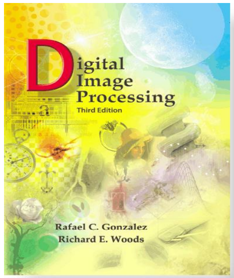

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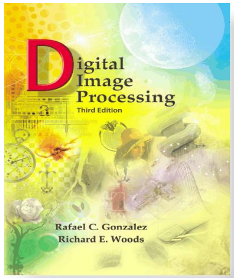
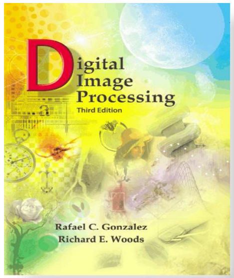
- 10.2.5 Basic Edge Detection 706
- 10.2.6 More Advanced Techniques for Edge Detection 714
- 10.2.7 Edge Linking and Boundary Detection



10.3 Thresholding
10.3.2 Basic Global Thresholding
10.3.4 Using Image Smoothing to Improve Global Thresholding
10.3.5 Using Edges to Improve Global Thresholding
10.3.6 Multiple Thresholds
10.3.7 Variable Thresholding
10.3.8 Multivariable Thresholding
10.4 Region-Based Segmentation
10.4.1 Region Growing
10.4.2 Region Splitting and Merging



Let R represent the entire spatial region occupied by an image. We may view image segmentation as a process that partitions R into n subregions, $R_1, R_2, \ldots, R_n$, such that

(a) $\bigcup_{i=1}^{n} R_i = R$.

(b) R_i is a connected set, $i = 1, 2, \ldots, n$.

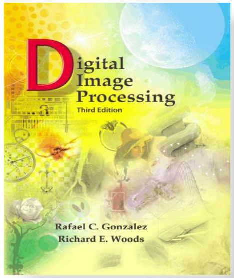
(c) $R_i \cap R_j = \emptyset$ for all i and j, $i \neq j$.

(d) $Q(R_i) = \text{TRUE}$ for $i = 1, 2, \ldots, n$.

(e) $Q(R_i \cup R_j) = \text{FALSE}$ for any adjacent regions R_i and R_j.

- Two approaches for segmentation:

1. Edge based segmentation
2. Region based segmentation



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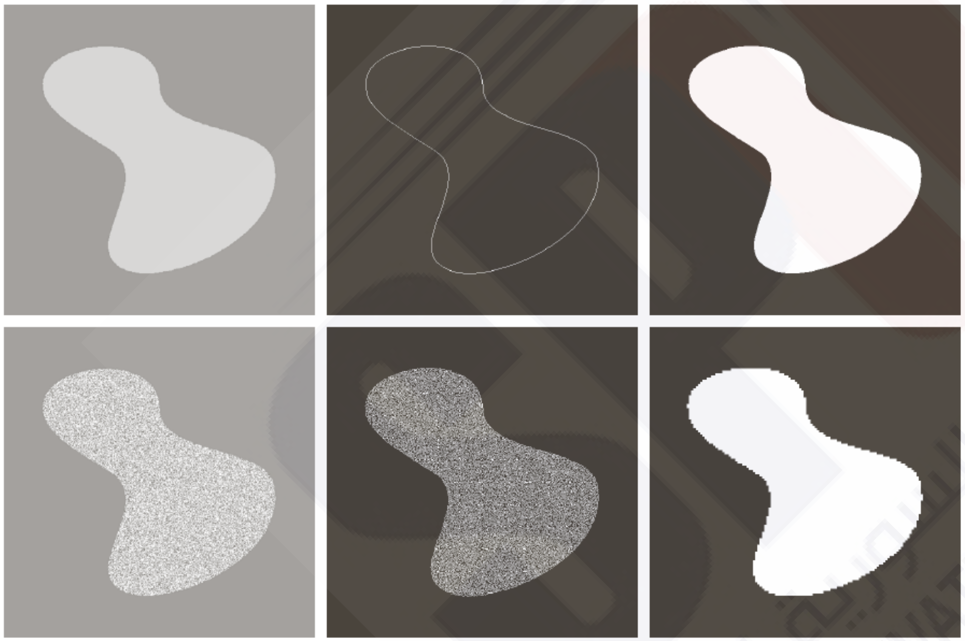
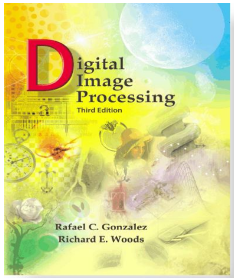
a b c
d e f



If a pixel is inside the boundary then label it white.

FIGURE 10.1 (a) Image containing a region of constant intensity. (b) Image showing the boundary of the inner region, obtained from intensity discontinuities. (c) Result of segmenting the image into two regions. (d) Image containing a textured region. (e) Result of edge computations. Note the large number of small edges that are connected to the original boundary, making it difficult to find a unique boundary using only edge information. (f) Result of segmentation based on region properties.

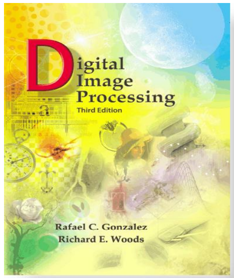


POINT ,LINE AND EDGE DETECTION

Segmentation based on detecting local sharp changes of intensity.

EDGE : local change in image intensity values

EDGE DETECTOR: local image processing method designed to detect edge pixels.



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

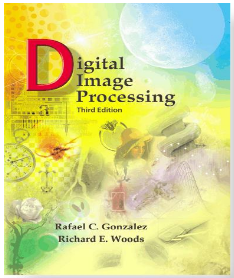
$$\frac{\partial^2 f}{\partial x^2} = \frac{\partial f'(x)}{\partial x} = f'(x+1) - f'(x)$$

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

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

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

First derivative must be 0 for areas of constant intensity.
Non zero for intensity step or ramps .
Second derivative is 0 for constant intensities area and non zero at the start and end of intensity ramp or step.



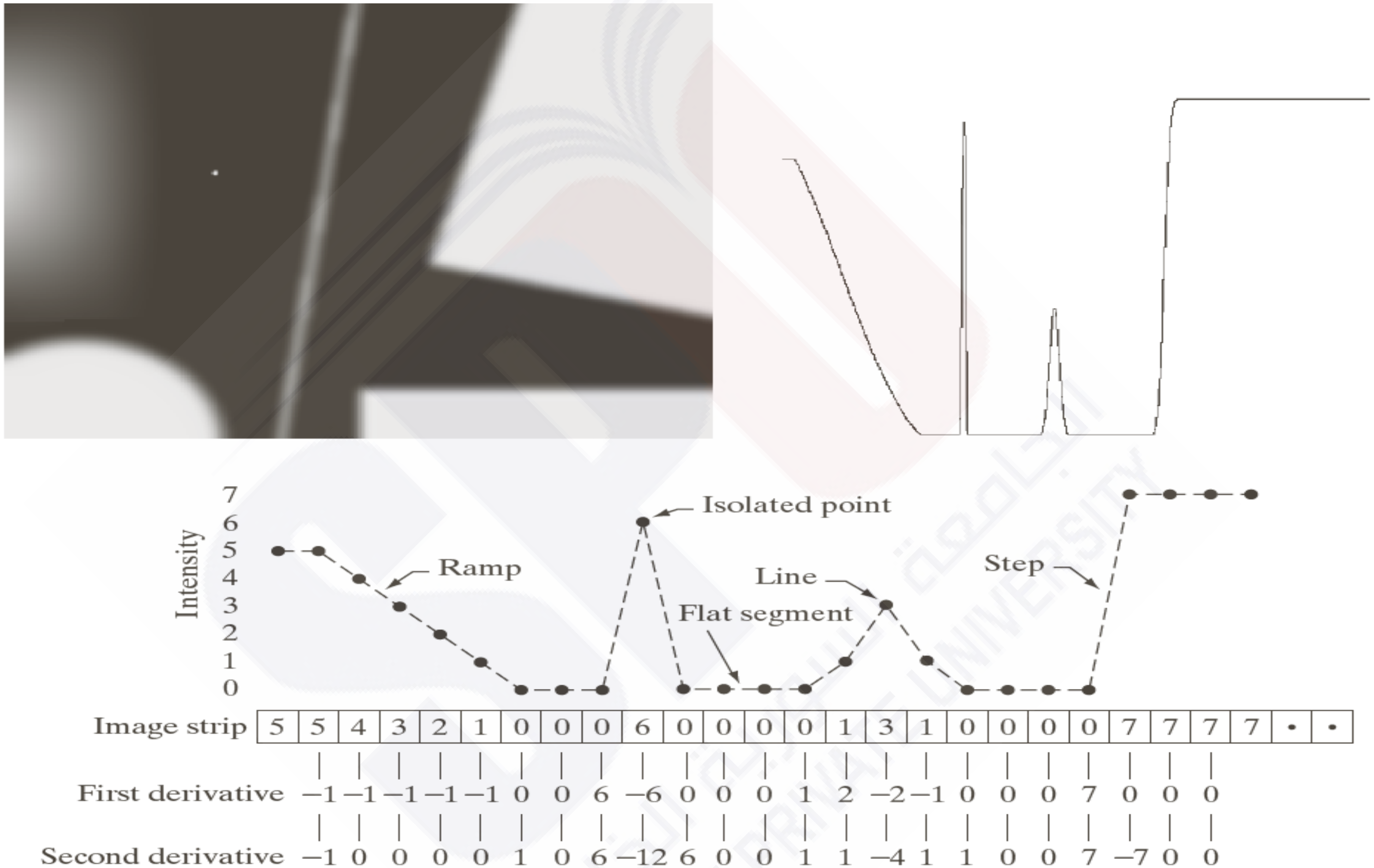
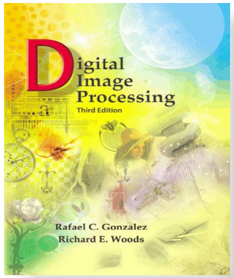


FIGURE 10.2 (a) Image. (b) Horizontal intensity profile through the center of the image, including the isolated noise point. (c) Simplified profile (the points are joined by dashes for clarity). The image strip corresponds to the intensity profile, and the numbers in the boxes are the intensity values of the dots shown in the profile. The derivatives were obtained using Eqs. (10.2-1) and (10.2-2).

