Segmentation: Preview

- Segmentation subdivides an image into its constituent regions or objects.
- The level to which the subdivision is carried depends on the problem being solved.
- Image segmentation algorithms generally are based on one of two basic properties of intensity values: discontinuity and similarity.
- In the intensity, such as approach in an image is to partition an image based on abrupt changes in intensity, such as edges in an image.

- The principal approaches in the second category are based on partitioning an image into regions that are similar according to a set of pre-defined criteria.
- Thresholding, region growing, and region splitting and merging are examples of methods in this category.

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Image Segmentation

FIGURE 10.1 A general 3×3 mask.

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

Point Detection

- Using the mask shown in Fig 10.2(a), we say that a point has been detected at the location on which the mask is centered if $|R| \geq T$.
- The idea is that an *isolated* point will be quite different from its surroundings, and thus be easily detectable by this type of mask.

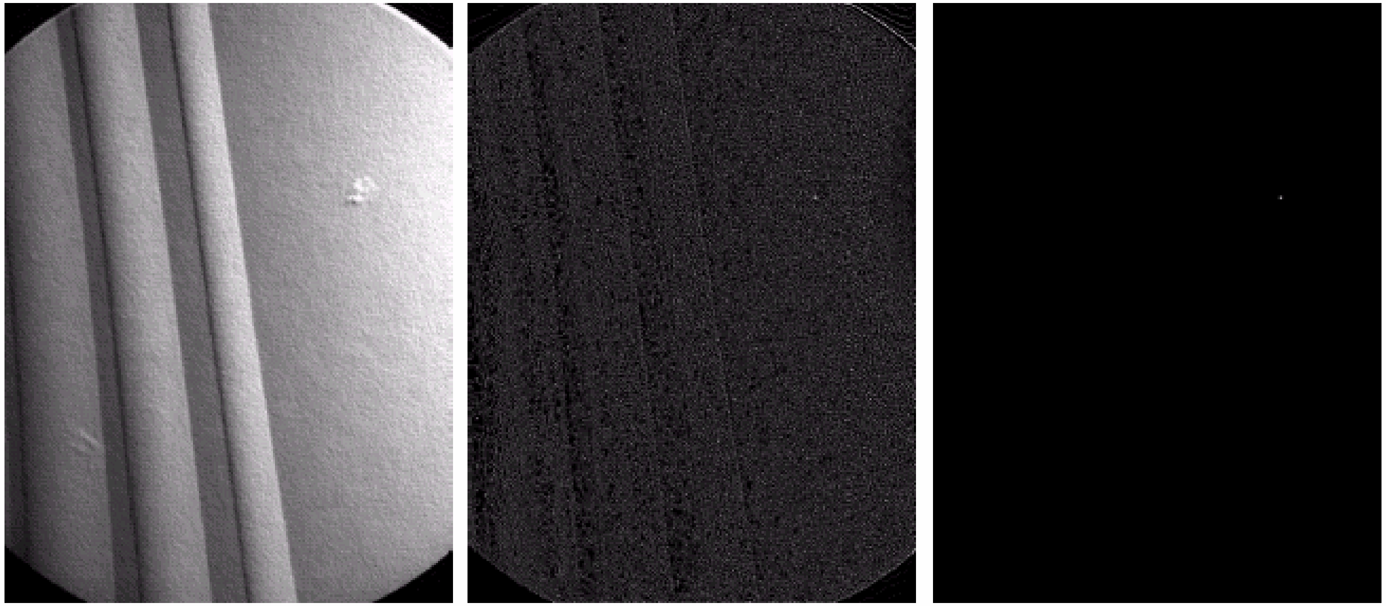
Detection of Discontinuities

- The most common way to look for discontinuities is to run a mask through the image in the manner described in Section 3.5.

$$
\begin{aligned}
R &= w_1 z_1 + w_2 z_2 + \cdots + w_9 z_9 \\
&= \sum_{i=1}^{9} w_i z_i
\end{aligned}
$$

Chapter 10
Image Segmentation

−1	−1	−1
−1	8	−1
−1	−1	−1



a
b c d

FIGURE 10.2 (a) Point detection mask. (b) X-ray image of a turbine blade with a porosity. (c) Result of point detection. (d) Result of using Eq. (10.1-2). (Original image courtesy of X-TEK Systems Ltd.)

Line Detection

- Consider the masks shown in Fig 10.3.
- If the first mask were moved around an image, it would respond more strongly to lines (one pixel thick) oriented horizontally.

FIGURE 10.3 Line masks.

Horizontal

−1	−1	−1
2	2	2
−1	−1	−1

+45°

−1	−1	2
−1	2	−1
2	−1	−1

Vertical

−1	2	−1
−1	2	−1
−1	2	−1

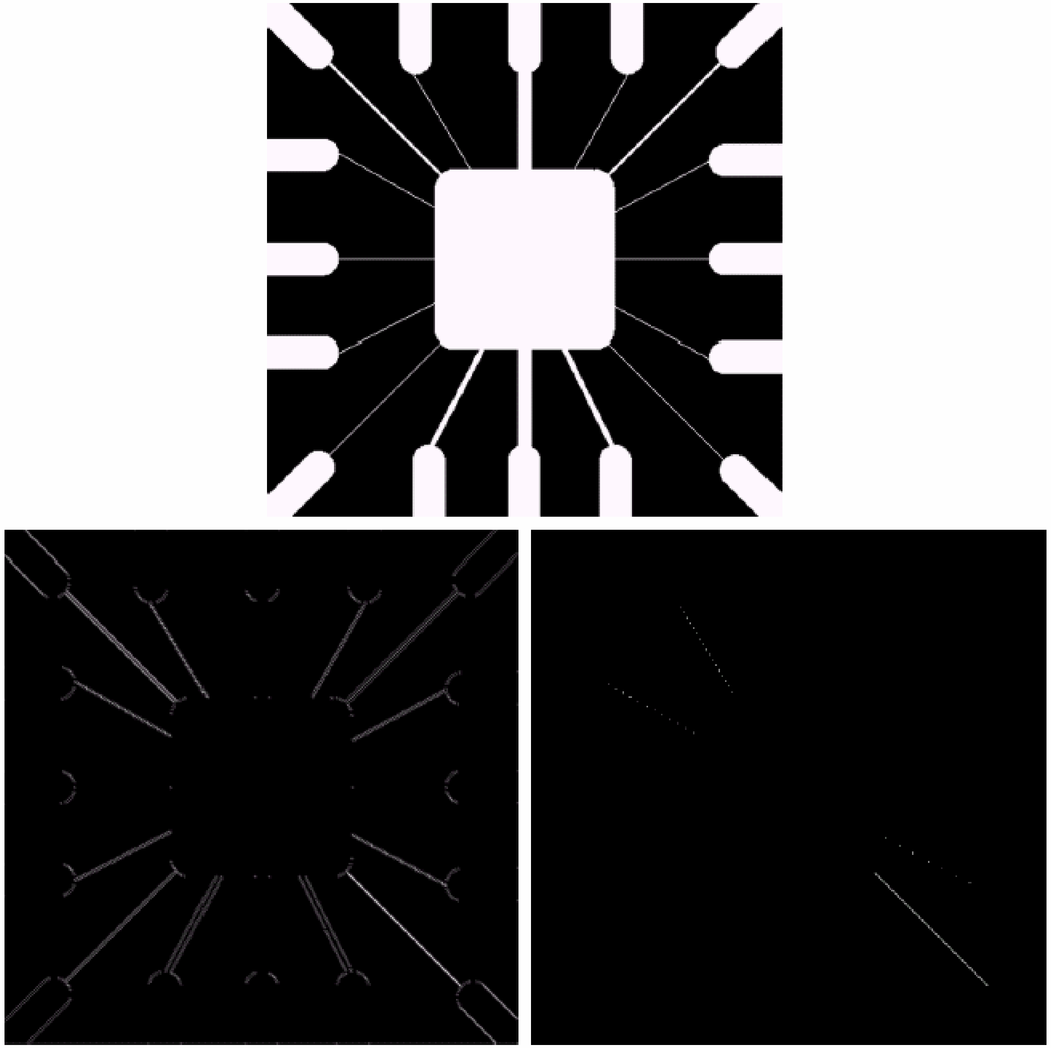
−45°

2	−1	−1
−1	2	−1
−1	−1	2

Line Detection

- Fig10.4(a) shows a digitized (binary) portion of a wire-bond mask for an electronic circuit.
- Suppose that we are interested in finding all the lines that are one pixel thick and are oriented at -45°.
- For the purpose, we use last mask shown in Fig. 10.3.

Chapter 10
Image Segmentation



a
b c

FIGURE 10.4 Illustration of line detection. (a) Binary wire-bond mask. (b) Absolute value of result after processing with −45° line detector. (c) Result of thresholding image (b).

Line Detection

- In order to determine which line best fit the mask, we simply threshold this image.
- The result of using a threshold equal to the maximum value in the image is shown in Fig 10.4(c).

Edge Detection

- Edge detection is by far the most common approach for detecting meaning discontinuities in gray level.
- Intuitively, an edge is a set of connected pixels that lie on the boundary between two regions.
- A reasonable definition of "edge" requires the ability to measure gray-level transitions in a meaningful way.

Edge Detection

- Intuitively, an ideal edge has the properties has the properties of the model shown in Fig 10.5(a).
- Edges are more closely modeled as having a "ramplike" profiles, such as the one shown in Fig 10.5(b),
- Blurred edges tend to be thick and sharp tend to be thin.

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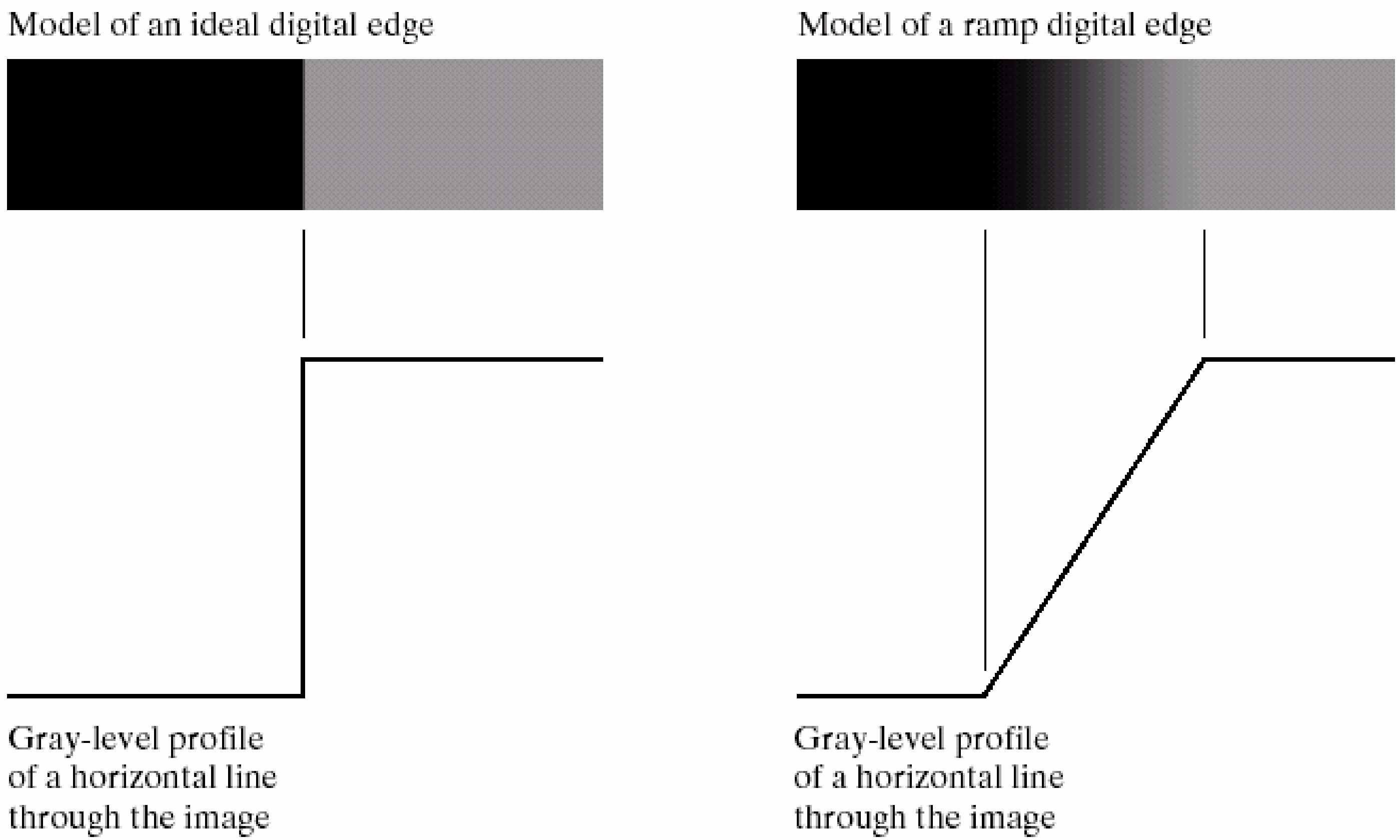
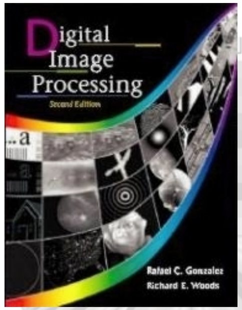
Image Segmentation



a b

FIGURE 10.5 (a) Model of an ideal digital edge. (b) Model of a ramp edge. The slope of the ramp is proportional to the degree of blurring in the edge.



