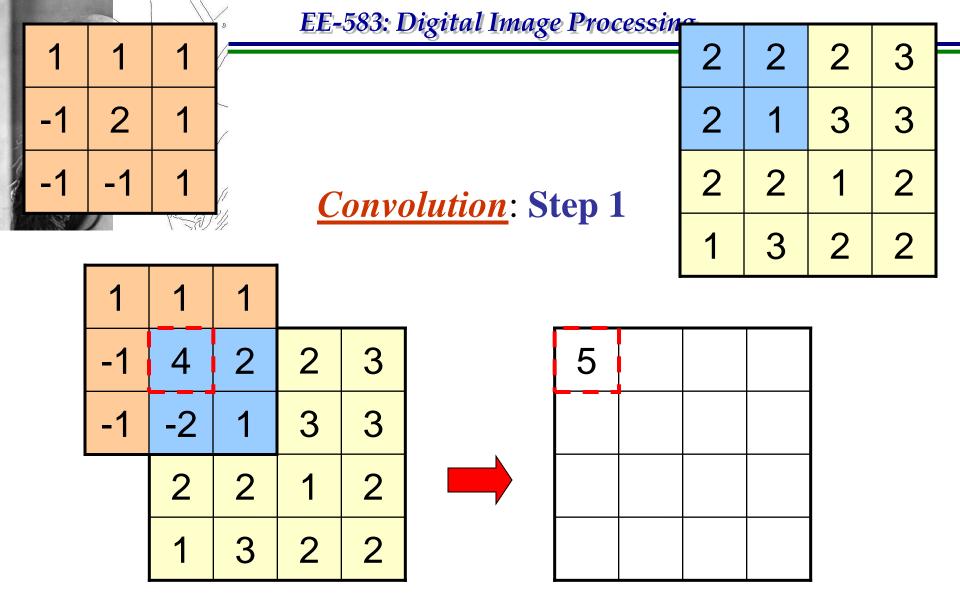
1	**************************************	-1
1	2	-1
1	1	1