In summary, we arrive at the following conclusions: (1) First-order derivatives generally produce thicker edges in an image. (2) Second-order derivatives have a stronger response to fine detail, such as thin lines, isolated points, and noise. (3) Second-order derivatives produce a double-edge response at ramp and step transitions in intensity. (4) The sign of the second derivative can be used to determine whether a transition into an edge is from light to dark or dark to light.



w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

FIGURE 10.3 A general 3×3 spatial filter mask.

$$R = w_1 z_1 + w_2 z_2 + \cdots + w_9 z_9 = \sum_{k=1}^{9} w_k z_k$$

Detection of isolated points

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

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

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

The Laplacian is then

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

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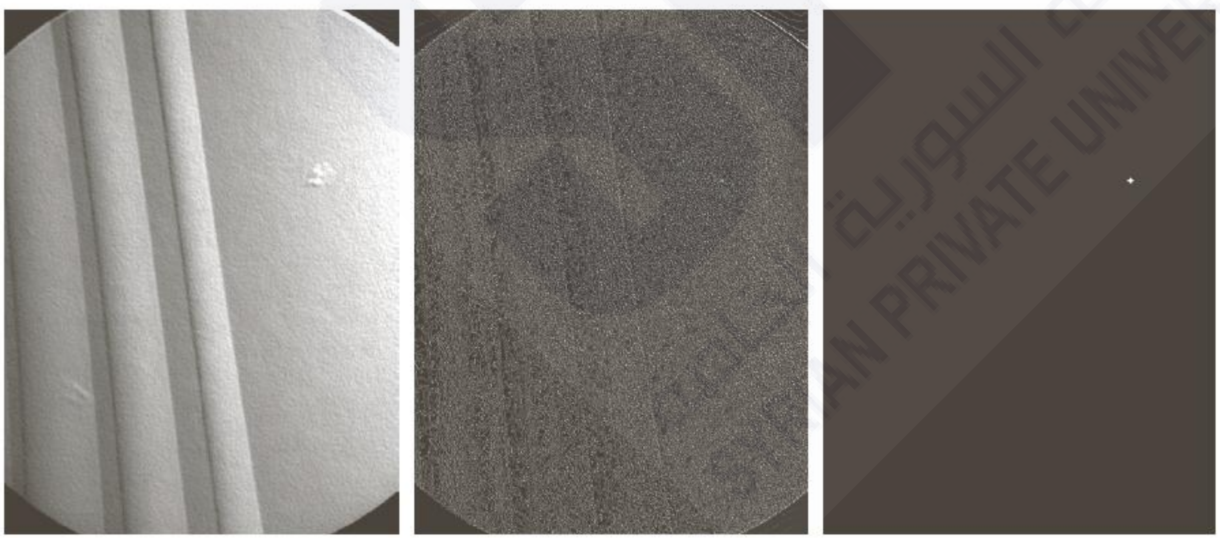
$$g(x, y) = \begin{cases} 1 & \text{if } |R(x, y)| \geq T \\ 0 & \text{otherwise} \end{cases}$$

1	1	1
1	−8	1
1	1	1



a
b c d

FIGURE 10.4 (a) Point detection (Laplacian) mask. (b) X-ray image of turbine blade with a porosity. The porosity contains a single black pixel. (c) Result of convolving the mask with the image. (d) Result of using Eq. (10.2-8) showing a single point (the point was enlarged to make it easier to see). (Original image courtesy of X-TEK Systems, Ltd.)

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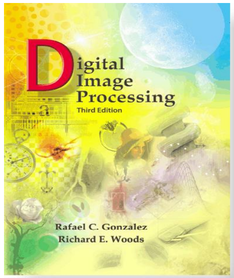


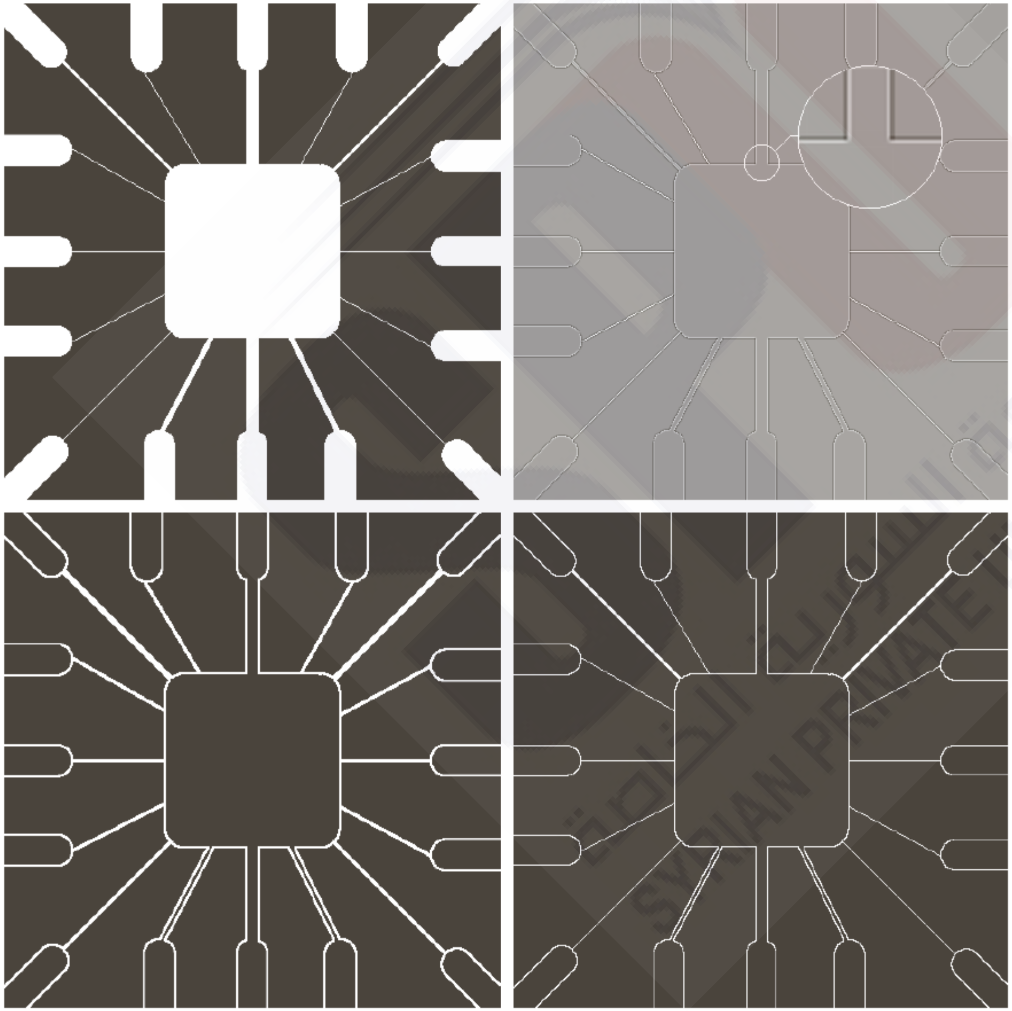


FIGURE 10.5
(a) Original image.
(b) Laplacian image; the magnified section shows the positive/negative double-line effect characteristic of the Laplacian.
(c) Absolute value of the Laplacian.
(d) Positive values of the Laplacian.

LINE DETECTION

Horizontal

−1	−1	−1
2	2	2
−1	−1	−1

+45°

2	−1	−1
−1	2	−1
−1	−1	2

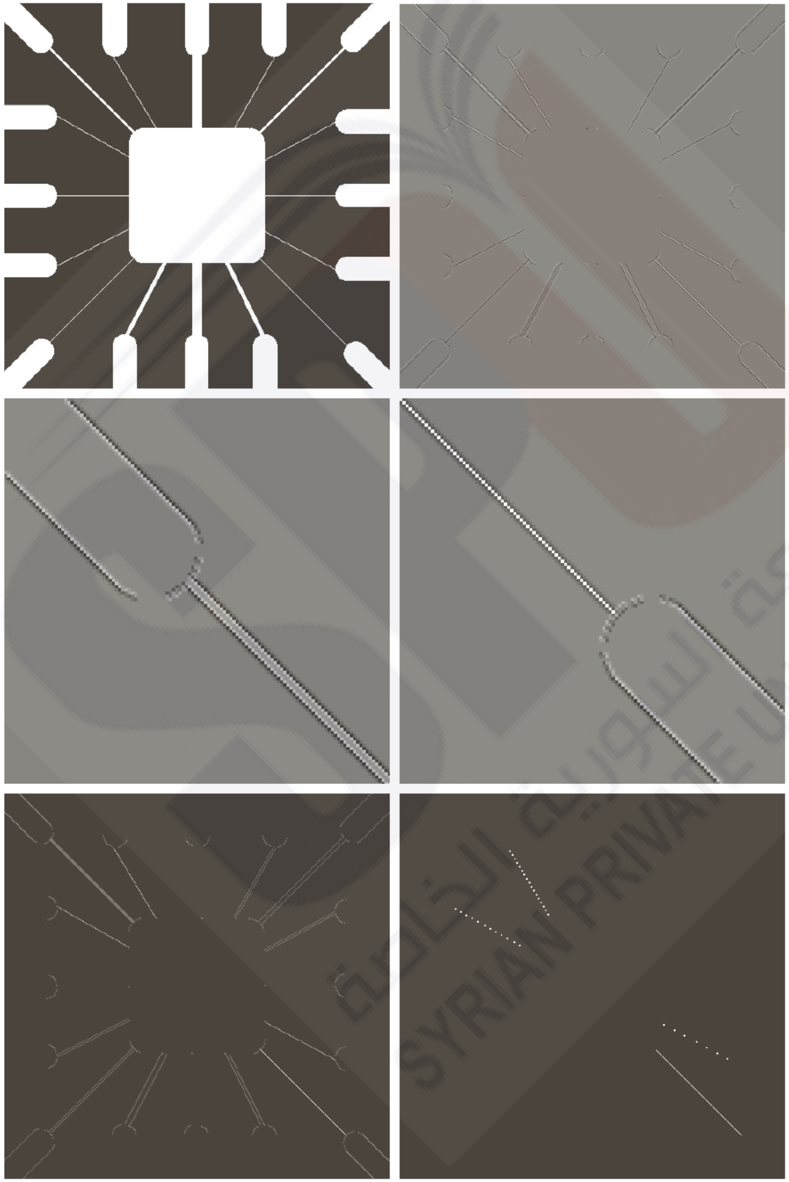
Vertical

−1	2	−1
−1	2	−1
−1	2	−1

−45°

−1	−1	2
−1	2	−1
2	−1	−1

FIGURE 10.6 Line detection masks. Angles are with respect to the axis system in Fig. 2.18(b).



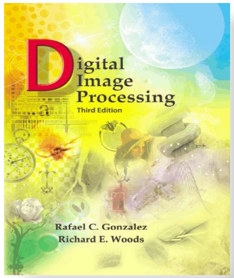
a	b
c	d
e	f

FIGURE 10.7 (a) Image of a wire-bond template. (b) Result of processing with the +45° line detector mask in Fig. 10.6. (c) Zoomed view of the top left region of (b). (d) Zoomed view of the bottom right region of (b). (e) The image in (b) with all negative values set to zero. (f) All points (in white) whose values satisfied the condition $g \geq T$, where g is the image in (e). (The points in (f) were enlarged to make them easier to see.)

Edge model

a b c

FIGURE 10.8 From left to right, models (ideal representations) of a step, a ramp, and a roof edge, and their corresponding intensity profiles.