Edge Detection

- We conclude from these observations that the magnitude of the first derivative can be used to detect the presence of an edge at a point in an image.
- Similarly, the sign of the second derivation can be used to determine whether an edge pixel lies on the dark or light side of an edge.

Edge Detection

- Two additional properties of the second derivative around an edge:
  - (1) It produces two value for every edge in an image
  - (2) an imaging straight line joining the extreme positive and negative values of the second derivative would cross zero near the midpoint of the edge.
- The *zero-crossing* property of the second derivative is quite useful for locating the centers of thick edges.

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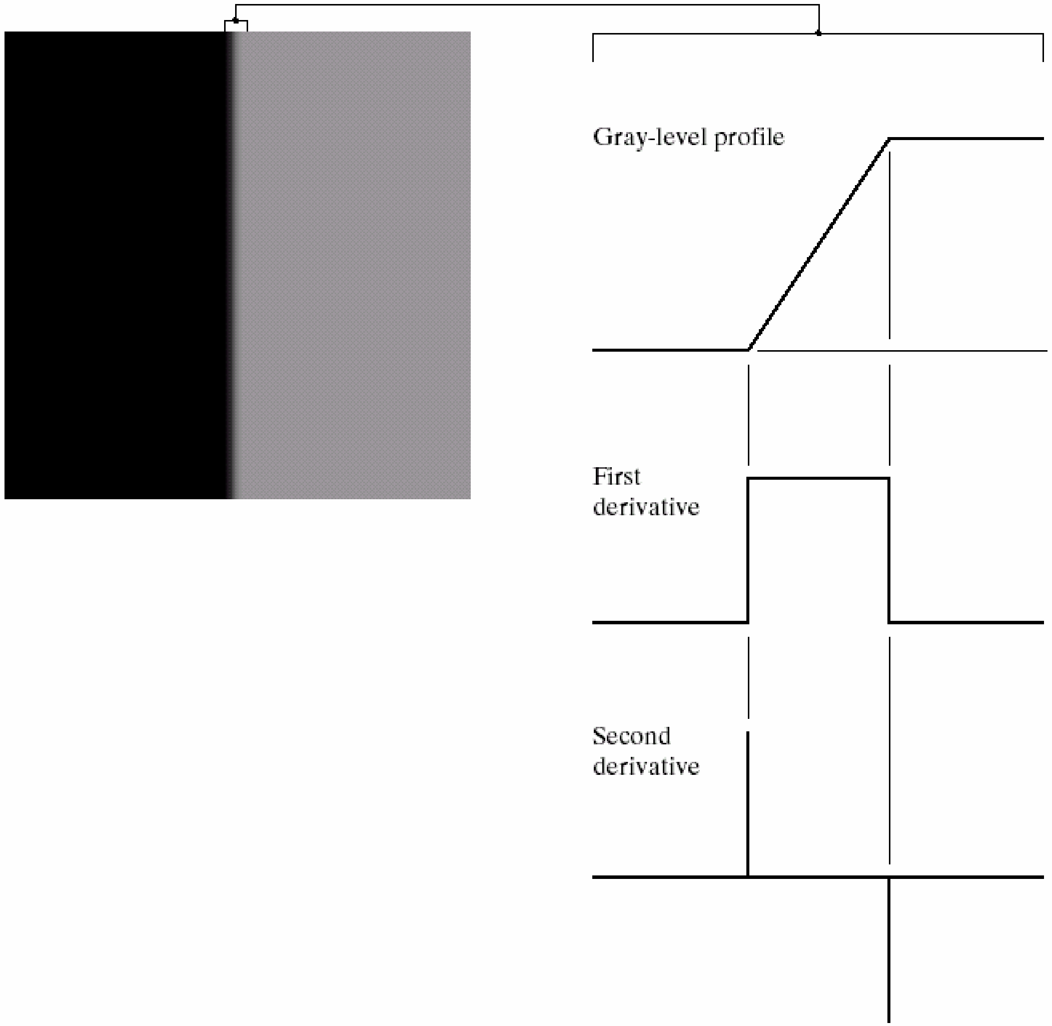
Image Segmentation



a b

FIGURE 10.6
(a) Two regions separated by a vertical edge.
(b) Detail near the edge, showing a gray-level profile, and the first and second derivatives of the profile.

Chapter 10
Image Segmentation

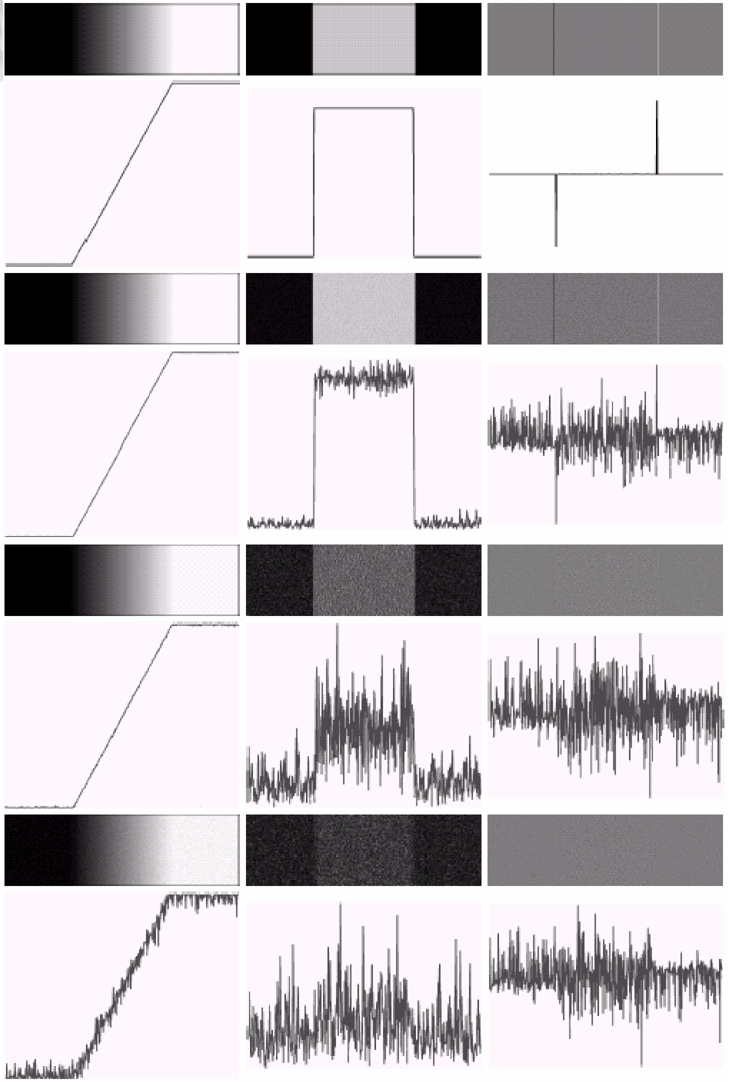
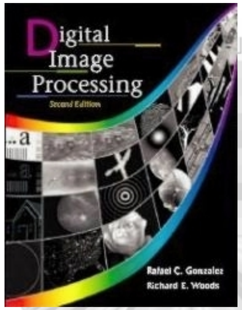


FIGURE 10.7 First column: images and gray-level profiles of a ramp edge corrupted by random Gaussian noise of mean 0 and σ = 0.0, 0.1, 1.0, and 10.0, respectively. Second column: first-derivative images and gray-level profiles. Third column: second-derivative images and gray-level profiles.

a
b
c
d

Edge Detection

- These examples are good illustrations of the sensitivity of derivatives to noise.
- The fact that fairly little noise can have such a significant impact on the two key derivatives used for edge detection in images is an important issue to keep im mind.
- In particular, image smoothing should be a serious consideration prior to the use of derivatives in applications where noise with levels similar to those we have just discussed is likely to be present.
- We define a point in an image as being an edge point if its two-dimensional first-order derivative is greater than a specified threshold.



Gradient operators

The gradient of an image $f(x,y)$ at location (x,y) is defined as the *vector*

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

$$\nabla f = mag(\nabla f) = \left[G_x^2 + G_y^2\right]^{1/2}$$

Let $\alpha(x,y)$ represent the direction angle of the vector $\bigtriangledown \mathbf{f}$ at (x,y). Then, from vector analysis, $\alpha(x, y) = \tan^{-1}\left(\dfrac{G_y}{G_x}\right)$

where the angle is measured with respect to the x-axis.
The direction of an edge at (x,y) is perpendicular to the direction
Of the gradient vector at that point.

Gradient operators

one of the simplest ways to implement a first-order partial derivative at point z_5 is to use the following *Roberts cross-gradient operators*:

$$G_x = (z_9 - z_5)$$
$$G_y = (z_8 - z_6)$$

An approach using masks of size 3x3 is given by

$$G_x = (z_7 + z_8 + z_9) - (z_1 + z_2 + z_3)$$
$$G_y = (z_3 + z_6 + z_9) - (z_1 + z_4 + z_7)$$

called the *Prewitt operators*

A slight variation of these two equations uses a weight of 2 in the center coefficient:

$$G_x = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)$$
$$G_y = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)$$

Gradient operators

- A weight value of 2 is used to achieve some smoothing by giving more importance to the center point, called the *Sobel* operators.
- The Prewitt and Sobel operators are among the most used im practice for computing digital gradients.
- Prewitt masks are simpler to implement than the Sobel masks, but the later have slightly superior noise-suppression characteristics, an important issue when dealing with derivatives.

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Image Segmentation

a

b c

d e

f g

FIGURE 10.8 A 3×3 region of an image (the z's are gray-level values) and various masks used to compute the gradient at point labeled z_5.

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

−1	0
0	1

0	−1
1	0

Roberts

−1	−1	−1
0	0	0
1	1	1

−1	0	1
−1	0	1
−1	0	1

Prewitt

−1	−2	−1
0	0	0
1	2	1

−1	0	1
−2	0	2
−1	0	1

Sobel

Gradient operators

- An approach used frequently is to approximate the gradient by absolute values: $\nabla f \approx |G_x| + |G_y|$
- The two additional Prewitt and Sobel masks for detecting discontinuities in the diagonal directions are shown in Fig. 10.9.

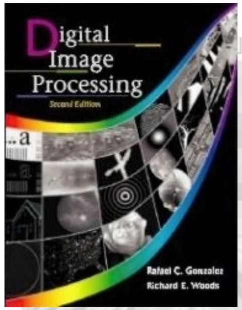

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Image Segmentation

a b
c d

0	1	1
−1	0	1
−1	−1	0

−1	−1	0
−1	0	1
0	1	1

Prewitt

0	1	2
−1	0	1
−2	−1	0

−2	−1	0
−1	0	1
0	1	2

Sobel

FIGURE 10.9 Prewitt and Sobel masks for detecting diagonal edges.

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Image Segmentation

a b
c d

FIGURE 10.10 (a) Original image. (b) $|G_x|$, component of the gradient in the x-direction. (c) $|G_y|$, component in the y-direction. (d) Gradient image, $|G_x| + |G_y|$.