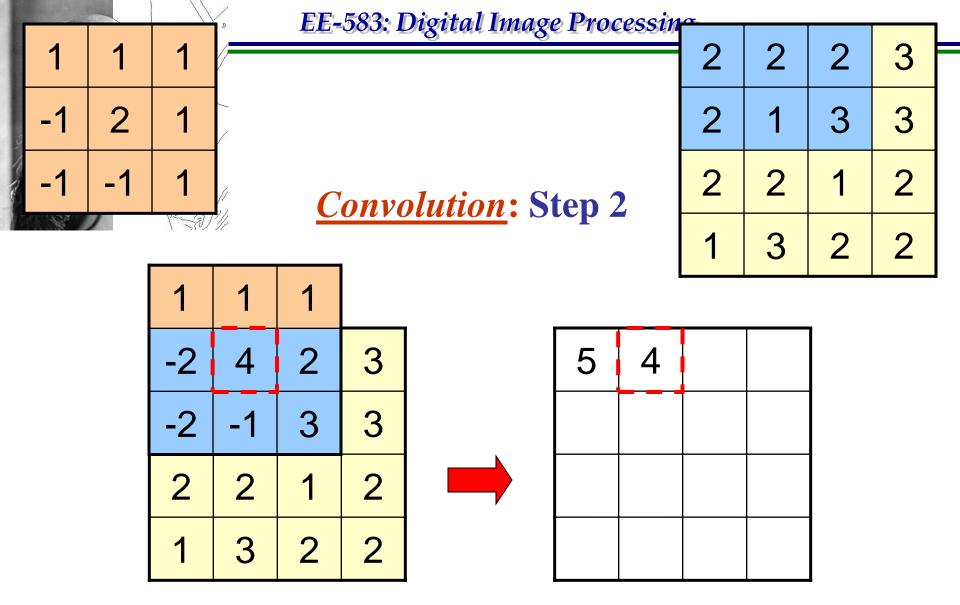
Rotate 180°

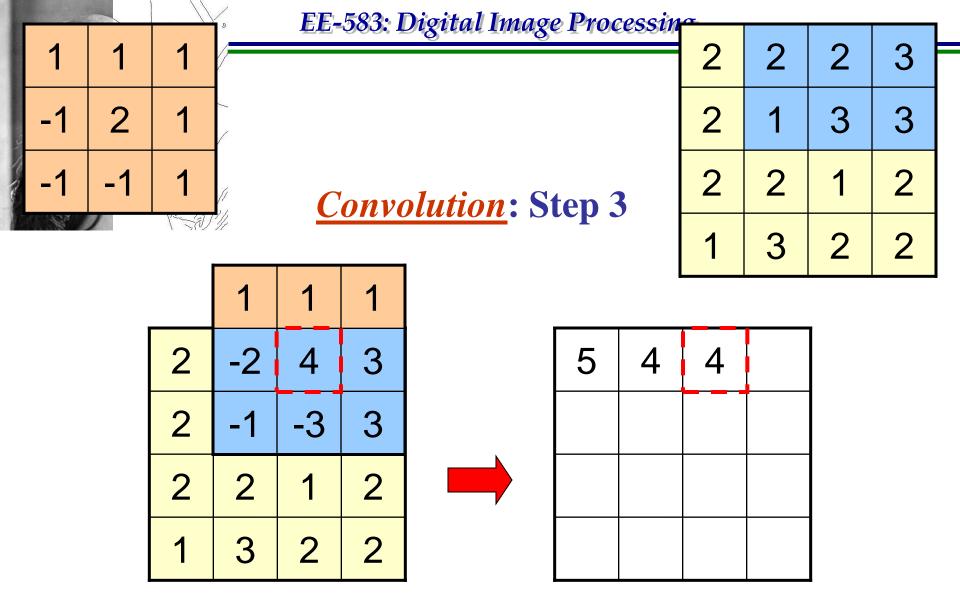
1	1	1
-1	2	1
-1	7	1

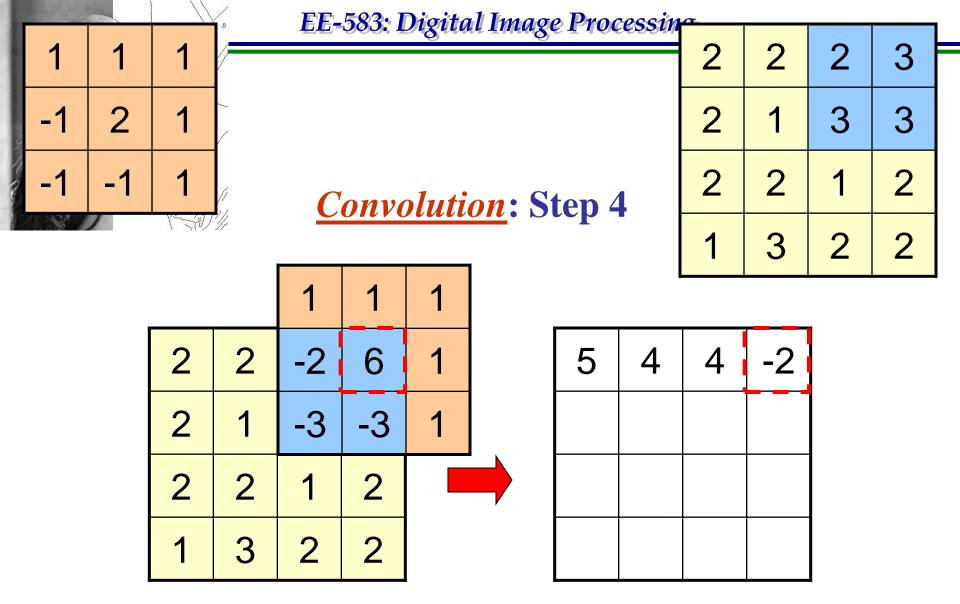
Input Image f

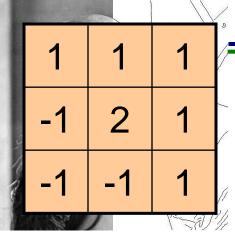
2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2











EE-583 :	Digital	Image	Process	in c
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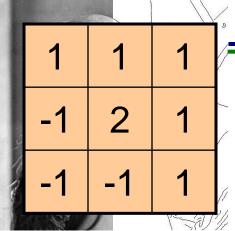
Convol	lution:	Step	5

2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2

1	2	2	2	3
-1	4	1	თ	3
-1	-2	2	1	2
	1	3	2	2



5	4	4	-2
9			



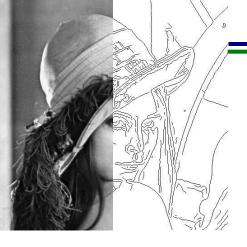
EE-583: Digital Image Processing

Convolution: Step 6

2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2

2	2	2	3
-2	2	3	3
-2	-2	1	2
1	3	2	2

Input Image, f



Convolution: Final Result

5	4	4	-2
9	6	14	5
11	7	6	5
9	12	8	5

Final output Image, g



Convolution and Correlation

• <u>Correlation</u> is nearly identical to convolution with only a minor difference, where instead of multiplying the pixel by the opposite in the kernel, you multiply it by the equivalent (i.e. top-left multiplied by top-left).