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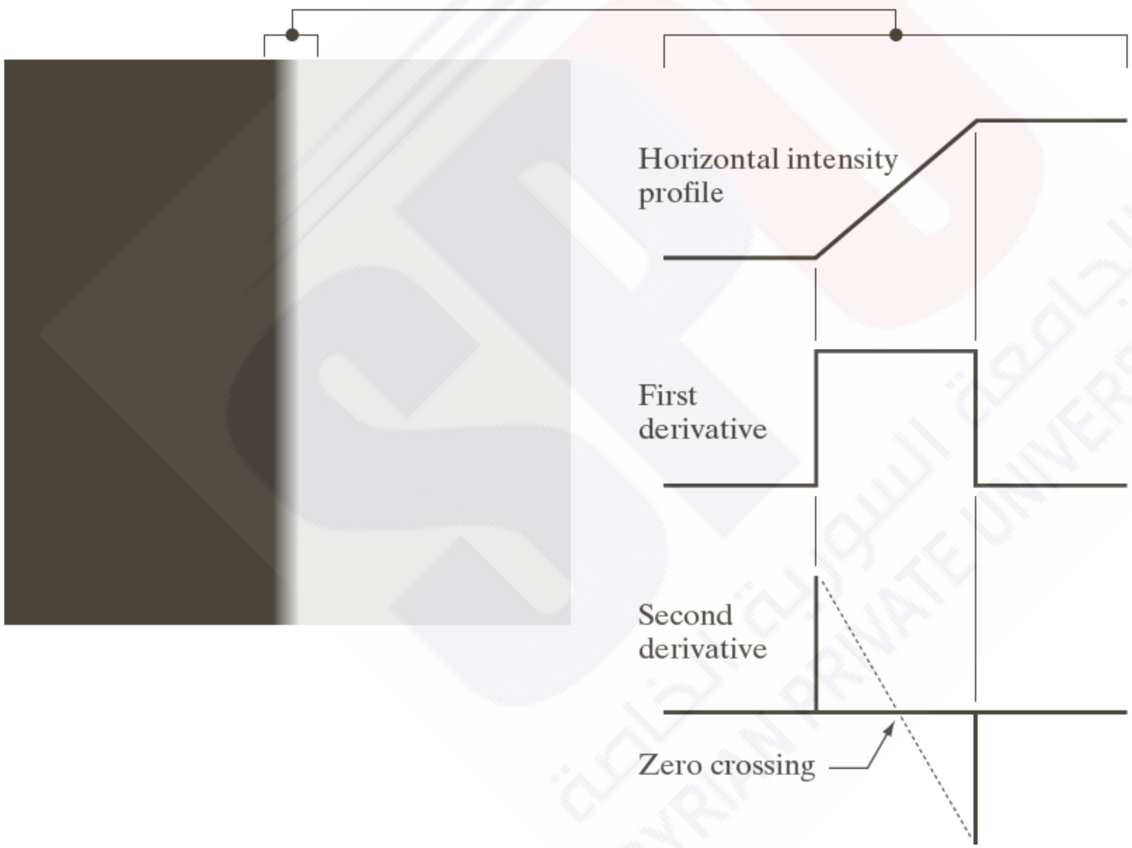

a b

FIGURE 10.10 (a) Two regions of constant intensity separated by an ideal vertical ramp edge. (b) Detail near the edge, showing a horizontal intensity profile, together with its first and second derivatives.

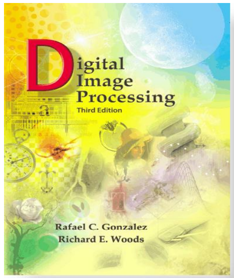

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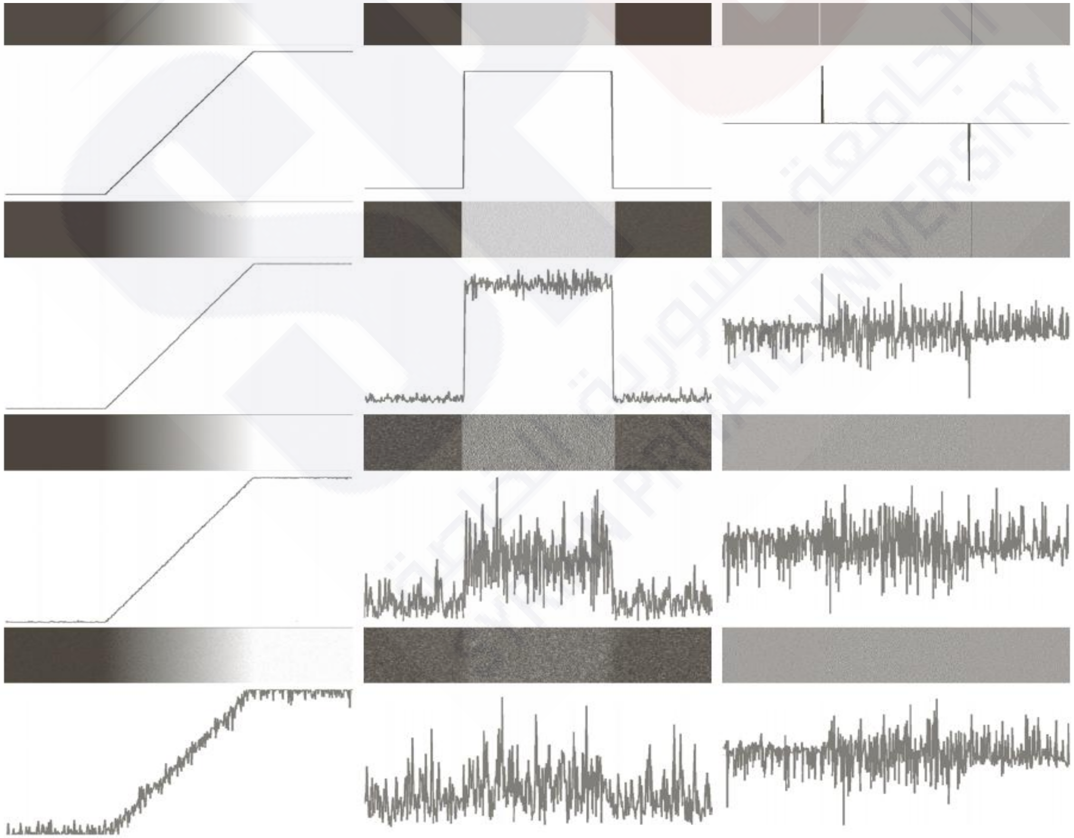
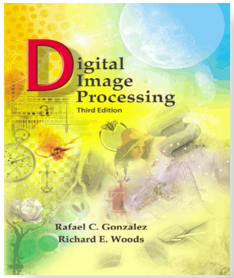
FIGURE 10.11 First column: Images and intensity profiles of a ramp edge corrupted by random Gaussian noise of zero mean and standard deviations of 0.0, 0.1, 1.0, and 10.0 intensity levels, respectively. Second column: First-derivative images and intensity profiles. Third column: Second-derivative images and intensity profiles.



Fundamental steps in edge detection:

1. *Image smoothing for noise reduction.* The need for this step is amply illustrated by the results in the second and third columns of Fig. 10.11.
2. *Detection of edge points.* As mentioned earlier, this is a local operation that extracts from an image all points that are potential candidates to become edge points.
3. *Edge localization.* The objective of this step is to select from the candidate edge points only the points that are true members of the set of points comprising an edge.



Basic edge detectors

$$\nabla f \equiv \text{grad}(f) \equiv \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \dfrac{\partial f}{\partial x} \\ \dfrac{\partial f}{\partial y} \end{bmatrix}$$

The *magnitude* (*length*) of vector ∇f, denoted as $M(x, y)$, where

$$M(x, y) = \text{mag}(\nabla f) = \sqrt{g_x^2 + g_y^2}$$

The *direction* of the gradient vector is given by the angle

$$\alpha(x, y) = \tan^{-1}\left[\frac{g_y}{g_x}\right]$$

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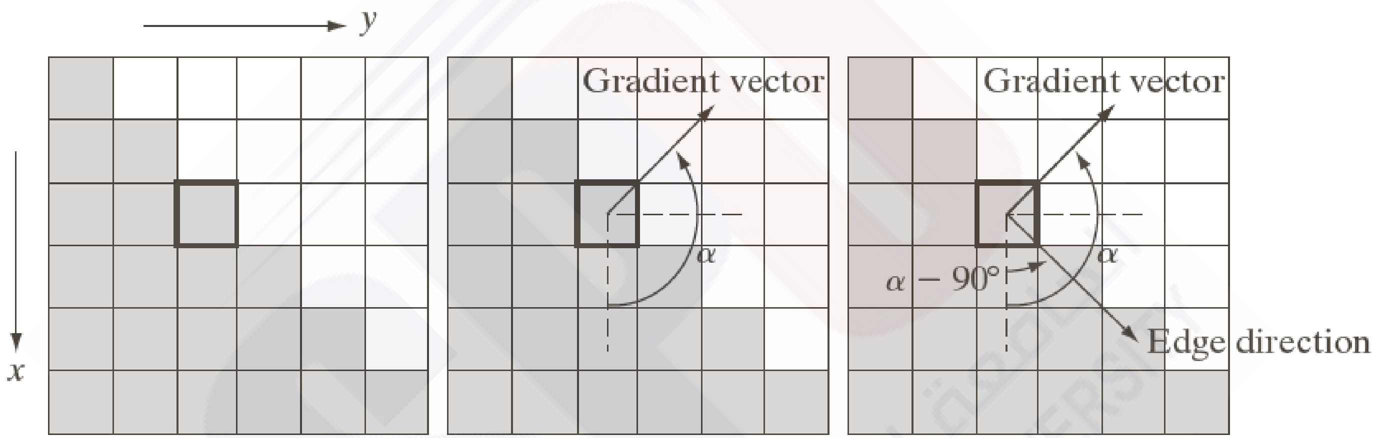
Segmentation



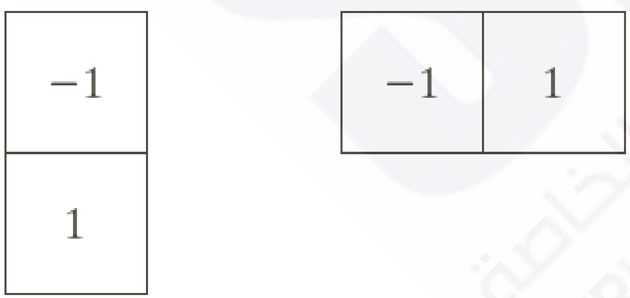
a b c

FIGURE 10.12 Using the gradient to determine edge strength and direction at a point. Note that the edge is perpendicular to the direction of the gradient vector at the point where the gradient is computed. Each square in the figure represents one pixel.