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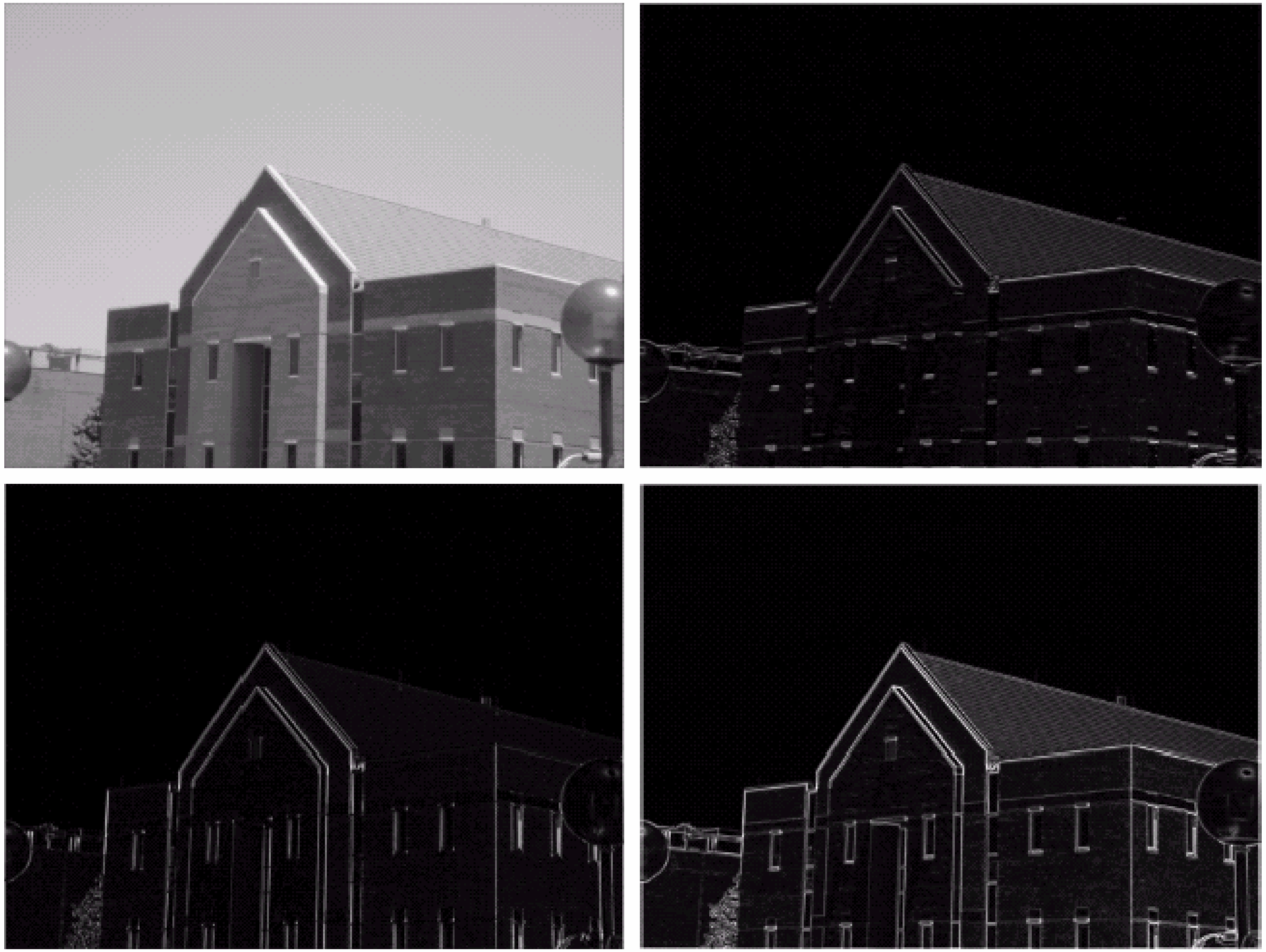


a b
c d

FIGURE 10.11 Same sequence as in Fig. 10.10, but with the original image smoothed with a 5 × 5 averaging filter.

a b

FIGURE 10.12 Diagonal edge detection. (a) Result of using the mask in Fig. 10.9(c). (b) Result of using the mask in Fig. 10.9(d). The input in both cases was Fig. 10.11(a).

The Laplacian

- The Laplacian of a 2-D function (x,y) is a second-order derivative defined as

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

- Digital approximations to the Laplacian were introduced in Section 3.7.2.
- For a 3x3 region, one of the two forms encountered most frequently in practice is

$$\nabla^2 f = 4z_5 - \left(z_2 + z_4 + z_6 + z_8\right)$$

FIGURE 10.13 Laplacian masks used to implement Eqs. (10.1-14) and (10.1-15), respectively.

0	−1	0
−1	4	−1
0	−1	0

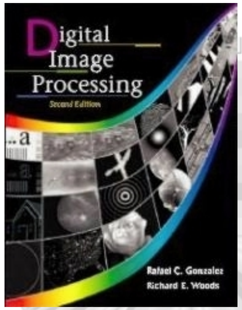
−1	−1	−1
−1	8	−1
−1	−1	−1

The Laplacian

- A digital approximation including the diagonal neighbors is given by

$$\nabla^2 f = 8z_5 - \left(z_1 + z_2 + z_3 + z_4 + z_5 + z_6 + z_7 + z_8 + z_9\right)$$

- As a senond-order derivative, the Laplacian typically is unacceptably sensitive to noise.
- The Laplacian is unable to detect edge direction.



The Laplacian

- Role of the Laplacian in segmentation consist of (1) using its zero-crossing property for edge location, (2) using it for the complementary purpose of establishing whether a pixel is on the dark or light side of an edge. $h(r) = -e^{-\frac{r^2}{2\sigma^2}}$ (Eq10.1-16)
- $\nabla^2 h(r) = -\left[\frac{r^2 - \sigma^2}{\sigma^4}\right] e^{-\frac{r^2}{2\sigma^2}}$ this function is commonly referred to as the *Laplacian of a Gaussian* (LoG) because Eq(10.1-16) is in the form of a Gaussian function.

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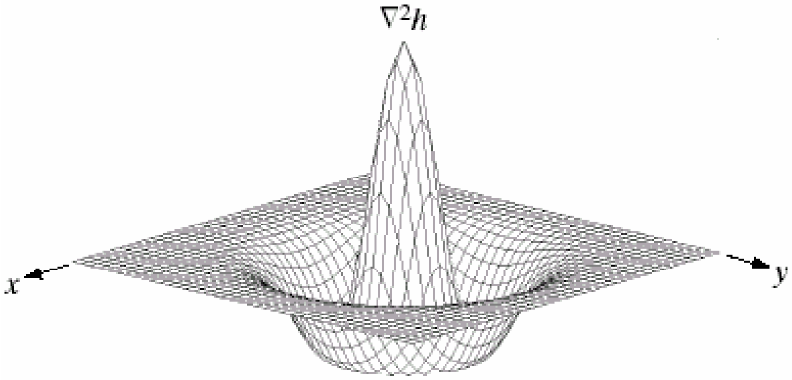
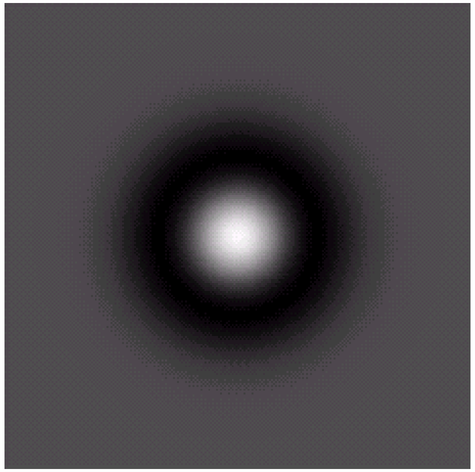
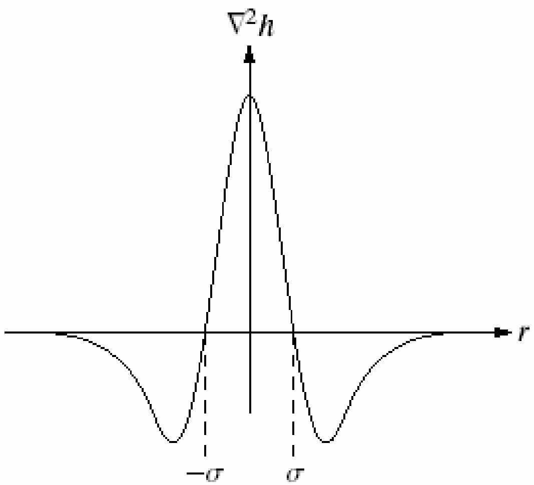
Image Segmentation







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

a	b
c	d

FIGURE 10.14 Laplacian of a Gaussian (LoG). (a) 3-D plot. (b) Image (black is negative, gray is the zero plane, and white is positive). (c) Cross section showing zero crossings. (d) 5×5 mask approximation to the shape of (a).

The Laplacian

- The LoG result in Fig. 10.15(e) is the image from which zero crossings are computed to find edges.
- One straightforward approach for approximating zero crossings is to threshold the LoG image by setting all its positive values to, say, white, and all negative values to black.

The Laplacian

- Compare Fig. 10.15(b) and (g) reveals several interesting and important differences.
- First, we denote that the edges in the zero-crossing image are thinner than the gradient edges.
- On the other hand, we see in Fig. 10.15(g) that the edges determined by zero crossings for, numerous closed loops.
- This so-called spaghettieffect is one of the most seties drawbacks of this method.

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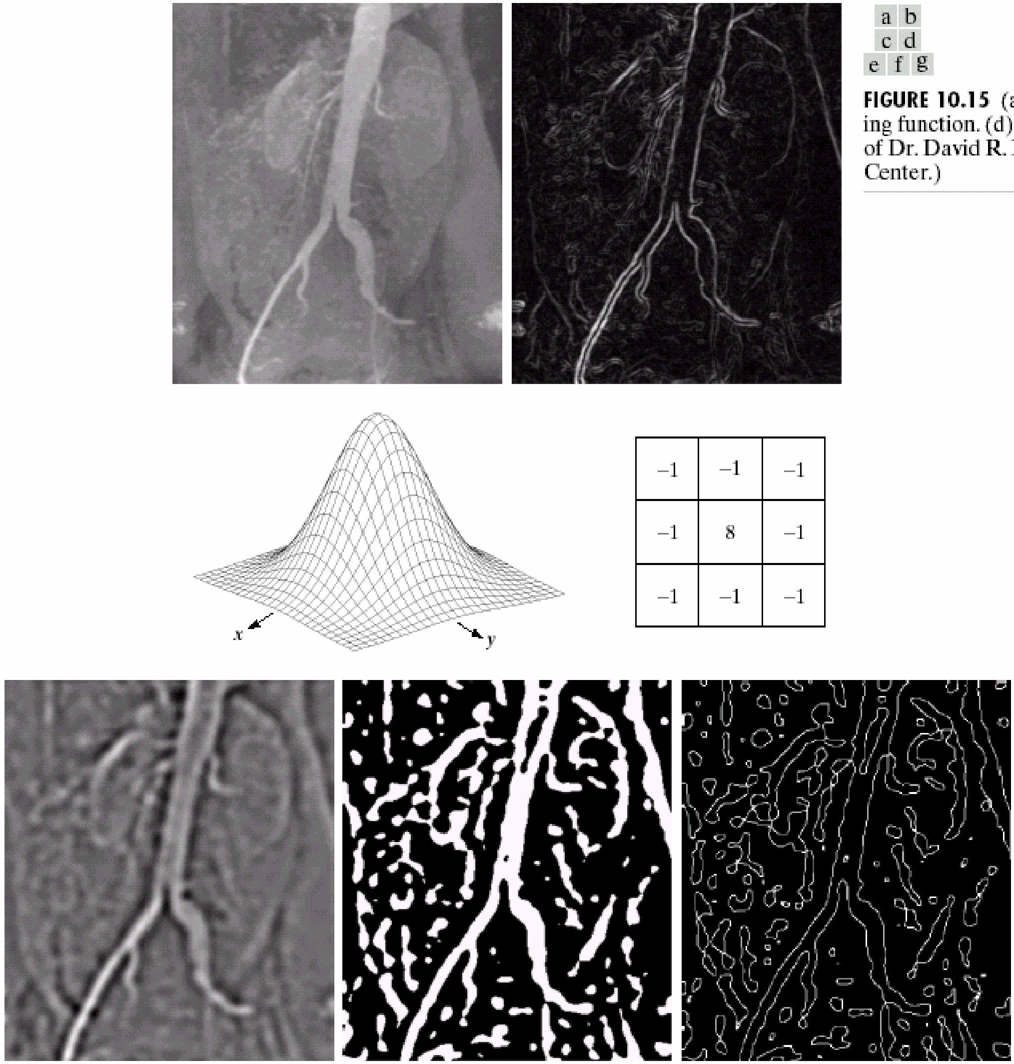
Image Segmentation



a b
c d
e f g

FIGURE 10.15 (a) Original image. (b) Sobel gradient (shown for comparison). (c) Spatial Gaussian smoothing function. (d) Laplacian mask. (e) LoG. (f) Thresholded LoG. (g) Zero crossings. (Original image courtesy of Dr. David R. Pickens, Department of Radiology and Radiological Sciences, Vanderbilt University Medical Center.)

Edge linking and Boundary Detection

- One of the simplest approaches for linking edge points is to analyze the characteristics of pixels in a small neighborhood (say, 3x3 or 5x5).
- All points that are similar according to a set of predefined criteria are linked.
- The two principal properties used for establishing similarity of edge pixels in this kind of analysis are (1) the strength of the response of the gradient operator used to produce the edge pixel; and (2) the direction of the gradient vector.