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

Consider a 3x3 neighborhood. Given a correlation kernel (mask) ω , and input image f,

Correlation operation

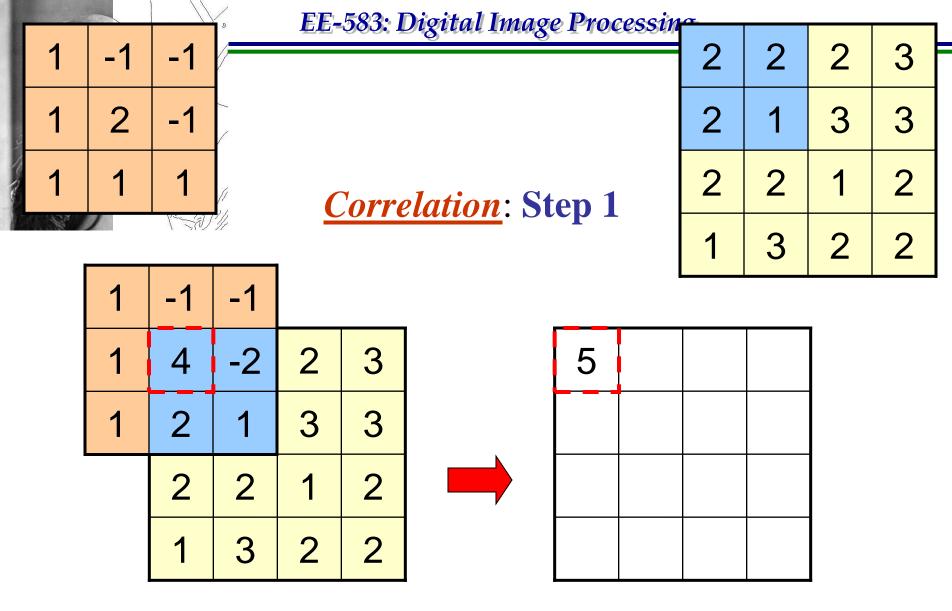
orrelation kernel	, (w
1 1/2		

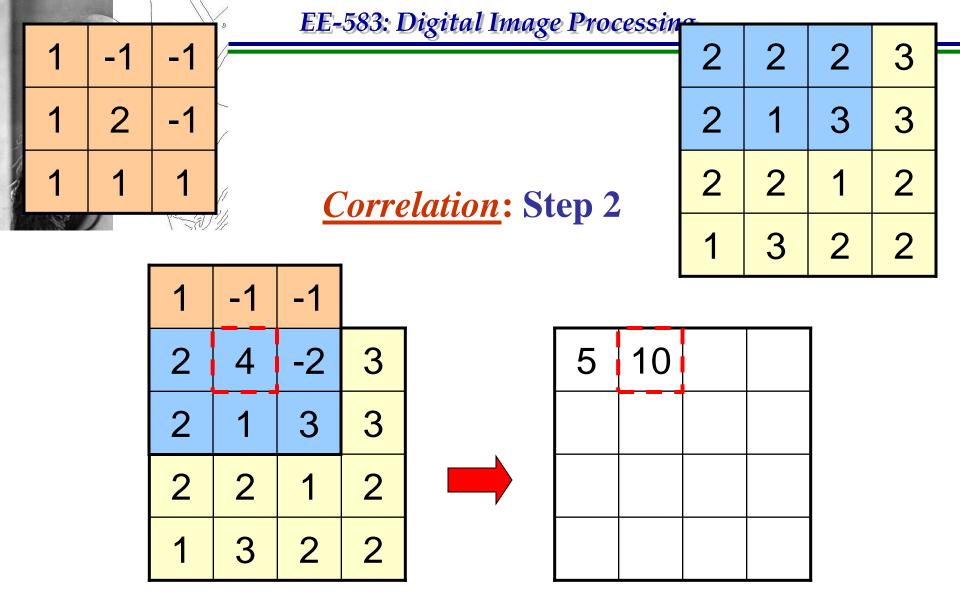