Gradient Operator

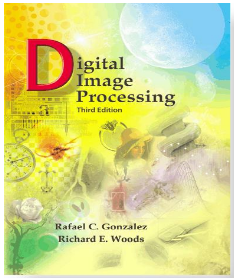
$$g_x = \frac{\partial f(x, y)}{\partial x} = f(x + 1, y) - f(x, y)$$

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



a b

FIGURE 10.13 One-dimensional masks used to implement Eqs. (10.2-12) and (10.2-13).



$$g_x = \frac{\partial f}{\partial x} = (z_7 + z_8 + z_9) - (z_1 + z_2 + z_3)$$

$$g_y = \frac{\partial f}{\partial y} = (z_3 + z_6 + z_9) - (z_1 + z_4 + z_7)$$

$$M(x, y) \approx |g_x| + |g_y|$$

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

Roberts

−1	0
0	1

0	−1
1	0

Prewitt

−1	−1	−1
0	0	0
1	1	1

−1	0	1
−1	0	1
−1	0	1

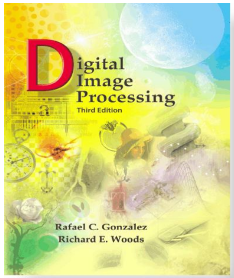
Sobel

−1	−2	−1
0	0	0
1	2	1

−1	0	1
−2	0	2
−1	0	1

a
b c
d e
f g

FIGURE 10.14 A 3 × 3 region of an image (the z's are intensity values) and various masks used to compute the gradient at the point labeled z_5.



(a) Prewitt

0	1	1
−1	0	1
−1	−1	0

(b) Prewitt

−1	−1	0
−1	0	1
0	1	1

Prewitt

(c) Sobel

0	1	2
−1	0	1
−2	−1	0

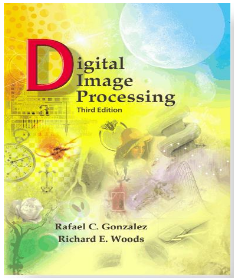
(d) Sobel

−2	−1	0
−1	0	1
0	1	2

Sobel

a b
c d

FIGURE 10.15 Prewitt and Sobel masks for detecting diagonal edges.



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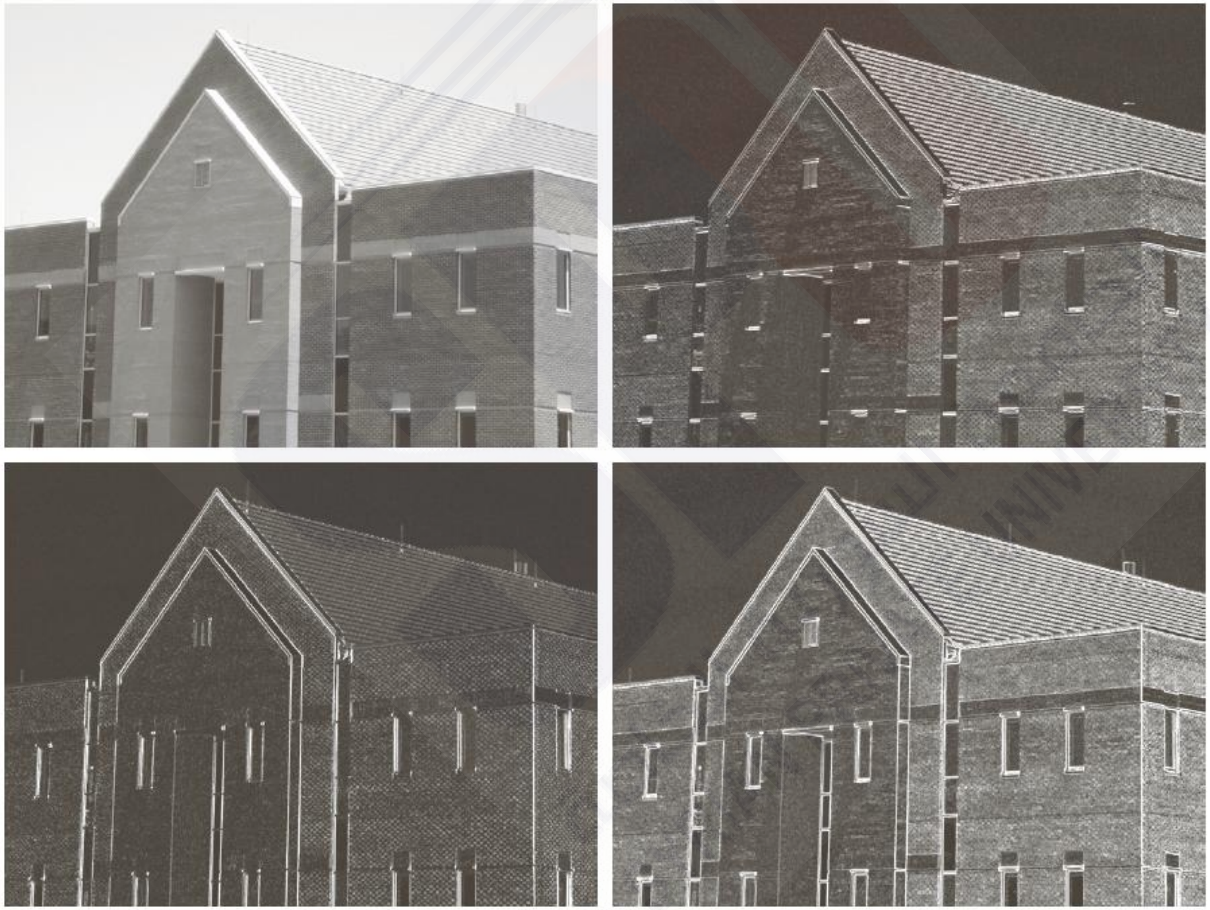
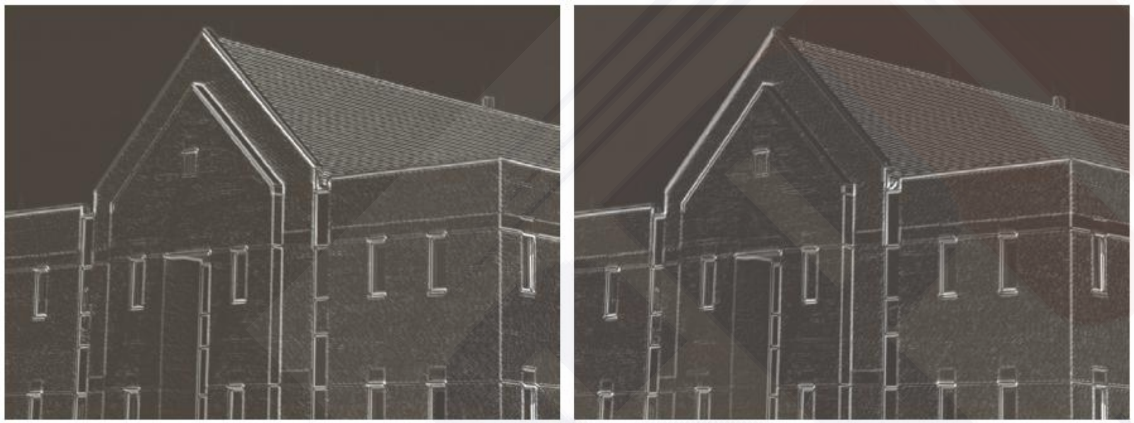


a b
c d

FIGURE 10.16
(a) Original image of size 834 × 1114 pixels, with intensity values scaled to the range [0, 1]. (b) $|g_x|$, the component of the gradient in the x-direction, obtained using the Sobel mask in Fig. 10.14(f) to filter the image. (c) $|g_y|$, obtained using the mask in Fig. 10.14(g). (d) The gradient image, $|g_x| + |g_y|$.

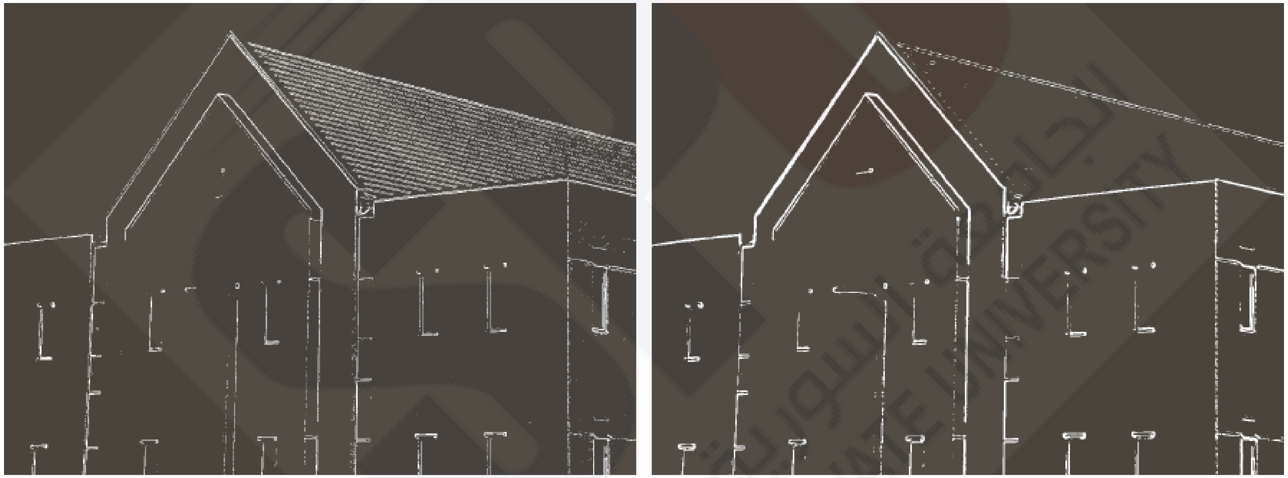
FIGURE 10.17 Gradient angle image computed using Eq. (10.2-11). Areas of constant intensity in this image indicate that the direction of the gradient vector is the same at all the pixel locations in those regions.



a b

FIGURE 10.19 Diagonal edge detection. (a) Result of using the mask in Fig. 10.15(c). (b) Result of using the mask in Fig. 10.15(d). The input image in both cases was Fig. 10.18(a).

Combining the gradient with thresholding



a b

FIGURE 10.20 (a) Thresholded version of the image in Fig. 10.16(d), with the threshold selected as 33% of the highest value in the image; this threshold was just high enough to eliminate most of the brick edges in the gradient image. (b) Thresholded version of the image in Fig. 10.18(d), obtained using a threshold equal to 33% of the highest value in that image.