Local Processing

- Thus an edge pixel with coordinates (x_0,y_0) in a predefined neighborhood of (x,y), is similar in magnitude to the pixel at (x,y) if $\left|\nabla f(x,y) - \nabla f(x_0,y_0)\right| \leq E$
- An edge pixel at (x_0,y_0) in the predefined neighborhood of (x,y) has an angle similar to the pixel at (x,y) if $\left|\alpha(x,y) - \alpha(x_0,y_0)\right| < A$

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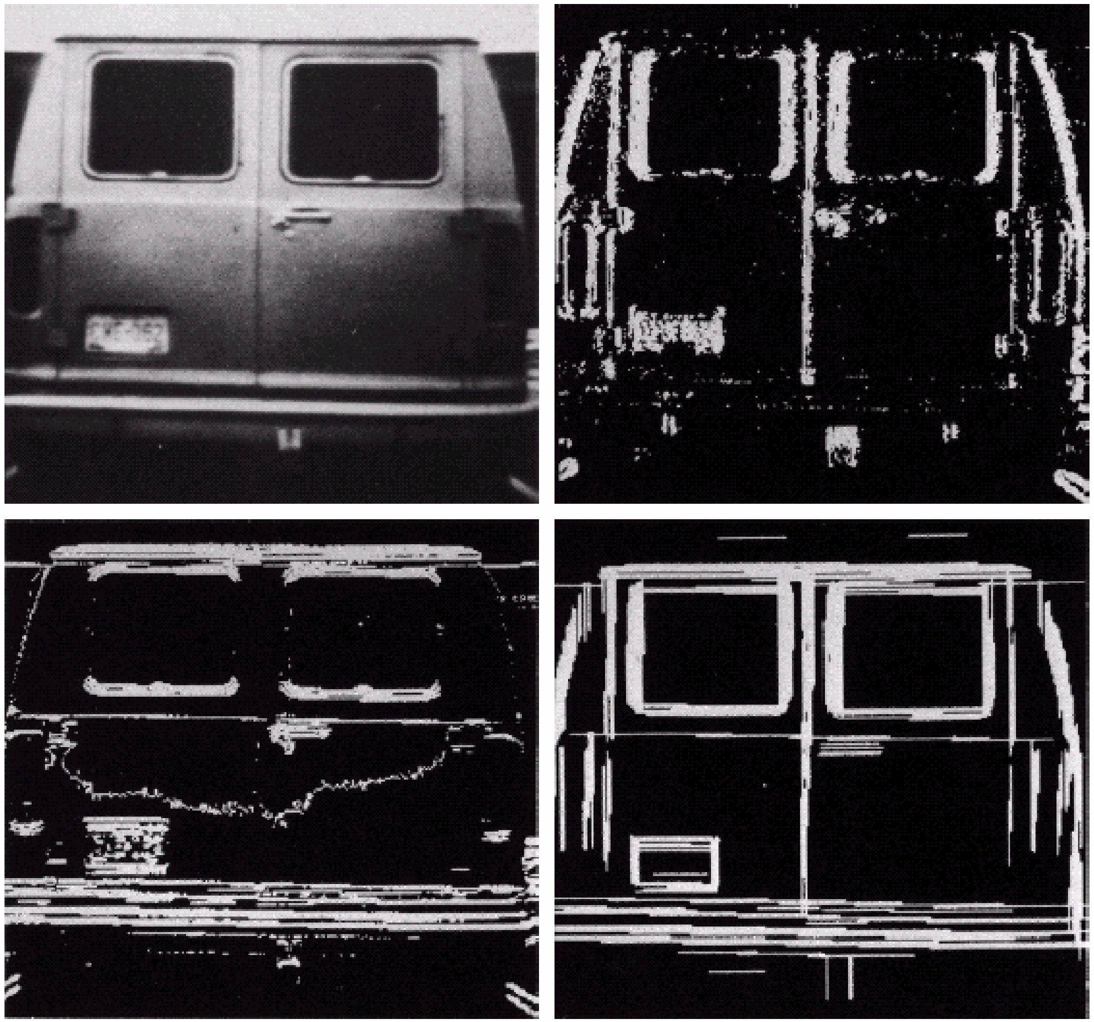
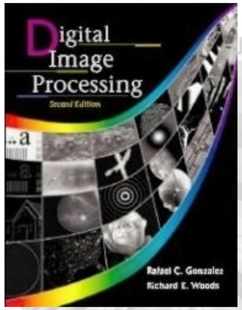
Image Segmentation



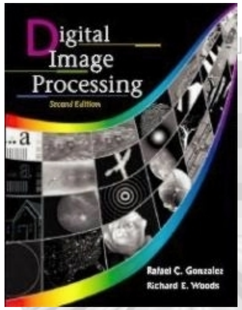
a b
c d

FIGURE 10.16 (a) Input image. (b) G_y component of the gradient. (c) G_x component of the gradient. (d) Result of edge linking. (Courtesy of Perceptics Corporation.)



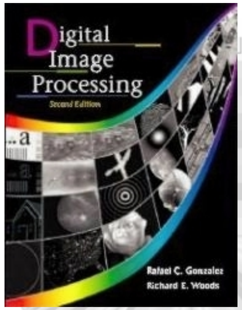
Local Processing

- Fig.10.16(d) shows the result of linking all points that simultaneously had a gradient value greater than 25 and whose gradient directions did not differ by more than 15°.



Global Processing via the Hough Transform

- In this section, points are linked by determining first if they lie on a curve of specified shape.
- An approach based on the Hough transform is as follows:
  - 1.Compute the gradient of an image and threshold it to obtain a binary image.
  - 2.Specify subdivisions in the $\rho\ \theta$ -plane.
  - 3.Examine the counts of the accumulator cells for high pixel concentrations.
  - 4.Examine the relationship (principally for continuity) between pixels in a chosen cell.



Global Processing via the Hough transform

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  - 3.Examine the counts of the accumulator cells for pixel concentrations
  - 4.Examine in the relationship (principally for continuity) between pixels in a chosen cell.

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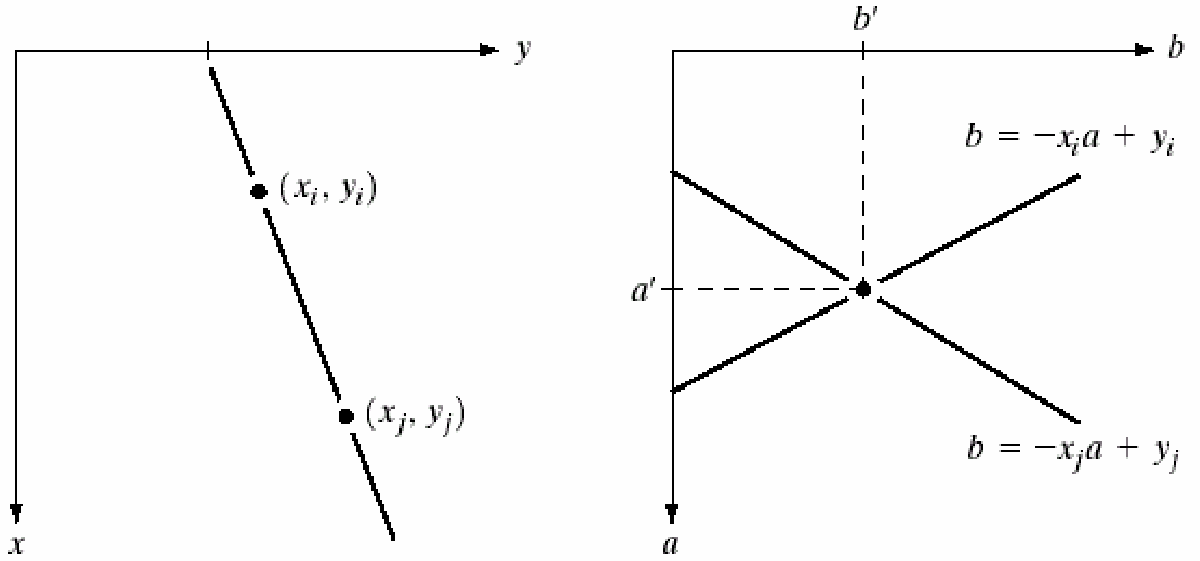
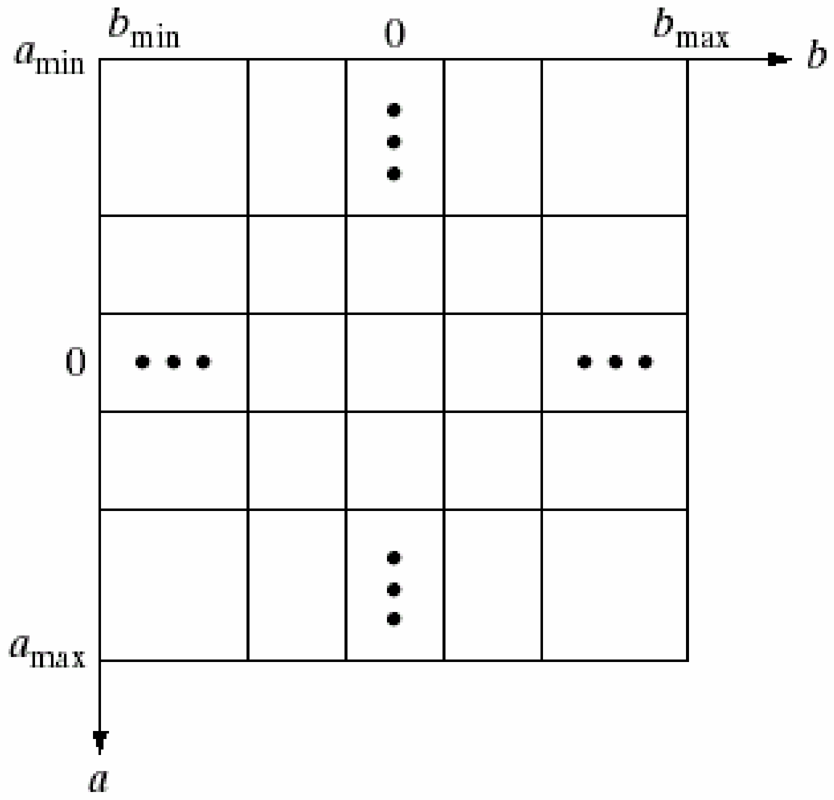


a b

FIGURE 10.17 (a) *xy*-plane. (b) Parameter space.

FIGURE 10.18 Subdivision of the parameter plane for use in the Hough transform.



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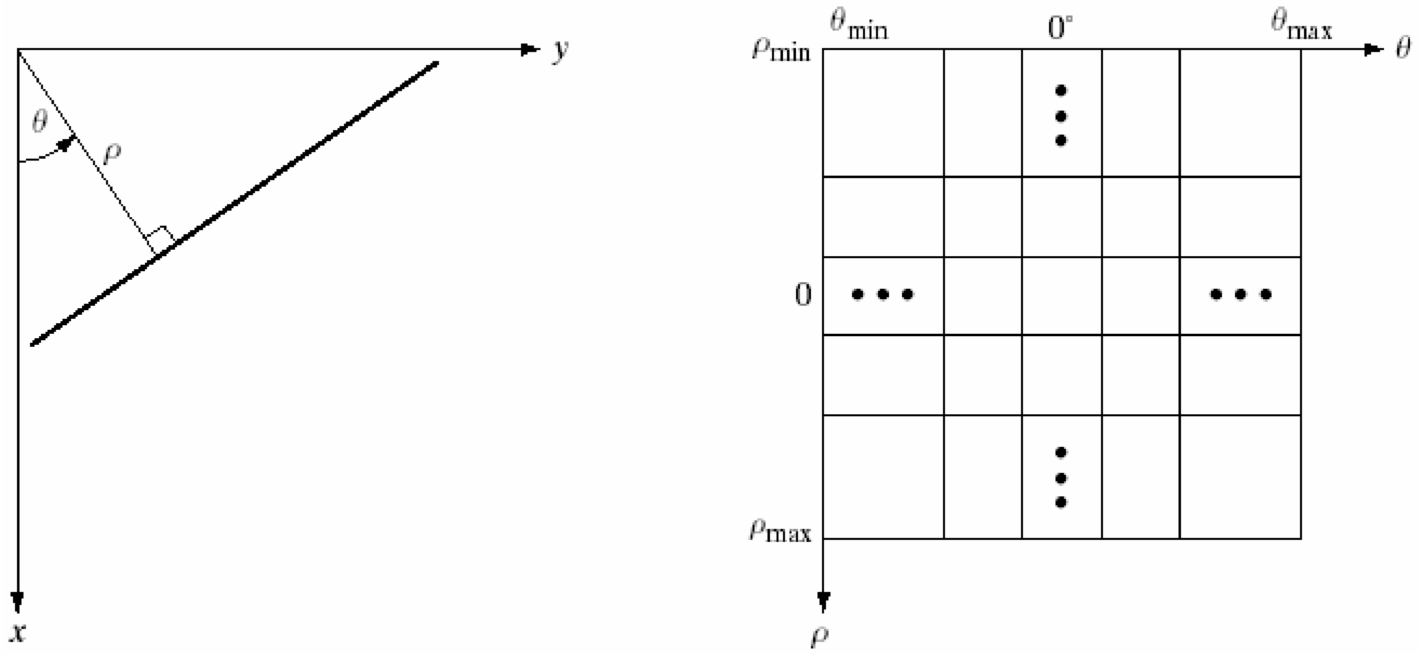

a b

FIGURE 10.19 (a) Normal representation of a line. (b) Subdivision of the $\rho\theta$-plane into cells.