1	1	-1
~	2	-1
1	1	1

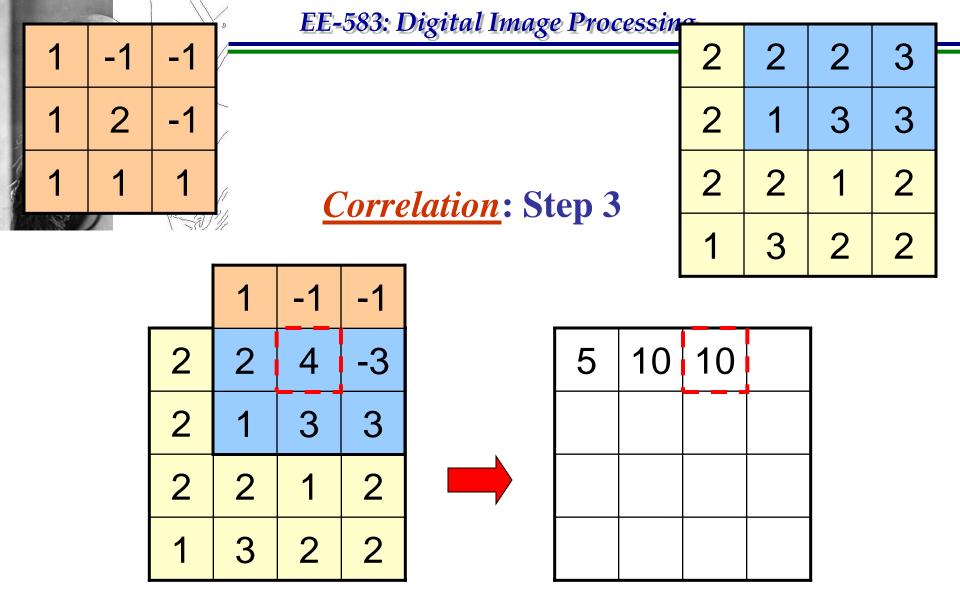
Don't rotate use it directly

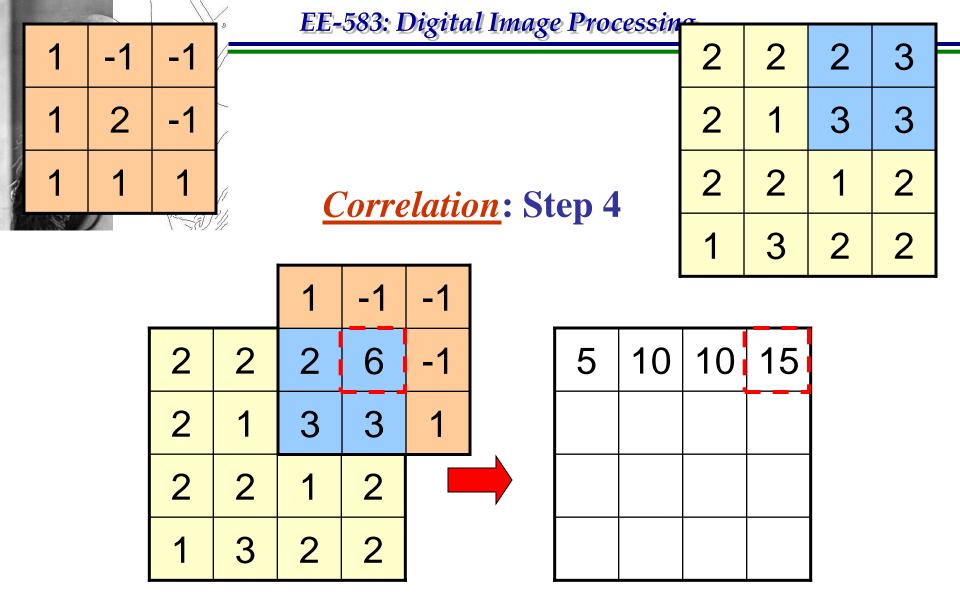
Input Image f

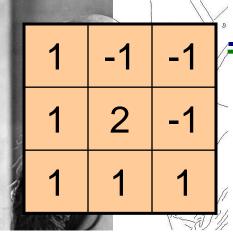
2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2