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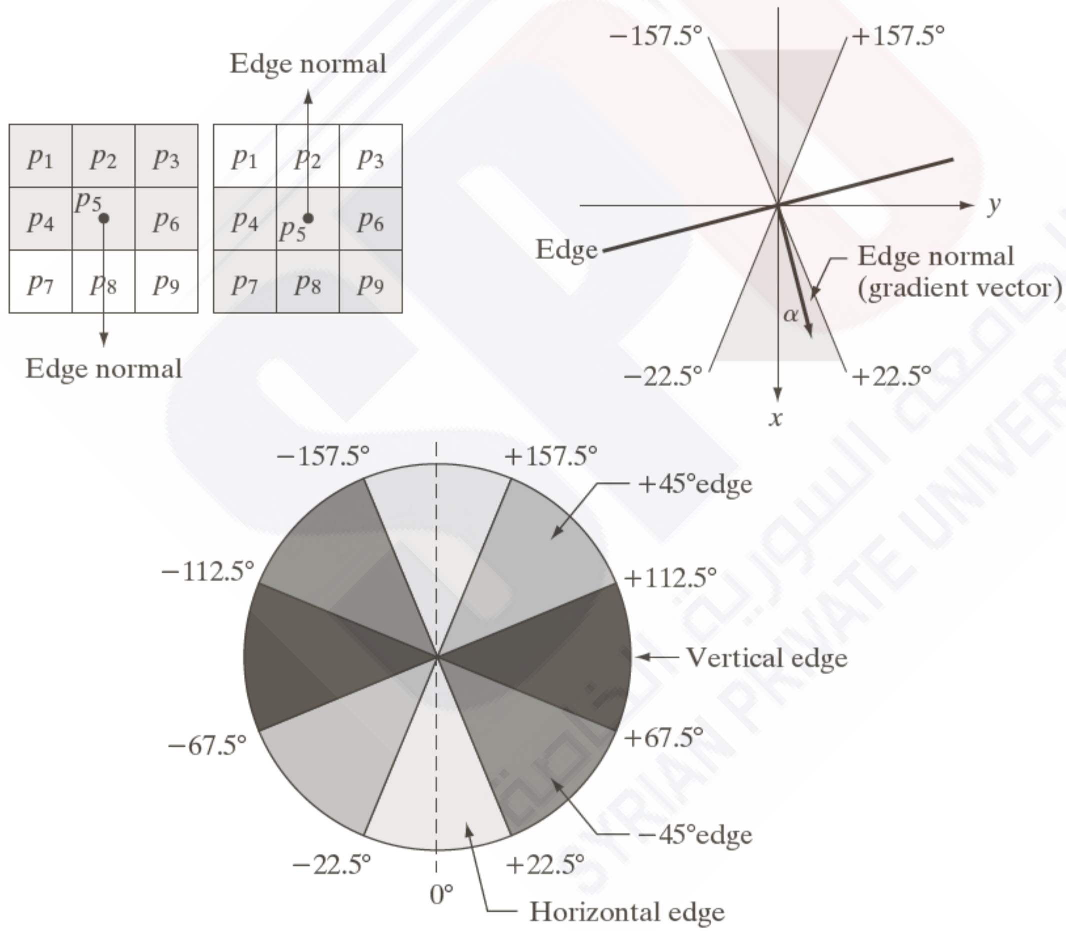


a b
c

FIGURE 10.24 (a) Two possible orientations of a horizontal edge (in gray) in a 3 × 3 neighborhood. (b) Range of values (in gray) of α, the direction angle of the *edge normal*, for a horizontal edge. (c) The angle ranges of the edge normals for the four types of edge directions in a 3 × 3 neighborhood. Each edge direction has two ranges, shown in corresponding shades of gray.

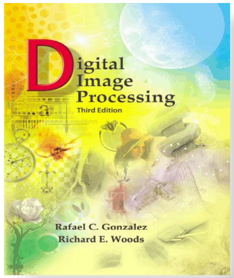
Edge linking and boundary detection

Edge detection should be followed by linking algorithms.

• **LOCAL PROCESSING**: to analyze the local characteristic in a small neighborhood 3×3 around the pixel like the magnitude and the direction of the gradient vector

$$|M(s,t) - M(x,y)| \leq E$$

$$|\alpha(s,t) - \alpha(x,y)| \leq A$$



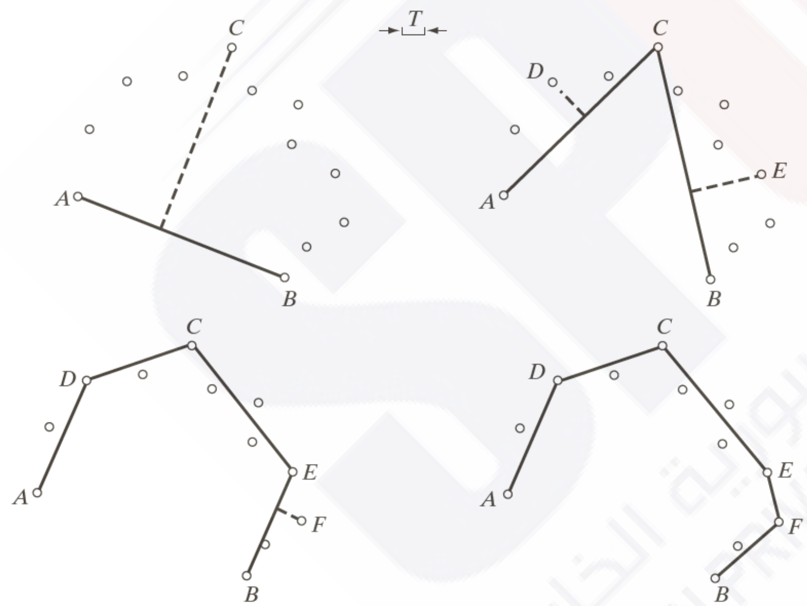
1. Compute the gradient magnitude and angle arrays, $M(x, y)$ and $\alpha(x, y)$, of the input image, $f(x, y)$.
2. Form a binary image, g, whose value at any pair of coordinates (x, y) is given by:

$$g(x, y) = \begin{cases} 1 & \text{if } M(x, y) > T_M \text{ AND } \alpha(x, y) = A \pm T_A \\ 0 & \text{otherwise} \end{cases}$$

   where T_M is a threshold, A is a specified angle direction, and $\pm T_A$ defines a "band" of acceptable directions about A.
3. Scan the rows of g and fill (set to 1) all gaps (sets of 0s) in each row that do not exceed a specified length, K. Note that, by definition, a gap is bounded at both ends by one or more 1s. The rows are processed individually, with no memory between them.
4. To detect gaps in any other direction, θ, rotate g by this angle and apply the horizontal scanning procedure in Step 3. Rotate the result back by $-\theta$.

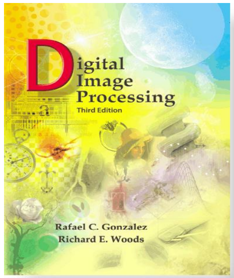
FIGURE 10.27 (a) A 534 × 566 image of the rear of a vehicle. (b) Gradient magnitude image. (c) Horizontally connected edge pixels. (d) Vertically connected edge pixels. (e) The logical OR of the two preceding images. (f) Final result obtained using morphological thinning. (Original image courtesy of Perceptics Corporation.)

Regional processing



a b
c d

FIGURE 10.28 Illustration of the iterative polygonal fit algorithm.



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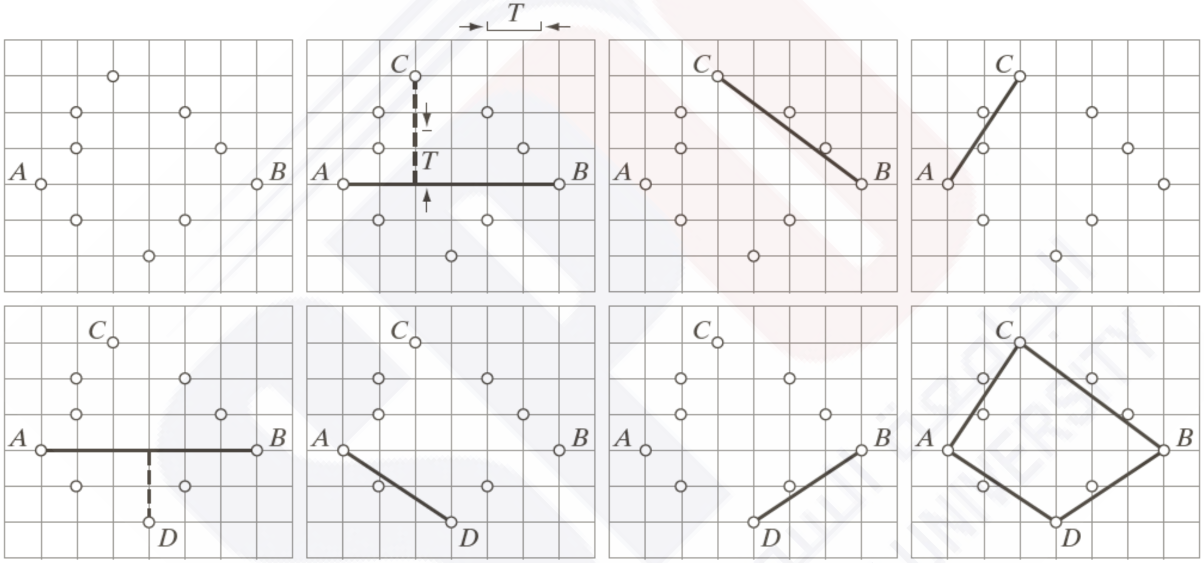


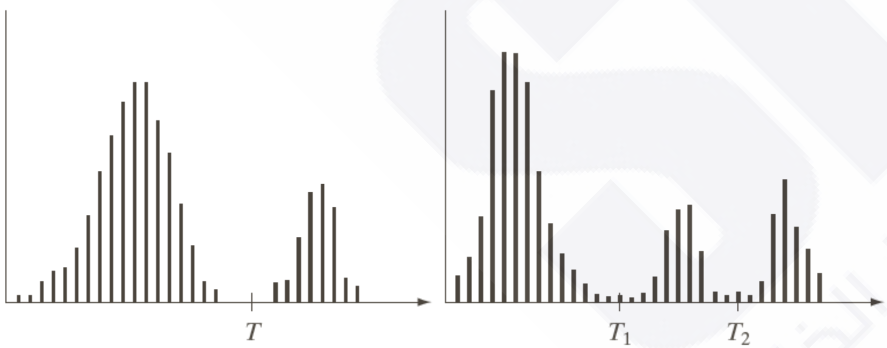
a	b	c	d
e	f	g	h

FIGURE 10.29 (a) A set of points in a clockwise path (the points labeled *A* and *B* were chosen as the starting vertices). (b) The distance from point *C* to the line passing through *A* and *B* is the largest of all the points between *A* and *B* and also passed the threshold test, so *C* is a new vertex. (d)–(g) Various stages of the algorithm. (h) The final vertices, shown connected with straight lines to form a polygon. Table 10.1 shows step-by-step details.

Thresholding

$$g(x, y) = \begin{cases} 1 & \text{if } f(x, y) > T \\ 0 & \text{if } f(x, y) \leq T \end{cases}$$

Object points
Background points



a b

FIGURE 10.35 Intensity histograms that can be partitioned (a) by a single threshold, and (b) by dual thresholds.

$$g(x, y) = \begin{cases} a & \text{if } f(x, y) > T_2 \\ b & \text{if } T_1 < f(x, y) \leq T_2 \\ c & \text{if } f(x, y) \leq T_1 \end{cases}$$

- Global threshoding: when T is constant over the entire image.
- Local (variable or dynamic) thresholding: when T changes over the image.