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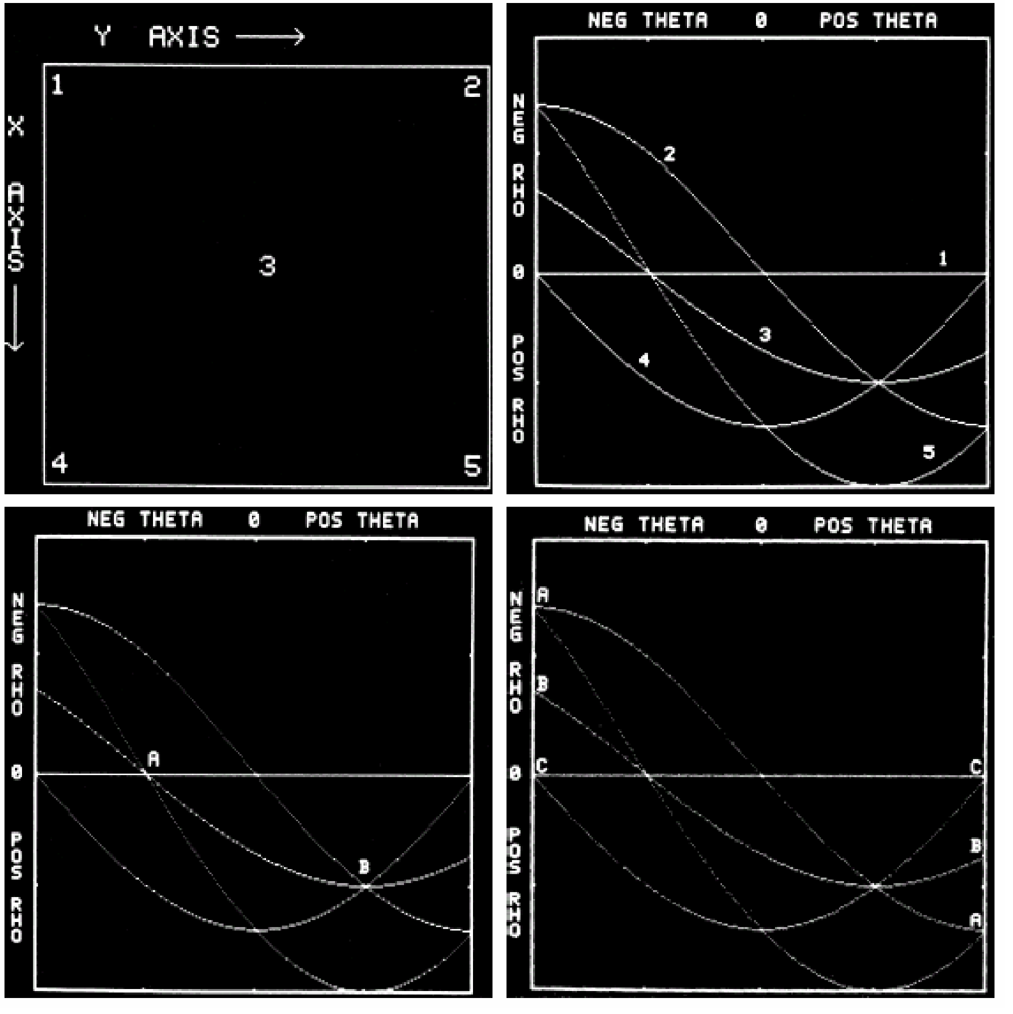
Image Segmentation



a b
c d

FIGURE 10.20 Illustration of the Hough transform. (Courtesy of Mr. D. R. Cate, Texas Instruments, Inc.)

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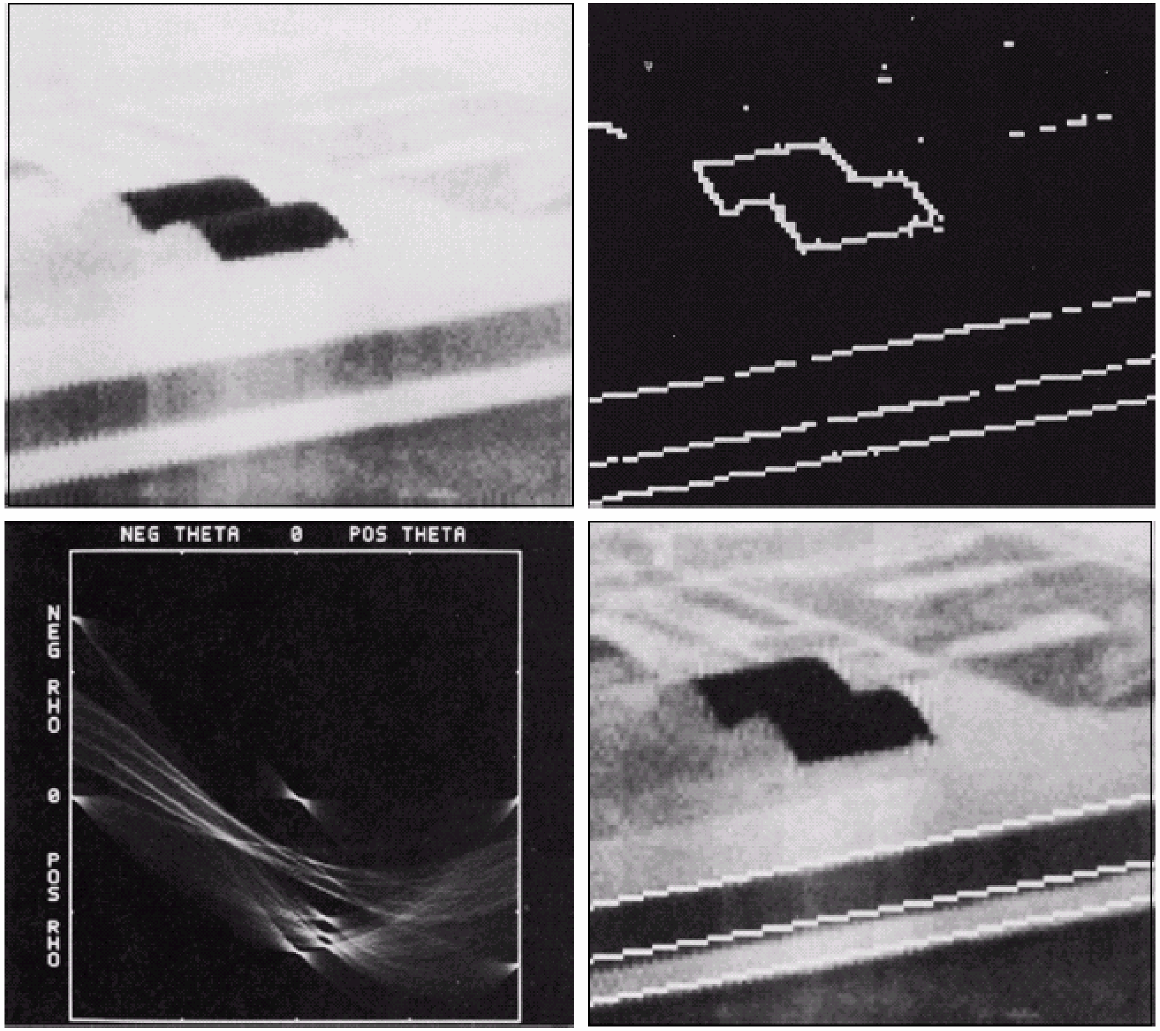

a b
c d

FIGURE 10.21 (a) Infrared image. (b) Thresholded gradient image. (c) Hough transform. (d) Linked pixels. (Courtesy of Mr. D. R. Cate, Texas Instruments, Inc.)

Global Processing via Graph-Theoretic Techniques

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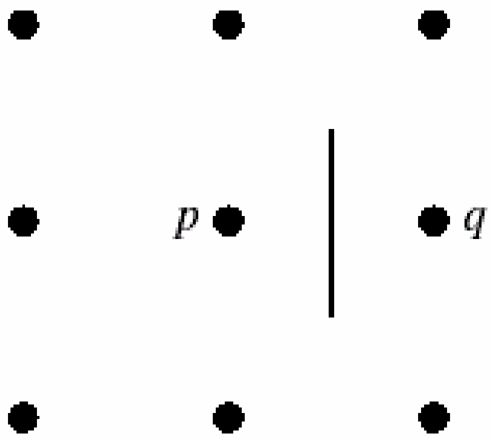
Image Segmentation

FIGURE 10.22
Edge element between pixels p and q.



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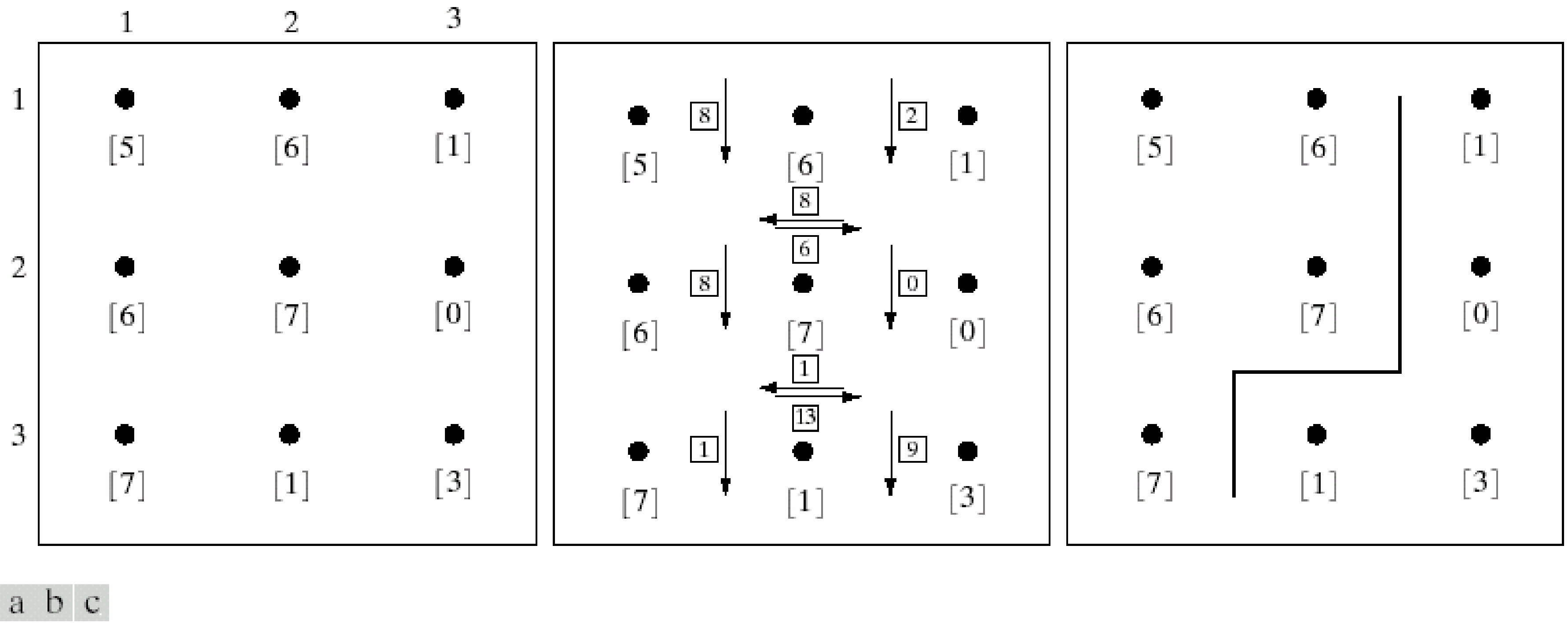

FIGURE 10.23 (a) A 3 × 3 image region. (b) Edge segments and their costs. (c) Edge corresponding to the lowest-cost path in the graph shown in Fig. 10.24.

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Image Segmentation

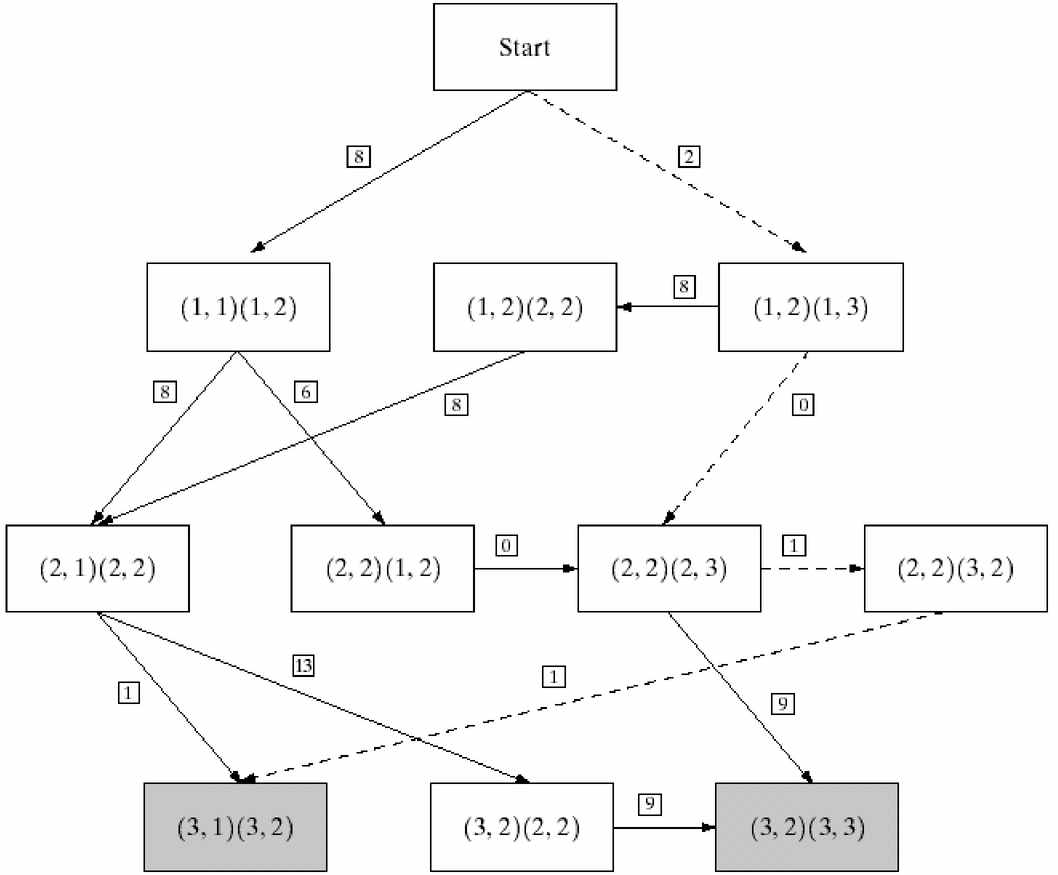

FIGURE 10.24 Graph for the image in Fig. 10.23(a). The lowest-cost path is shown dashed.