EE-583: Digital Image Processing

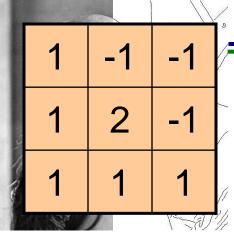
Correlation: Step 5

2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2

1	-2	-2	2	3
1	4	-1	3	3
1	2	2	1	2
	1	3	2	2

5	10	10	15
3			

Input Image, f



EE-583: Digital Image Processing

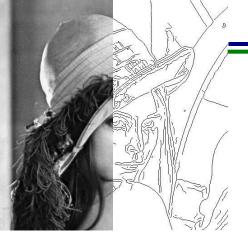
Correlation: Step 6

2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2

2	-2	-2	3
2	2	-3	3
2	2	1	2
1	3	2	2

5	10	10	15
3	4		

Input Image, f



Correlation: Final Result

5	10	10	15
3	4	6	11
7	11	4	9
-5	4	4	5

Final output Image, g



Smoothing Linear Filters/ Averaging Filters

- •The idea behind smoothing filters is to replace the value of every pixel in an image by the average of the gray levels defined by the filter mask.
- •Random noise consists of sharp transitions in gray levels. So, the most obvious application is noise reduction.
- •The undesirable effects of the averaging filters is the blurring of edges.

	1	1	1	
$\frac{1}{9}$ ×	1	1	1	
	1	1	1	
4				

box filter

	1	2	1
- ×	2	4	2
	1	2	1
*			

weighted average filter

FIGURE 3.34 Two 3 × 3 smoothing (averaging) filter masks. The constant multipli er in front of each mask is equal to the sum of the values of its coefficients, as is required to compute an average.



Smoothing Linear Filters/ Gaussian Smoothing

1D Gaussian distribution:
$$G(x) = \frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{x^2}{2\sigma^2}}$$

0.4
0.3

$$\Xi$$
 0.2
0.1
0.4
-2
0
2

$$(\sigma = \sigma_x = \sigma_y)$$

$$G(x,y) = rac{1}{2\pi\sigma^2} e^{-rac{x^2+y^2}{2\sigma^2}}$$

$$\frac{1}{16} \left[\begin{array}{ccc} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{array} \right]$$

$$\frac{1}{256} \begin{bmatrix}
1 & 4 & 6 & 4 & 1 \\
4 & 16 & 24 & 16 & 4 \\
6 & 24 & 36 & 24 & 6 \\
4 & 16 & 24 & 16 & 4 \\
1 & 4 & 6 & 4 & 1
\end{bmatrix}$$

5x5 mask/kernel



Smoothing Linear Filters/ Averaging Filters

•The general implementation of an $M \times N$ image with a weighted averaging filter of size $m \times n$ is given by:

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

Sum of the mask coefficients, which is constant.

Smoothing Linear Filters/ Averaging Filters



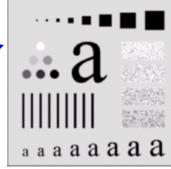


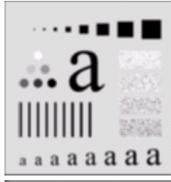
FIGURE 3.35 (a) Original image, of size 500×500 pixels. (b)–(f) Results of smoothing with square averaging filter masks of sizes n=3,5,9,15, and 35, respectively. The black squares at the top are of sizes 3,5,9,15,25,35,45, and 55 pixels, respectively; their borders are 25 pixels apart. The letters at the bottom range in size from 10 to 24 points, in increments of 2 points; the large letter at the top is 60 points. The vertical bars are 5 pixels wide and 100 pixels high; their separation is 20 pixels. The diameter of the circles is 25 pixels, and their borders are 15 pixels apart; their gray levels range from 0% to 100% black in increments of 20%. The background of the image is 10% black. The noisy rectangles are of size 50×120 pixels.