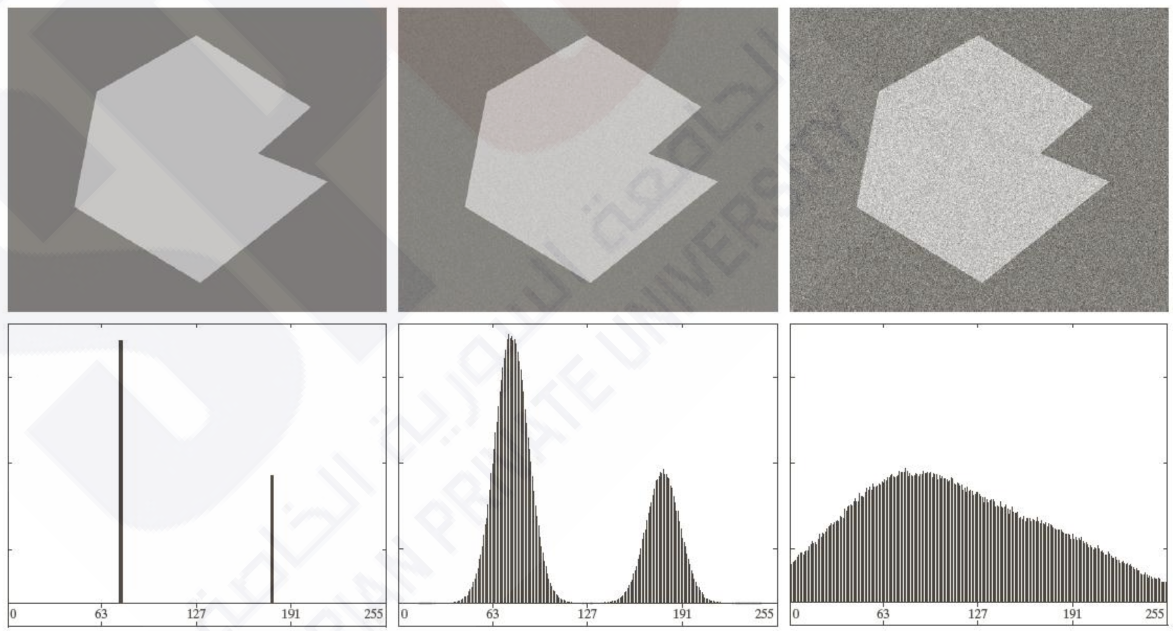
the success of intensity thresholding is directly related to the width and depth of the valley(s) separating the histogram modes. In turn, the key factors affecting the properties of the valley(s) are: (1) the separation between peaks (the further apart the peaks are, the better the chances of separating the modes); (2) the noise content in the image (the modes broaden as noise increases); (3) the relative sizes of objects and background; (4) the uniformity of the illumination source; and (5) the uniformity of the reflectance properties of the image.

The role of noise in image thresholding

Mean and variance

$$m = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x, y)$$

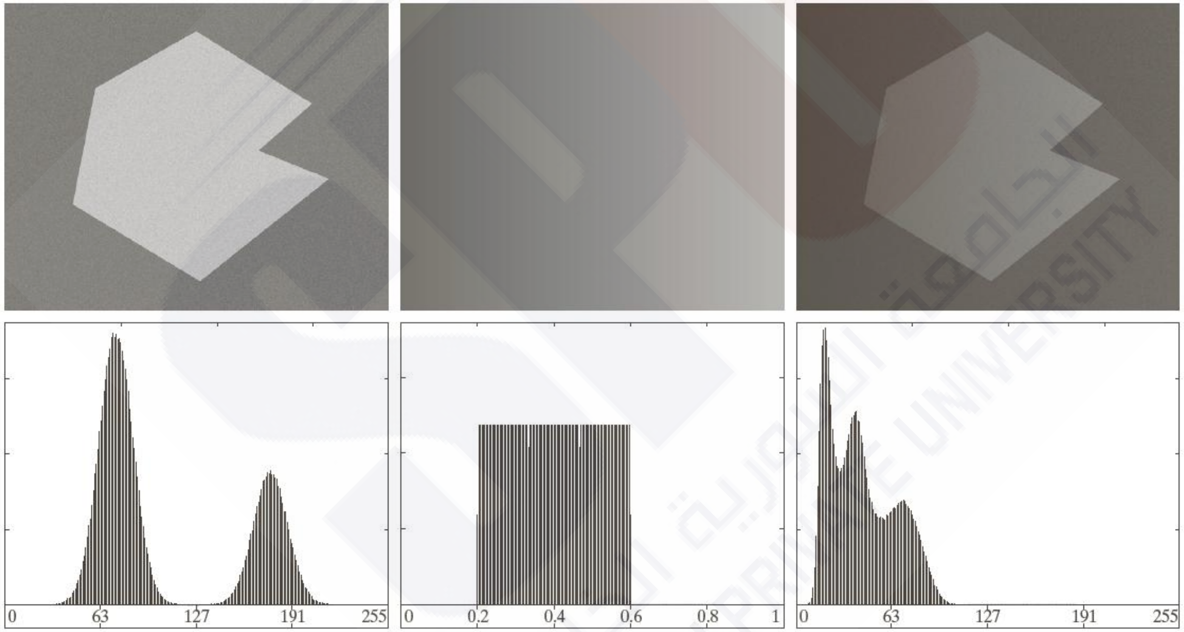
$$\sigma^2 = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left[f(x, y) - m\right]^2$$



a	b	c
d	e	f

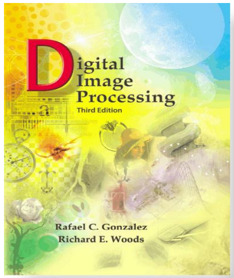
FIGURE 10.36 (a) Noiseless 8-bit image. (b) Image with additive Gaussian noise of mean 0 and standard deviation of 10 intensity levels. (c) Image with additive Gaussian noise of mean 0 and standard deviation of 50 intensity levels. (d)–(f) Corresponding histograms.

The role of illumination and reflectance



a b c
d e f

FIGURE 10.37 (a) Noisy image. (b) Intensity ramp in the range [0.2, 0.6]. (c) Product of (a) and (b). (d)–(f) Corresponding histograms.



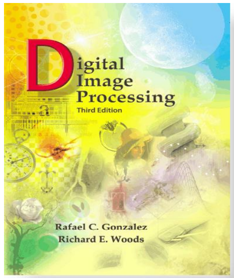
10.3.2 Basic Global Thresholding

Estimating automatically the threshold value:

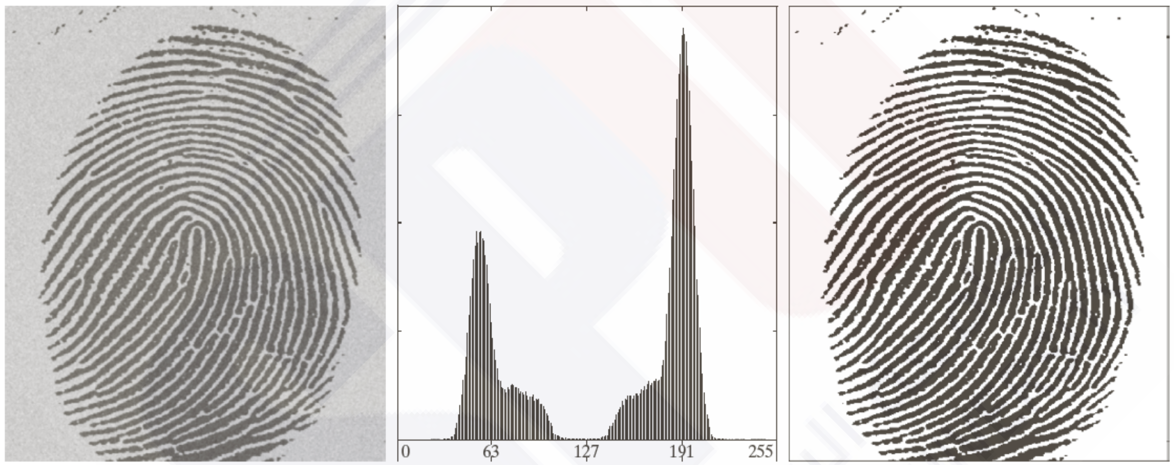
1. Select an initial estimate for the global threshold, T.
2. Segment the image using T in Eq. (10.3-1). This will produce two groups of pixels: G_1 consisting of all pixels with intensity values $> T$, and G_2 consisting of pixels with values $\leq T$.
3. Compute the average (mean) intensity values m_1 and m_2 for the pixels in G_1 and G_2, respectively.
4. Compute a new threshold value:

$$T = \frac{1}{2}(m_1 + m_2)$$

5. Repeat Steps 2 through 4 until the difference between values of T in successive iterations is smaller than a predefined parameter ΔT.



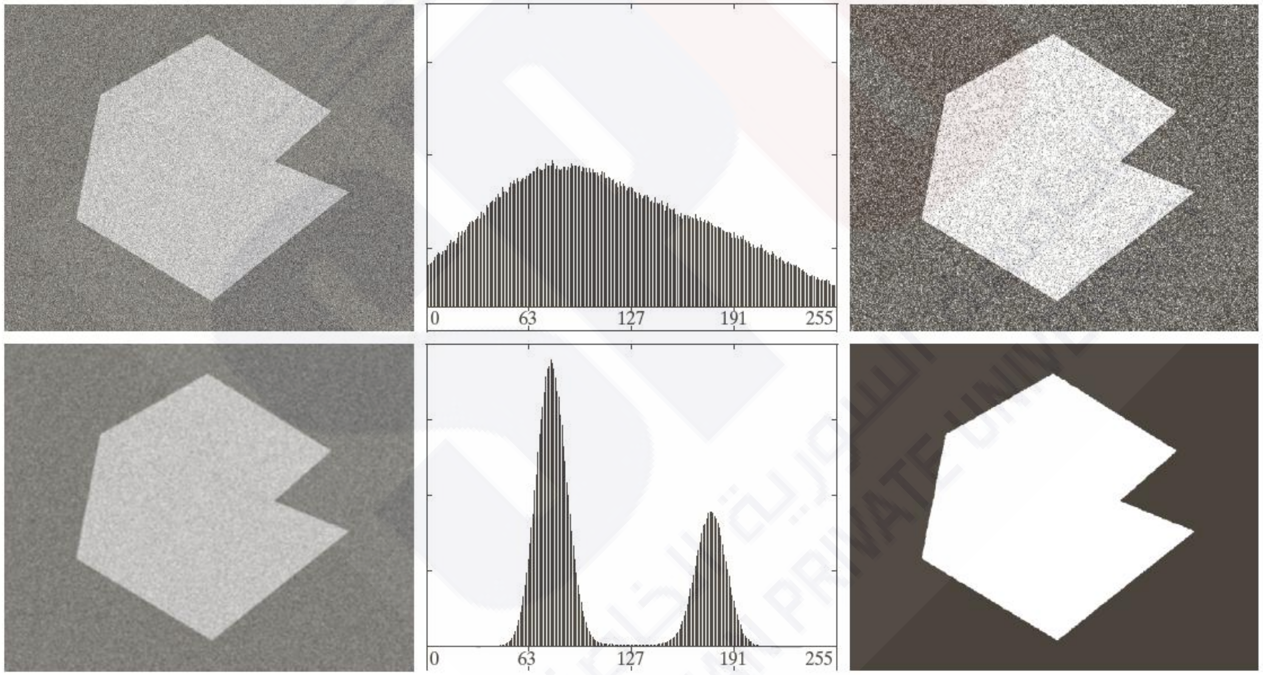
Chapter 10
Segmentation



a b c

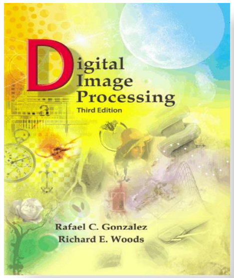
FIGURE 10.38 (a) Noisy fingerprint. (b) Histogram. (c) Segmented result using a global threshold (the border was added for clarity). (Original courtesy of the National Institute of Standards and Technology.)