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FIGURE 10.25 Image of noisy chromosome silhouette and edge boundary (in white) determined by graph search.

Thresholding

- Because of its intuitive properties and simplicity of implementation, image thresholding enjoys a central position in applications of image segmentation.

Foundation

- One obvious way to extract the objects from the background is to select a threshold *T* that separates these modes.
- Then any point (x,y) for which $f(x,y)>T$ is called an *object point*; otherwise, the point is called a *background point*.

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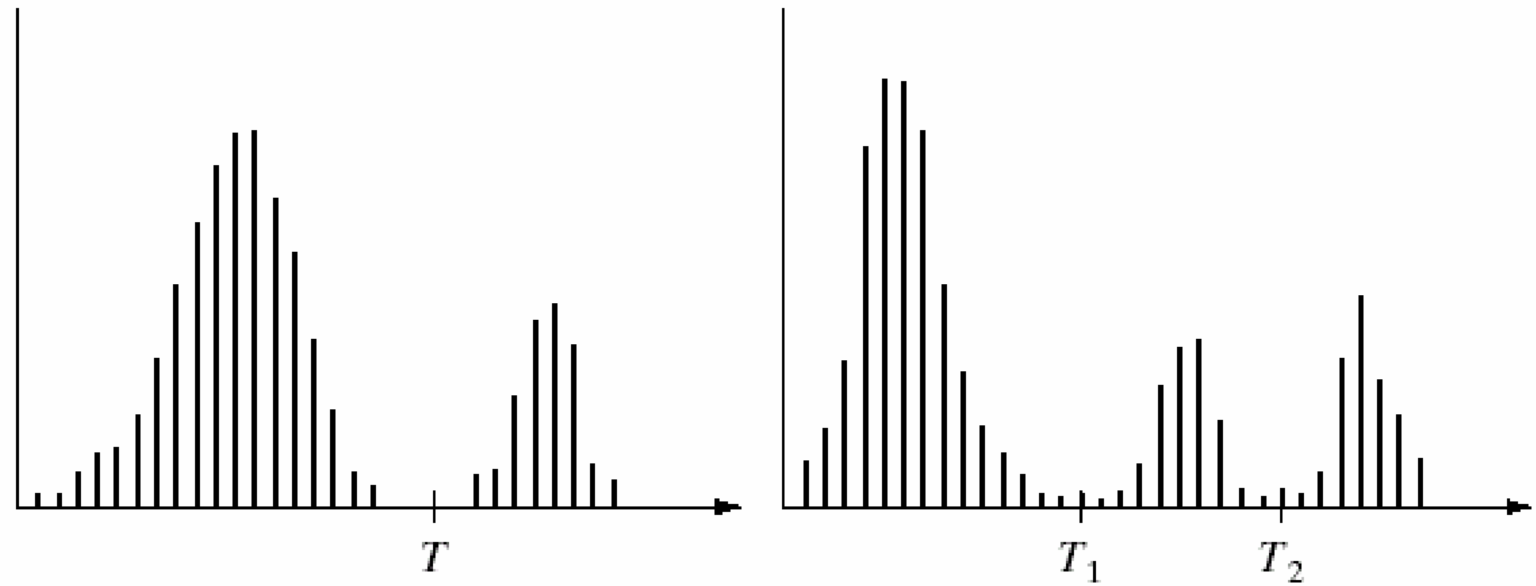

a b

FIGURE 10.26 (a) Gray-level histograms that can be partitioned by (a) a single threshold, and (b) multiple thresholds.

Foundation

- Thresholding may be viewed as an operation that involves tests against a function *T* of the form $T = T\left[x, y, p(x, y), f(x, y)\right]$ where $f(x,y)$ is the gray level of point (x,y) and $p(x,y)$ denotes some local property of this point.
- When *T* depends only on $f(x,y)$ (that is, only on gray-level values) the threshold is called *global*.
- If *T* depends on both $f(x,y)$ and $p(x,y)$, the threshold is called *local*.
- If, in addition, *T* depends on the spatial coordinates *x* and *y*, the threshold is called *dynamic* or *adaptive*.

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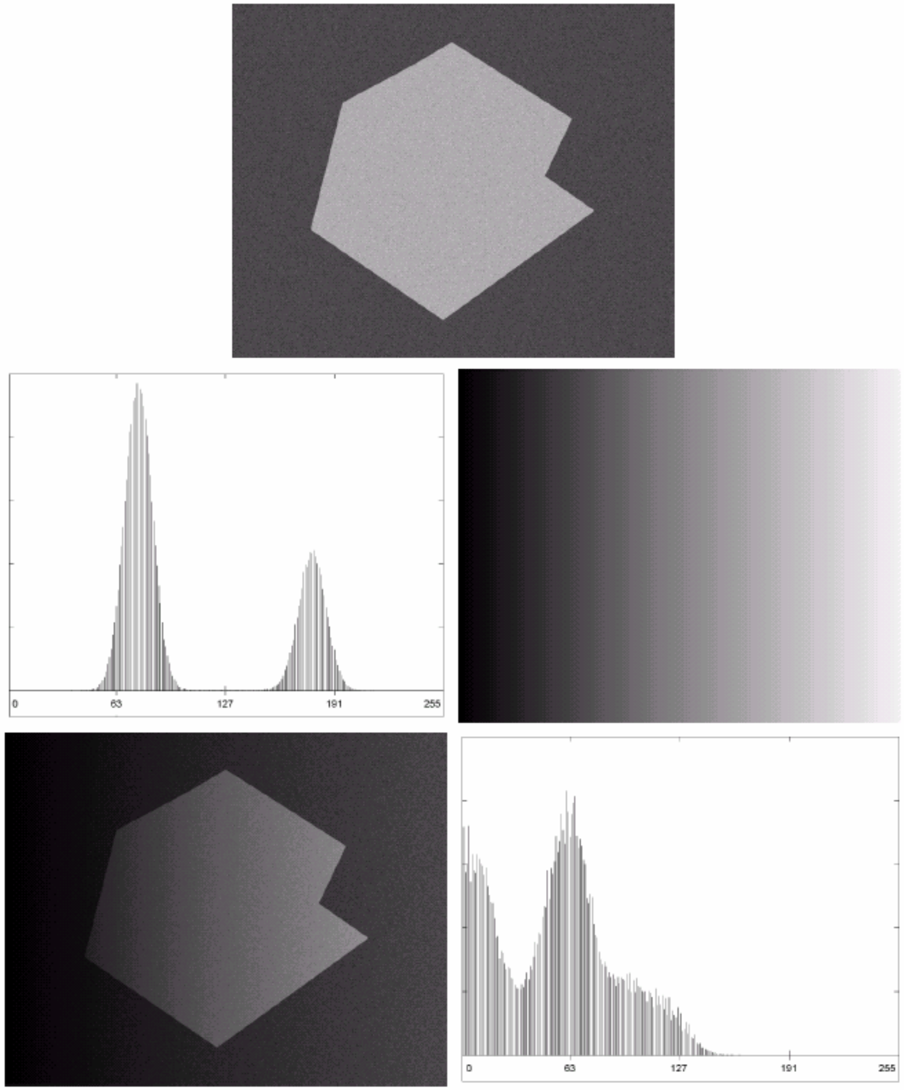


a
b c
d e

FIGURE 10.27 (a) Computer generated reflectance function. (b) Histogram of reflectance function. (c) Computer generated illumination function. (d) Product of (a) and (c). (e) Histogram of product image.

Basic Global Thresholding

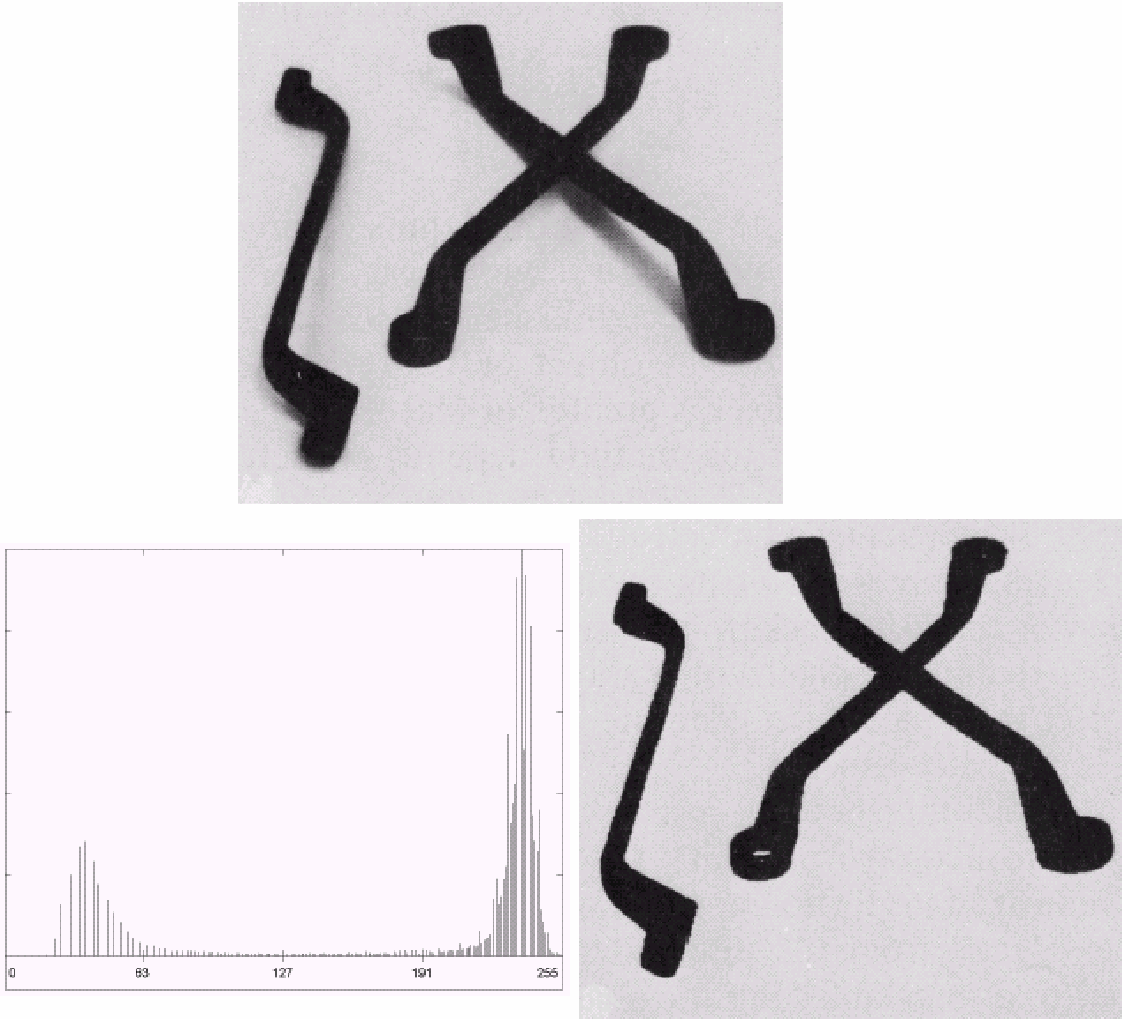
- The following algorithm can be used to obtain *T* automatically:
  - 1.Select an initial estimate for *T*.
  - 2.Segment the image using *T*. This will produce two groups of pixels: G_1 consisting of all pixels with gray level > *T* and G_2 consisting of pixels with values $\leqq T$.
  - 3.Compute the average gray level value μ_1 and μ_2 for the pixels in regions G_1 and G_2.

Basic Global Thresholding

– 4.Compute a new threshold value: $T = \frac{1}{2}(\mu_1 + \mu_2)$

– 5.Repeat step 2 though 4 until the difference in *T* in successive iterations is smaller than a predefined parameter T_0.