5x5 mask

15x15 mask

original





3x3 mask

...a

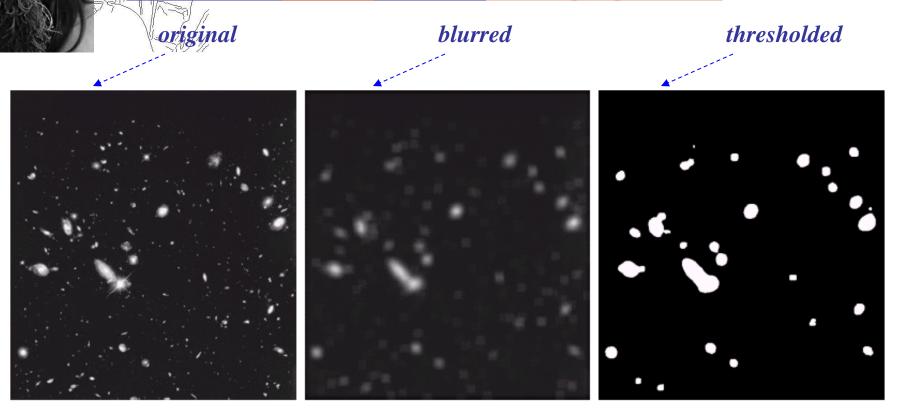


9x9 *mask*

35x35 *mask*

Prepared By: Dr. Hasan Demirel, PhD

Smoothing Linear Filters/ Averaging Filters



a b c

FIGURE 3.36 (a) Image from the Hubble Space Telescope. (b) Image processed by a 15 × 15 averaging mask. (c) Result of thresholding (b). (Original image courtesy of NASA.)



Order-Statistics Filters

- •The order-statistics filters are nonlinear spatial filters whose response is based on the ordering/ranking of the pixels contained image area encompassed by the filter.
- •The center pixel is replaced with the value determined by the ranking result.
- •The best known ordered –statistics filter is the median filter.
- •The median filter is excellent for random noise reduction with considerably less blurring than the linear smoothing filters.
- •Median filters is very effective for impulsive noise which is also called salt-andpepper noise (noise introducing white and black dots on the image)
- •Given a **3x3** neighborhood having (10, 20, 20, 20, 100, 20, 20, 25, 15) gray level values. The sorted values of the neighborhood will be: (10, 15, 20, 20, $\frac{20}{20}$, 20, 20, 20, 100) and the center pixel will be forced to the median value which is 20.

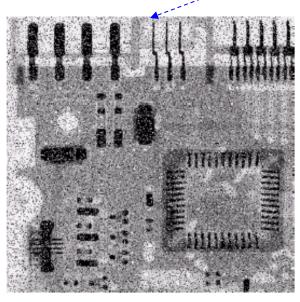


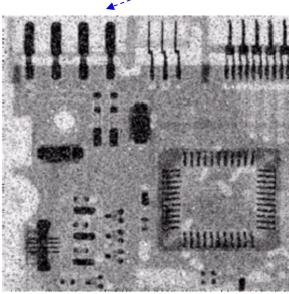
Order-Statistics Filters

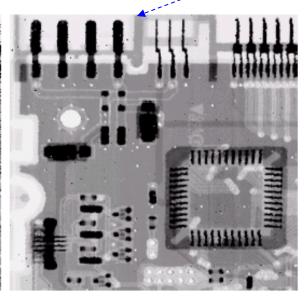
Corrupted by salt and pepper noise

Averaging filter

median filter







a b c

FIGURE 3.37 (a) X-ray image of circuit board corrupted by salt-and-pepper noise. (b) Noise reduction with a 3 × 3 averaging mask. (c) Noise reduction with a 3 × 3 median filter. (Original image courtesy of Mr. Joseph E. Pascente, Lixi, Inc.)



Sharpening Spatial Filters

- •Sharpening is the operation to highlight fine details or enhance the details that has been blurred.
- •Blurring is based on the averaging in a neighborhood which is analogous to integration. Therefore the sharpening could be accomplished by differentiation.
- •The derivative of a digital function is defined in terms of differences, where a first order derivative of a one dimensional function f(x) is:

$$\frac{\partial f}{\partial x} = f(x+1) - f(x)$$

•Second order derivative can be defined by:

$$\frac{\partial^2 f}{\partial x^2} = f(x+1) - f(x) - (f(x) - f(x-1))$$

$$= f(x+1) + f(x-1) - 2f(x)$$



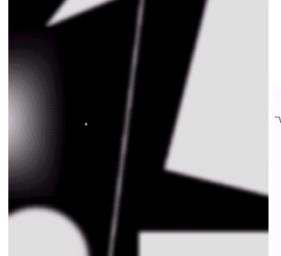
Sharpening Spatial Filters

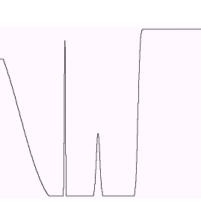
•The effect of the first and second-order derivatives on an image are:



FIGURE 3.38

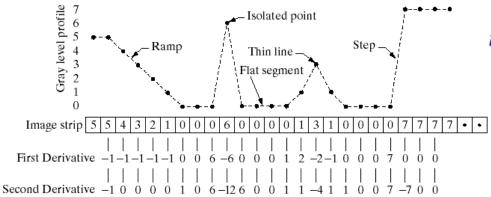
(a) A simple image. (b) 1-D horizontal gray-level profile along the center of the image and including the isolated noise point. (c) Simplified profile (the points are joined by dashed lines to simplify interpretation).





- •First-order derivative
 - Zero in flat segments.
 - Nonzero at ramps.

- •Second-order derivative
 - Zero in Flat segments.
- Nonzero at the beginning and the end of ramps.
- Zero in along ramps.



Prepared By: Dr. Hasan Demirel, PhD



Second-order Derivatives for Enhancement - The Laplacian

- •Second-order derivative is used to construct a Laplacian filter mask. Laplacian is an isotropic filter where the response of the filter is independent of the direction of the discontinuities in the image.
- •Isotropic filters are rotation invariant, which means that if you rotate and filter the image or if you filter and then rotate the image you get the same result.
- •Given an image f(x,y) the Laplacian operator is defined by:

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

•The operator is a linear operator and can be expressed in discrete form in x-direction by:

$$\frac{\partial^2 f}{\partial x^2} = f(x+1, y) + f(x-1, y) - 2f(x, y)$$



Second-order Derivatives for Enhancement - The Laplacian

•The operator can be expressed in discrete form in y-direction by:

$$\frac{\partial^2 f}{\partial y^2} = f(x, y+1) + f(x, y-1) - 2f(x, y)$$

•Then,2-D Laplacian is:

$$\nabla^2 f = [f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1)]$$
$$-4f(x, y)$$



Second-order Derivatives for Enhancement - The Laplacian

•The filter masks used to implement the digital Laplacian:

considers x and y coordinates Isotropic results for 90°

							_
	0	1	0	1	1	1	
	1	-4	1	1	-8	an	nsiders x, y d two diagonal
0	0	1	0	1	1		ordinates. otropic for 45 ⁰
	0	-1	0	-1	-1	-1	
	-1	4	-1	-1	8	-1	
	0	-1	0	-1	-1	-1	

a b c d

FIGURE 3.39

(a) Filter mask used to d two diagonal implement the digital Laplacian, as defined in Eq. (3.7-4). (b) Mask used to implement an extension of this equation that includes the diagonal neighbors. (c) and (d) Two other implementations of the Laplacian.



Second-order Derivatives for Enhancement - The Laplacian

- •The Laplacian operator highlights gray level discontinuities and de-emphasizes the slowly varying gray-levels.
- The result of Laplacian operator will give edge lines and other discontinuities on a dark and featureless background.
- •The background features can be recovered and sharpening effect can be preserved by adding the Laplacian image to the original image.
- •Depending on the choice of the Laplacian coefficients the following criteria is used for enhancement:

$$g(x,y) = \begin{cases} f(x,y) - \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of the} \\ f(x,y) + \nabla^2 f(x,y) & \text{If the center coefficient of$$

- Laplacian mask is positive

Second-order Derivatives for Enhancement - The Laplacian

a b

FIGURE 3.40

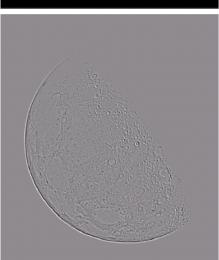
(a) Image of the North Pole of the moon.
(b) Laplacian-filtered image.
(c) Laplacian image scaled for display purposes.
(d) Image enhanced by using Eq. (3.7-5).
(Original image courtesy of NASA.)