10.3.4 Using Image Smoothing to Improve Global Thresholding



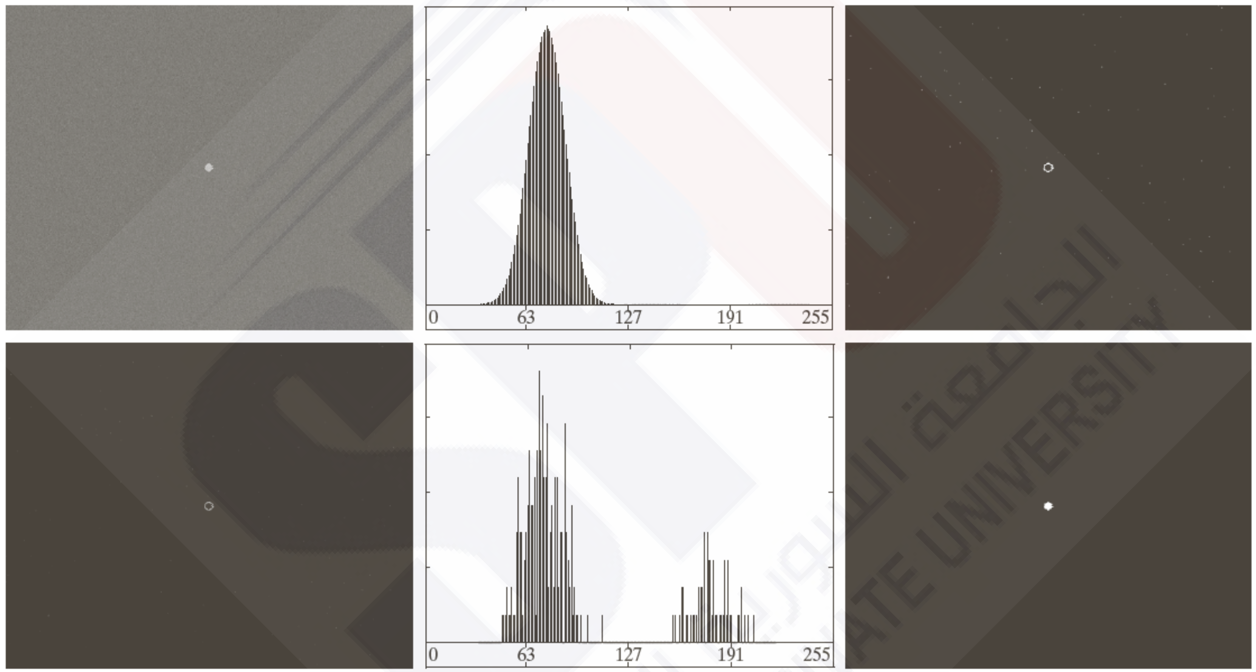
a b c
d e f

FIGURE 10.40 (a) Noisy image from Fig. 10.36 and (b) its histogram. (c) Result obtained using Otsu's method. (d) Noisy image smoothed using a 5 × 5 averaging mask and (e) its histogram. (f) Result of thresholding using Otsu's method.



10.3.5 Using Edges to Improve Global Thresholding

1. Compute an edge image as either the magnitude of the gradient, or absolute value of the Laplacian, of $f(x, y)$ using any of the methods discussed in Section 10.2.
2. Specify a threshold value, T.
3. Threshold the image from Step 1 using the threshold from Step 2 to produce a binary image, $g_T(x, y)$. This image is used as a *mask image* in the following step to select pixels from $f(x, y)$ corresponding to "strong" edge pixels.
4. Compute a histogram using only the pixels in $f(x, y)$ that correspond to the locations of the 1-valued pixels in $g_T(x, y)$.
5. Use the histogram from Step 4 to segment $f(x, y)$ globally using, for example, Otsu's method.

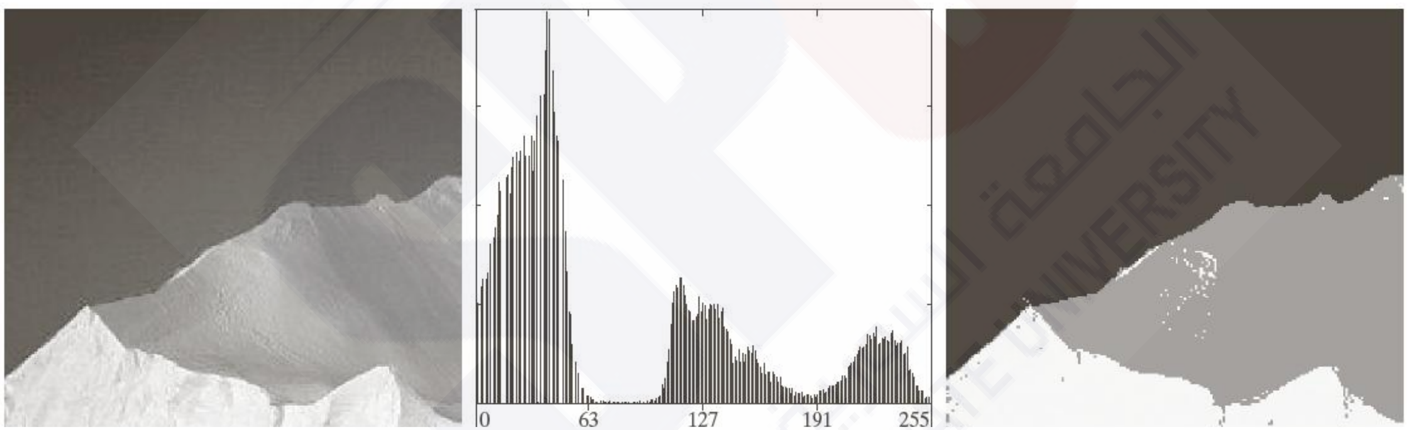


a	b	c
d	e	f

FIGURE 10.42 (a) Noisy image from Fig. 10.41(a) and (b) its histogram. (c) Gradient magnitude image thresholded at the 99.7 percentile. (d) Image formed as the product of (a) and (c). (e) Histogram of the nonzero pixels in the image in (d). (f) Result of segmenting image (a) with the Otsu threshold based on the histogram in (e). The threshold was 134, which is approximately midway between the peaks in this histogram.

Multiple Thresholds

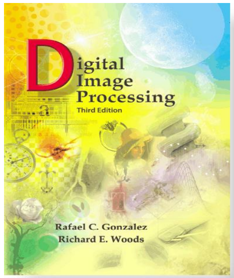
$$g(x, y) = \begin{cases} a & \text{if } f(x, y) \le k_1^* \\ b & \text{if } k_1^* < f(x, y) \le k_2^* \\ c & \text{if } f(x, y) > k_2^* \end{cases}$$



a b c

FIGURE 10.45 (a) Image of iceberg. (b) Histogram. (c) Image segmented into three regions using dual Otsu thresholds. (Original image courtesy of NOAA.)

Variable thresholding:
the value of the threshold will vary over the image according to local criteria.



• image partitioning

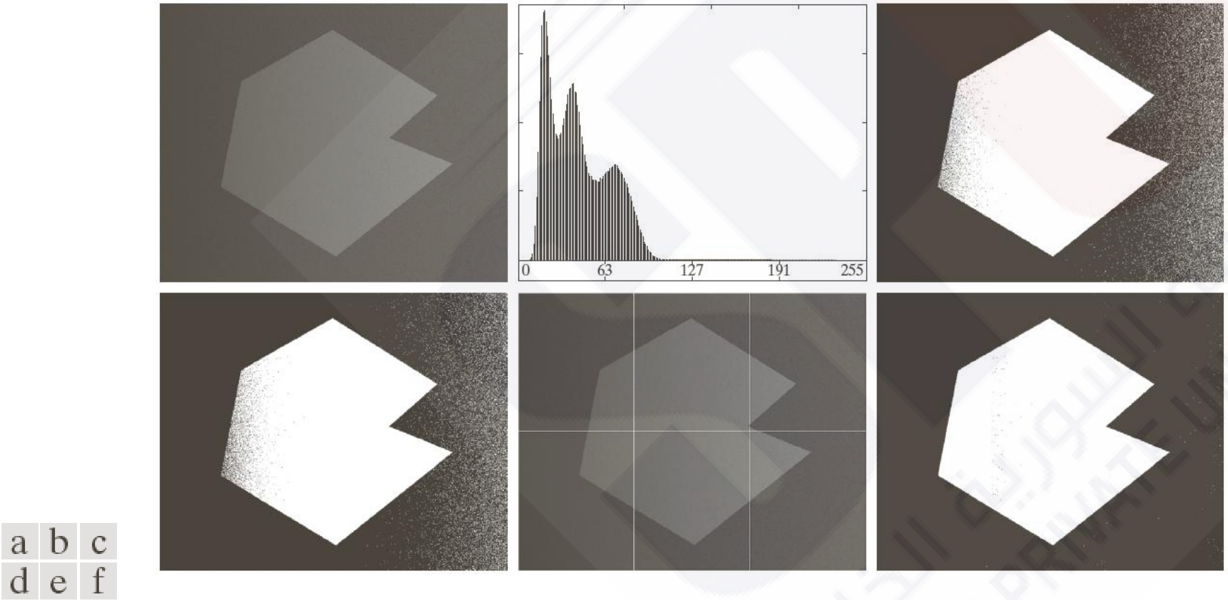


FIGURE 10.46 (a) Noisy, shaded image and (b) its histogram. (c) Segmentation of (a) using the iterative global algorithm from Section 10.3.2. (d) Result obtained using Otsu's method. (e) Image subdivided into six subimages. (f) Result of applying Otsu's method to each subimage individually.