Chapter 10
Image Segmentation



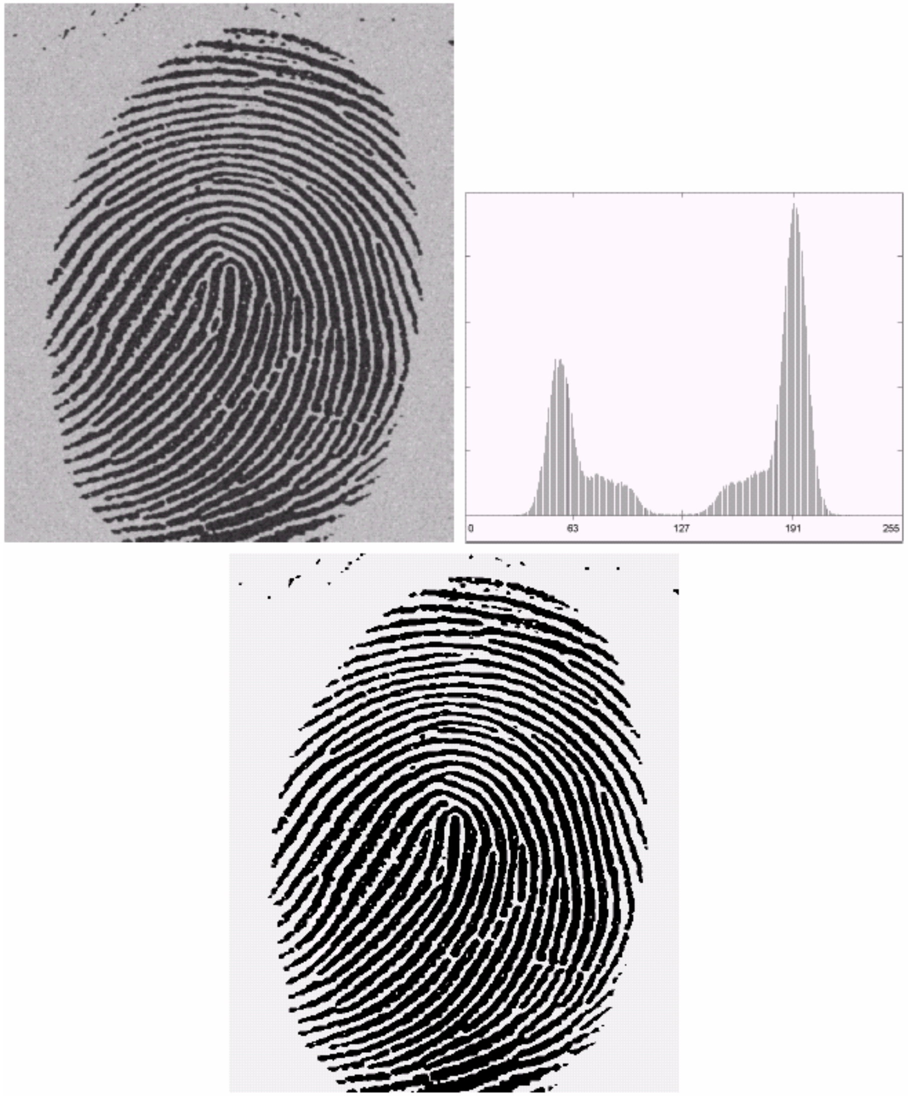
a
b c

FIGURE 10.28 (a) Original image. (b) Image histogram. (c) Result of global thresholding with T midway between the maximum and minimum gray levels.

Basic Adaptive Thresholding

- Divide the original image into subimages and then utilize a different threshold to segment each subimage.
- The key issues in this approach are how to subdivide the image and how to estimate the threshold for each resulting subimage.

Chapter 10
Image Segmentation



a b
c

FIGURE 10.29 (a) Original image. (b) Image histogram. (c) Result of segmentation with the threshold estimated by iteration. (Original courtesy of the National Institute of Standards and Technology.)

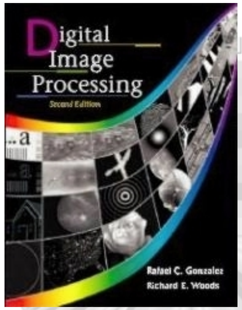


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Image Segmentation

a b
c d

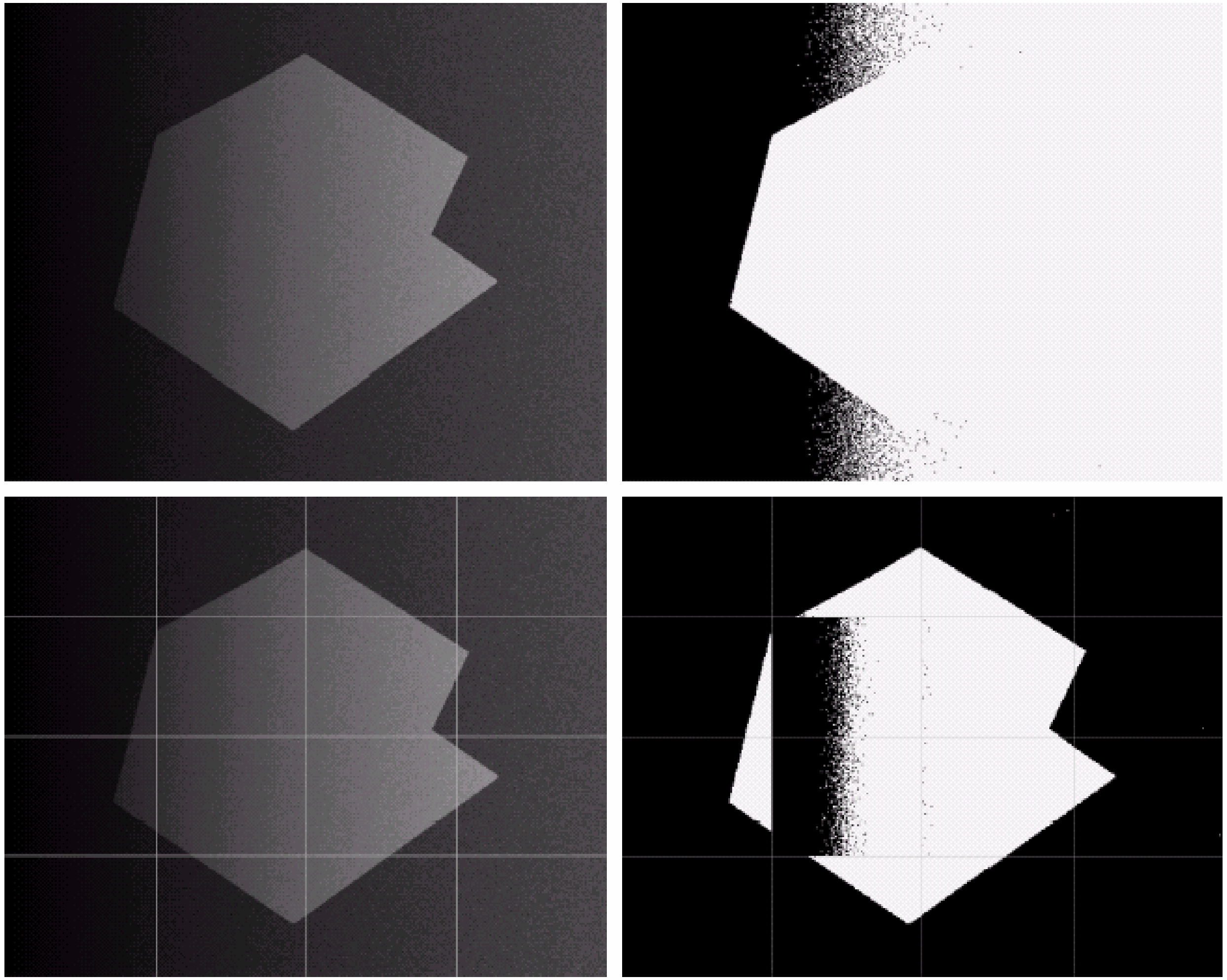

FIGURE 10.30 (a) Original image. (b) Result of global thresholding. (c) Image subdivided into individual subimages. (d) Result of adaptive thresholding.

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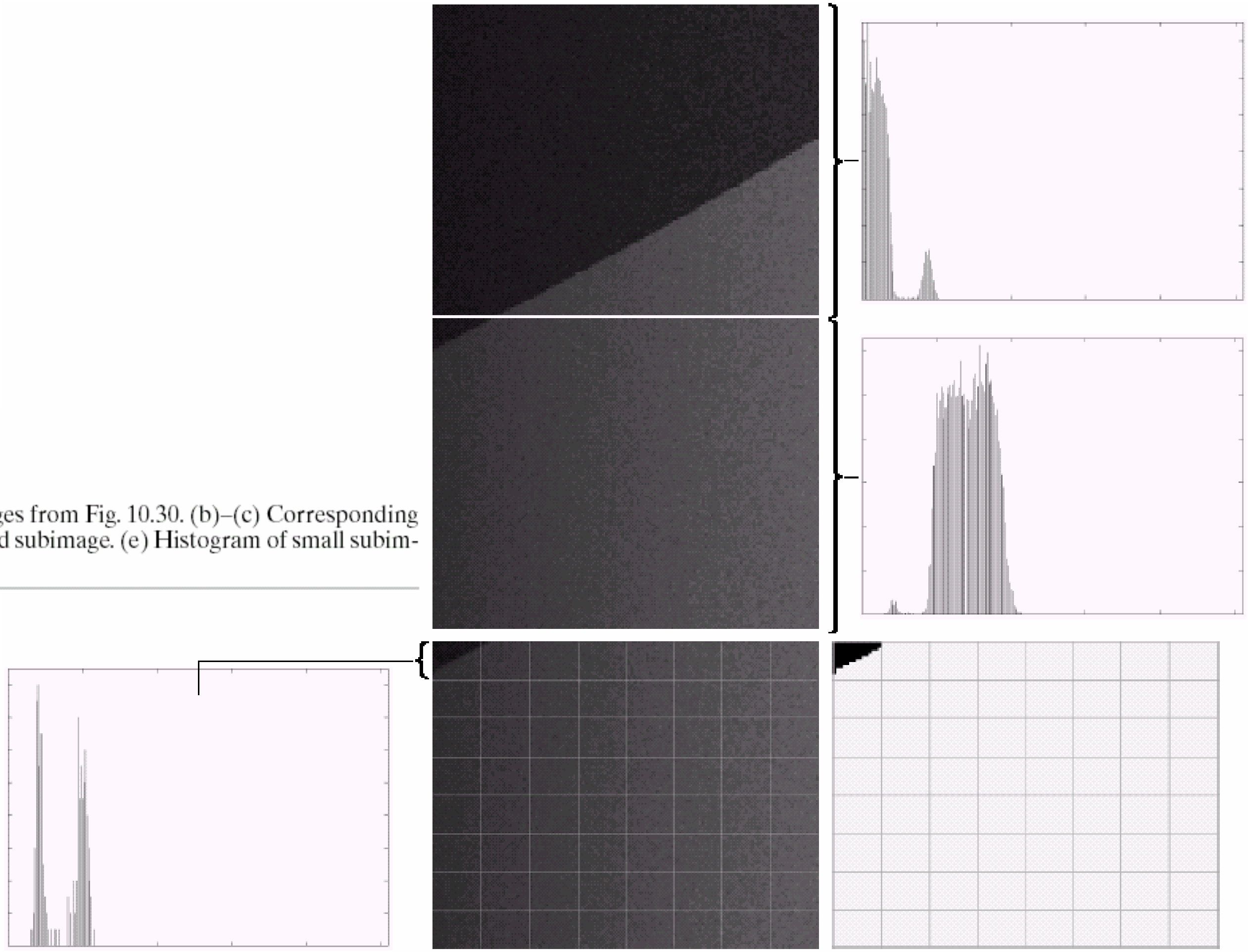
Image Segmentation



a b c
e d f

FIGURE 10.31 (a) Properly and improperly segmented subimages from Fig. 10.30. (b)–(c) Corresponding histograms. (d) Further subdivision of the improperly segmented subimage. (e) Histogram of small subimage at top, left. (f) Result of adaptively segmenting (d).

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Image Segmentation

FIGURE 10.32 Gray-level probability density functions of two regions in an image.