Laplacian image $\nabla^2 f(x, y)$

Original image f(x, y)





Enhanced image

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

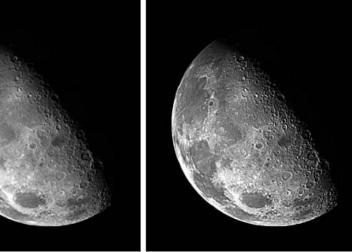
Second-order Derivatives for Enhancement - The Laplacian



Original image

Enhanced image using the mask with Center coefficient -8

Enhanced image using the mask with Center coefficient -4



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The First Derivatives for Enhancement - The Gradient

•The first derivatives in image processing are implemented by using the magnitude of the gradient.

• The gradient of f at coordinates (x,y) is defined by the two-dimensional column

vector:

$$\nabla \mathbf{f} = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

•The magnitude of this vector, is referred to as the gradient, which is:

$$\nabla f = mag(\nabla \mathbf{f}) = \left[G_x^2 + G_y^2\right]^{1/2} = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$



The First Derivatives for Enhancement - The Gradient

•The magnitude of the gradient can be approximated by using the absolute values instead of squares and square roots, which is cheaper to compute and still preserves changes in the gray levels.

$$\nabla f \approx \left| G_{x} \right| + \left| G_{y} \right|$$

•If we consider a 3x3 filter mask then an approximation around the center pixel will be as follows:

z_1	z_2	<i>z</i> ₃
Z ₄	z ₅	Z ₆
z ₇	z_8	Z9

$$\nabla f \approx |G_x| + |G_y| = |(z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)|$$

$$+ |(z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)|$$

EE-583: Digital Image Processing



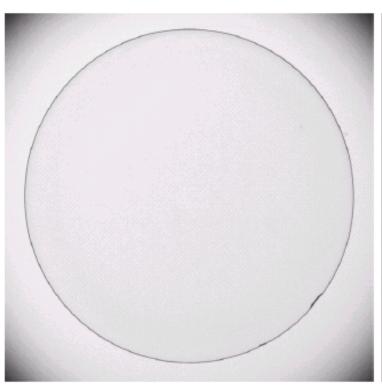
The First Derivatives for Enhancement - The Gradient

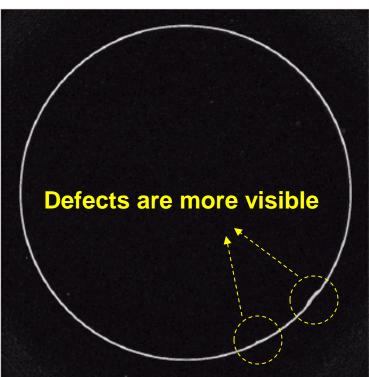
-1	-2	-1	
0	0	0	
1	2	1	

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

- •The above masks are called the Sobel operators and can be used to implement gradient operation.
- •The idea behind using weight value of 2 is to achieve some smoothing by giving more importance to the center point.
- •The mask on the left approximates the derivative in x-direction (row 3- row 1).
- •The mask on the right approximates the derivative in y-direction (col 3- col 1).







a b

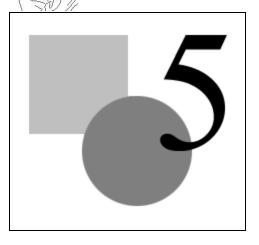
FIGURE 3.45

Optical image of contact lens (note defects on the boundary at 4 and 5 o'clock). (b) Sobel gradient. (Original image courtesy of Mr. Pete Sites, Perceptics

Corporation.)



• Edge Detection: Consider the following image and the respective sobel operators



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

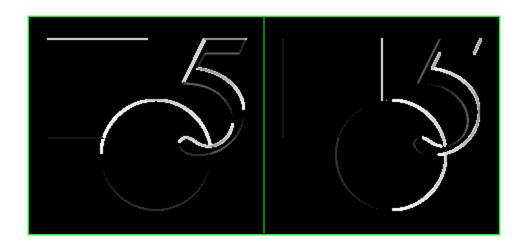
Horizontal Operator

Vertical Operator

•If the image is convolved(or correlated) by using the sobel operators given above. Then,



• Edge Detection:



 g_h Horizontal Sobel Operator
highlights the horizontal
edges

 $m{g}_{v}$ Vertical Sobel Operator highlights the vertical edges



Edge Detection:



•The Gradient for each pixel can be defined to extract edges.

$$g(x, y) = \sqrt{g(x, y)_h^2 + g(x, y)_v^2}$$

•Edges are detected by combining horizontal and vertical images obtained using respective Sobel operators.