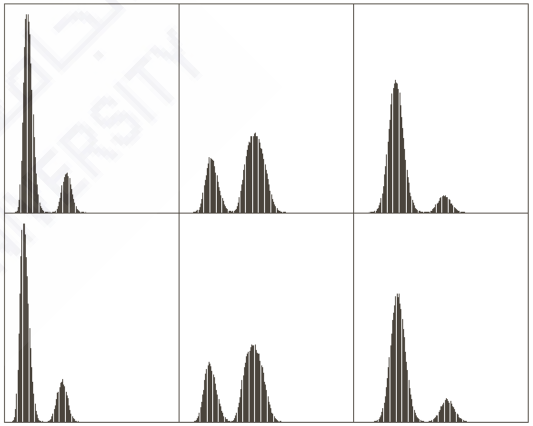


FIGURE 10.47 Histograms of the six subimages in Fig. 10.46(e).

Variable thresholding based on local image properties

Local mean value and local variance

$$T_{xy} = a\sigma_{xy} + bm_{xy} \qquad T_{xy} = a\sigma_{xy} + bm_G$$

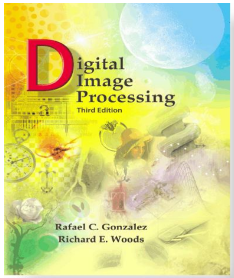
$$g(x, y) = \begin{cases} 1 & \text{if } f(x, y) > T_{xy} \\ 0 & \text{if } f(x, y) \le T_{xy} \end{cases}$$

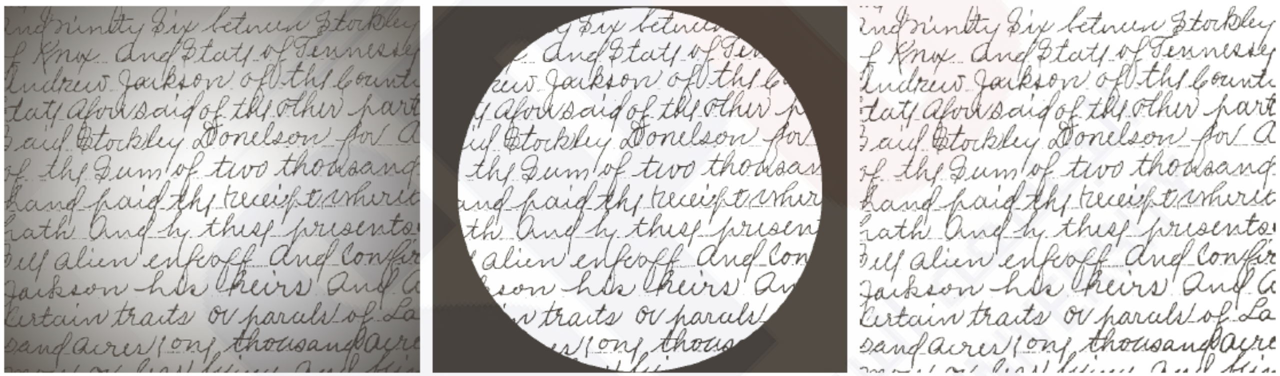
Using moving averages

computing a moving average along scan lines of an image

$$m(k+1) = \frac{1}{n} \sum_{i=k+2-n}^{k+1} z_i$$

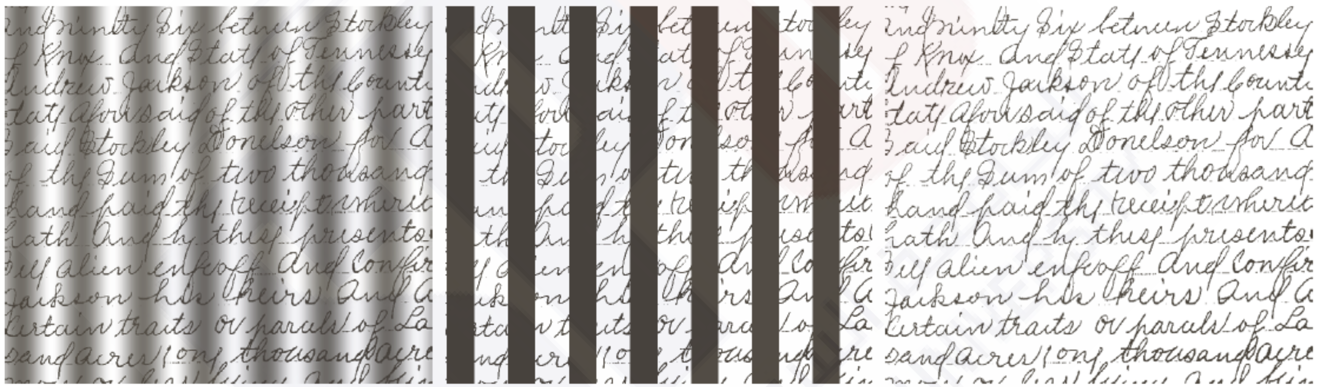
with $T_{xy} = bm_{xy}$ where b is constant and m_{xy}





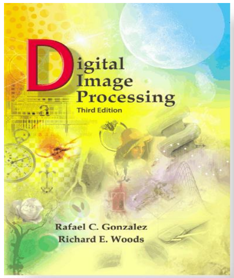
a b c

FIGURE 10.49 (a) Text image corrupted by spot shading. (b) Result of global thresholding using Otsu's method. (c) Result of local thresholding using moving averages.



a b c

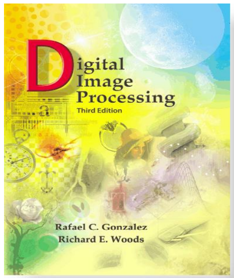
FIGURE 10.50 (a) Text image corrupted by sinusoidal shading. (b) Result of global thresholding using Otsu's method. (c) Result of local thresholding using moving averages.



10.4 Region-Based Segmentation

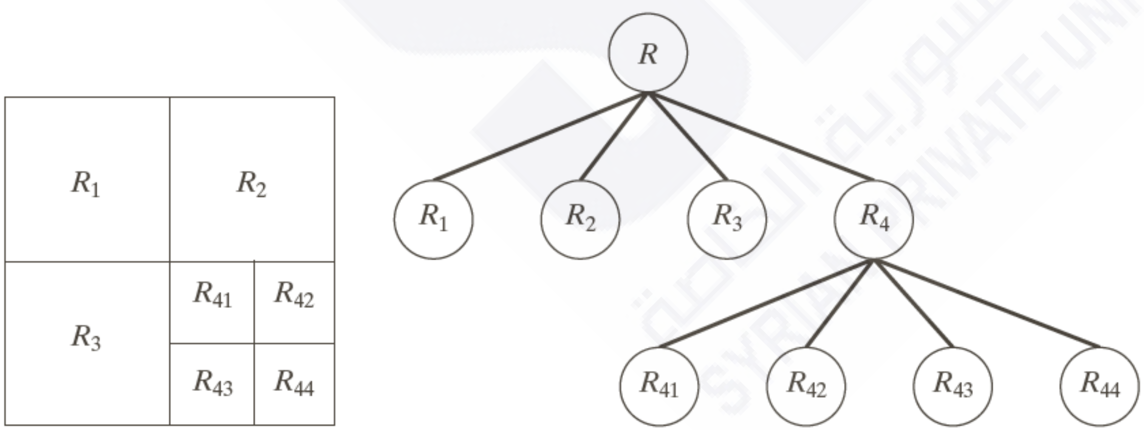
10.4.1 Region Growing

As its name implies, *region growing* is a procedure that groups pixels or subregions into larger regions based on predefined criteria for growth. The basic approach is to start with a set of "seed" points and from these grow regions by appending to each seed those neighboring pixels that have predefined properties similar to the seed (such as specific ranges of intensity or color).



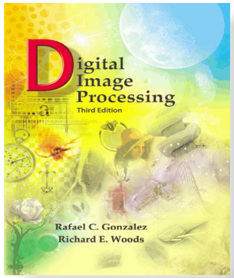
10.4.2 Region Splitting and Merging

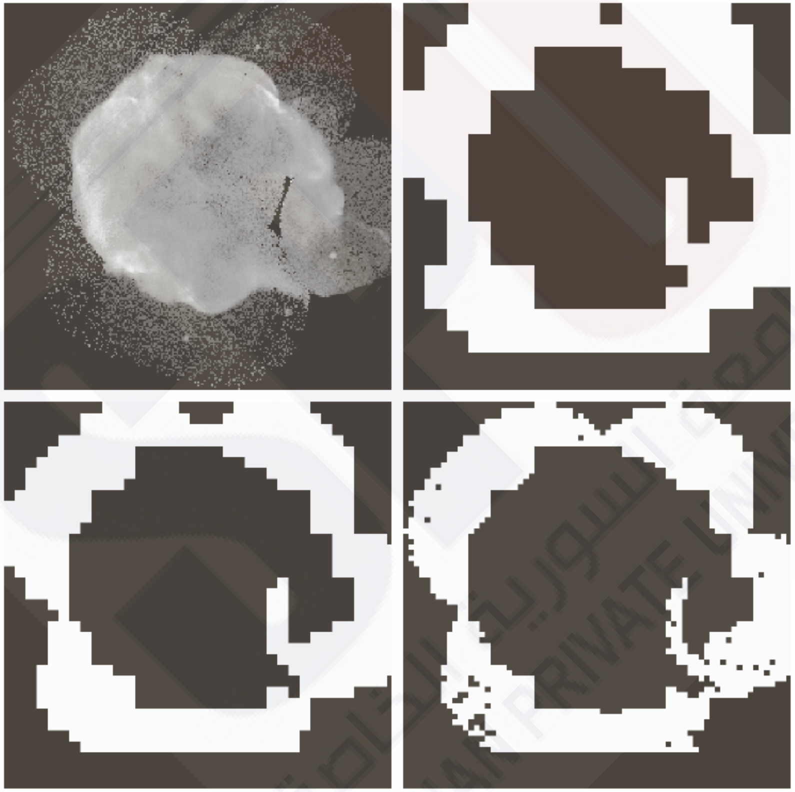
1. Split into four disjoint quadrants any region R_i for which $Q(R_i) = \text{FALSE}$.
2. When no further splitting is possible, merge any adjacent regions R_j and R_k for which $Q(R_j \cup R_k) = \text{TRUE}$.
3. Stop when no further merging is possible.



a b

FIGURE 10.52 (a) Partitioned image. (b) Corresponding quadtree. R represents the entire image region.





a b
c d

FIGURE 10.53 (a) Image of the Cygnus Loop supernova, taken in the X-ray band by NASA's Hubble Telescope. (b)–(d) Results of limiting the smallest allowed quadregion to sizes of 32 × 32, 16 × 16, and 8 × 8 pixels, respectively. (Original image courtesy of NASA.)

END OF PRESENTATION