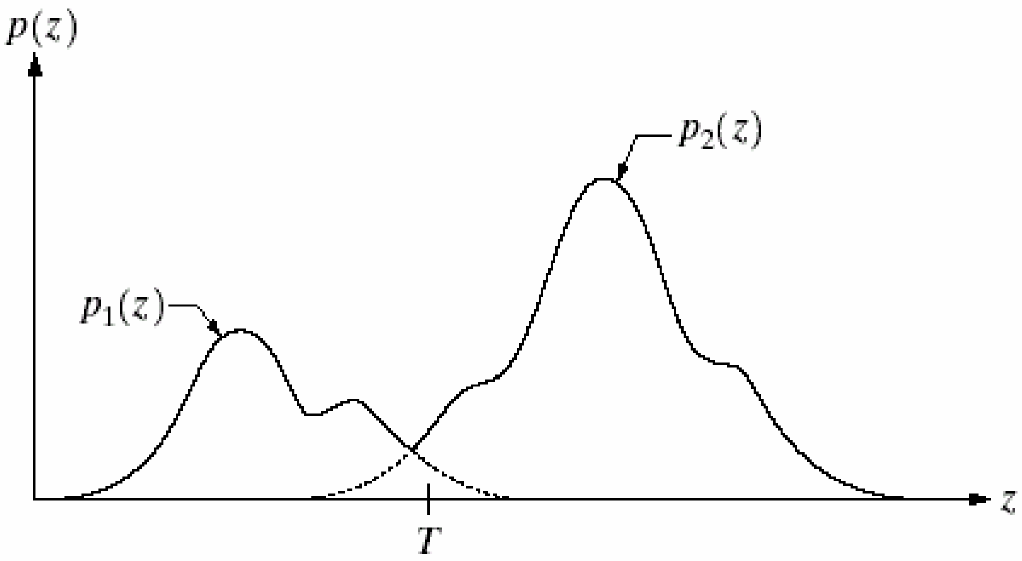

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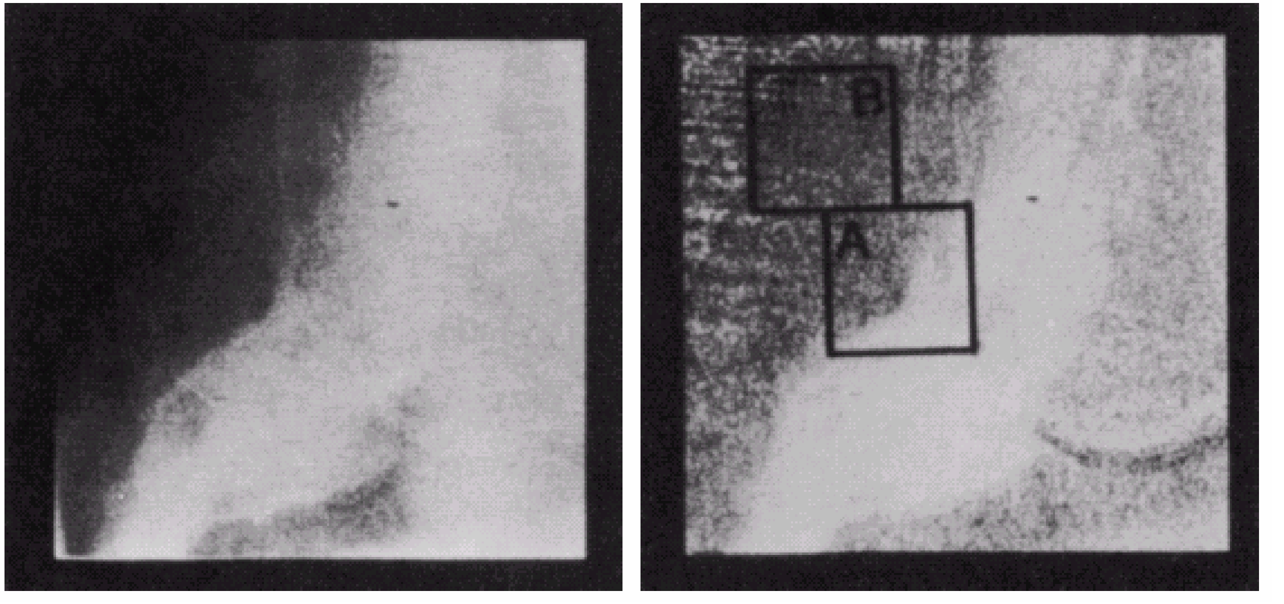
Image Segmentation



a b

FIGURE 10.33 A cardioangiogram before and after preprocessing. (Chow and Kaneko.)

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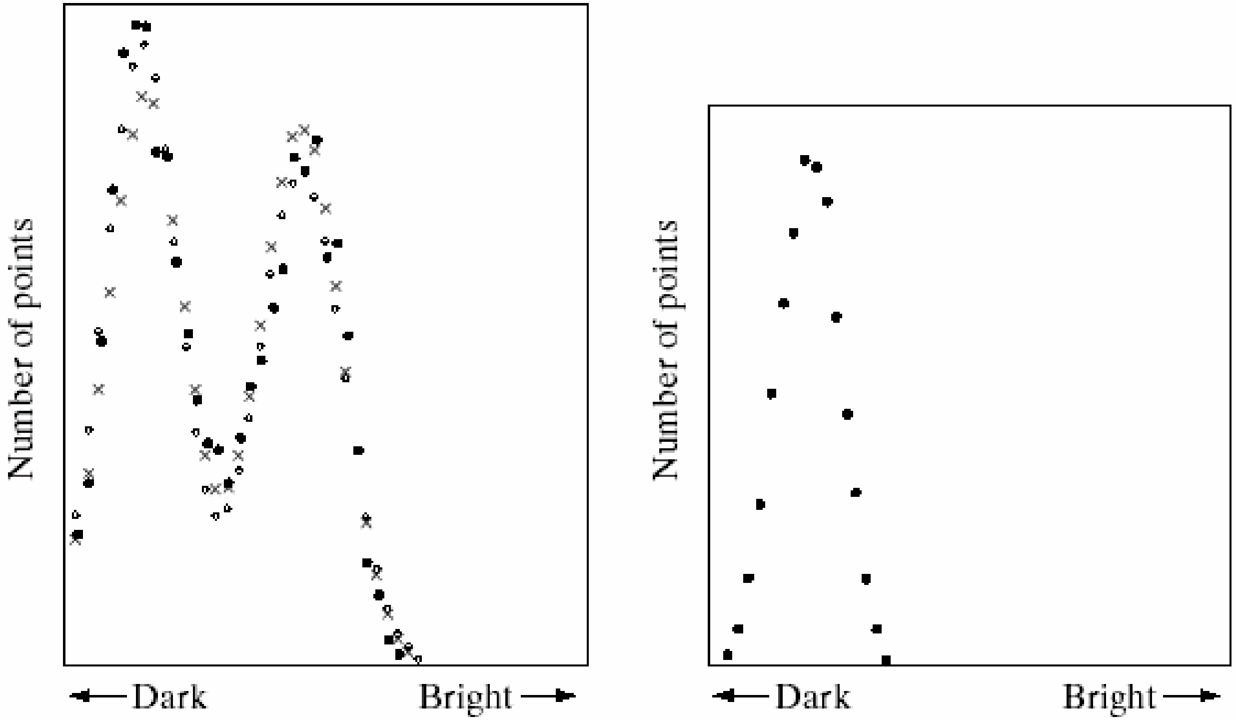
Image Segmentation



a b

FIGURE 10.34 Histograms (black dots) of (a) region *A*, and (b) region *B* in Fig. 10.33(b). (Chow and Kaneko.)

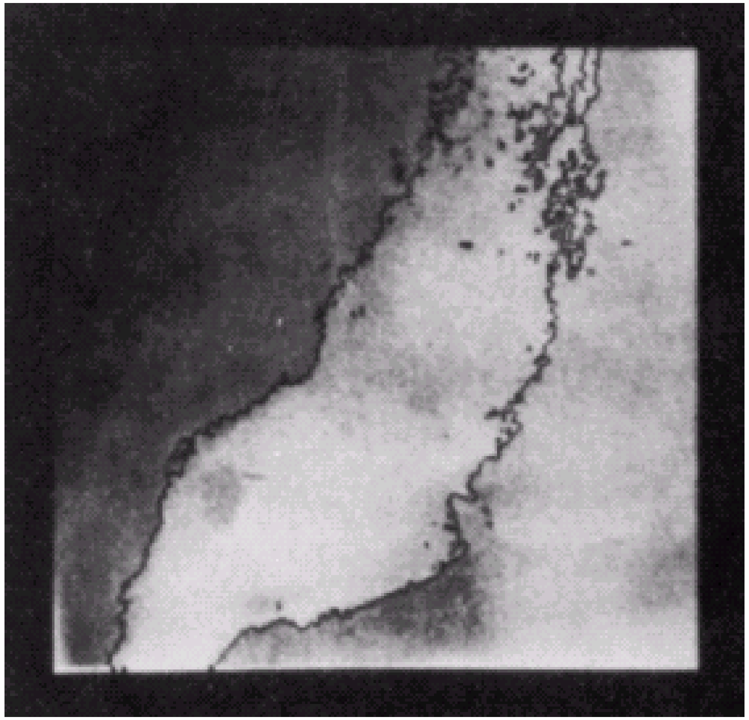


FIGURE 10.35 Cardioangiogram showing superimposed boundaries. (Chow and Kaneko.)

Use of Boundary Characteristics for Histogram Improvement and Local Thresholding

- Using pixels that satisfy some simple measures based on gradient and Laplacian operators has a tendency to deepen the valley between histogram peaks.
- An indication of whether a pixel is on an edge may be obtained by computing its gradient.
- In addition, use of the Laplacian can yields information regarding whether a given pixel lies on the dark or light side of an edge.

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Image Segmentation

FIGURE 10.36 Image of a handwritten stroke coded by using Eq. (10.3-16). (Courtesy of IBM Corporation.)

Use of Boundary Characteristics for Histogram Improvement and Local Thresholding

- (1)all pixels that are not on an edge (as determined by ∇f being less than *T*) are labeled 0.
- (2)all pixels on the dark side of an edge are labeled +.
- (3)all pixels on the light side of an edge are labeled -.

$$s(x,y)=\begin{cases} 0 & if\ \nabla f < T \\ + & if\ \nabla f \geq T \text{ and } \nabla^2 f \geq 0 \\ - & if\ \nabla f \geq T \text{ and } \nabla^2 f < 0 \end{cases}$$

Use of Boundary Characteristics for Histogram Improvement and Local Thresholding

- The transition (along a horizontal or vertical scan line) from a light background to a dark object must be characterized by the occurrence of a – followed by a + in $s(x,y)$.
- The interior of the object is composed of pixels that are labeled either 0 or +.
- Finally, the transition from the object back to the background is characterized by the occurrence of a + followed by a -.
- The innermost parentheses contains object points and are labeled 1.
- All other pixels along the same scan line are labeled 0, with the exception of any other sequence of (0 or +) bounded by (-,+) and (+,-).

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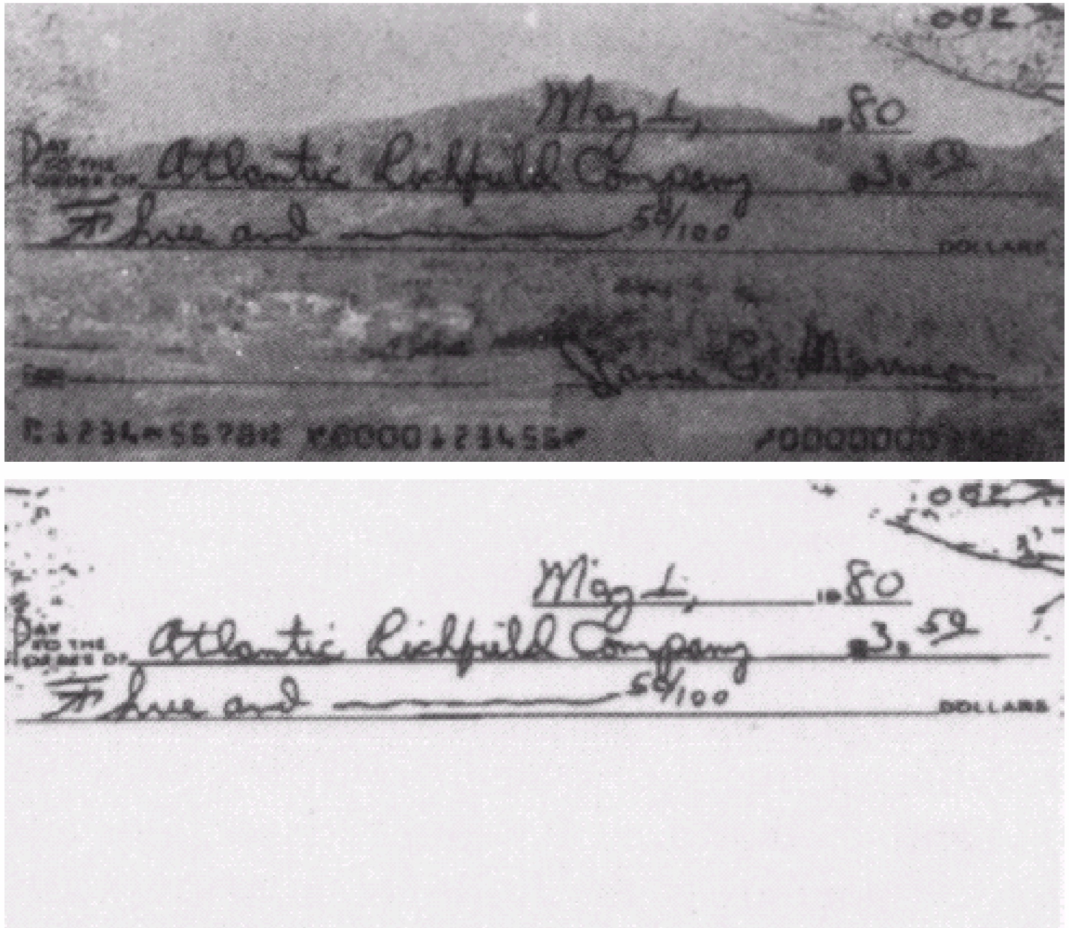
Image Segmentation



a
b

FIGURE 10.37 (a) Original image. (b) Image segmented by local thresholding. (Courtesy of IBM Corporation.)

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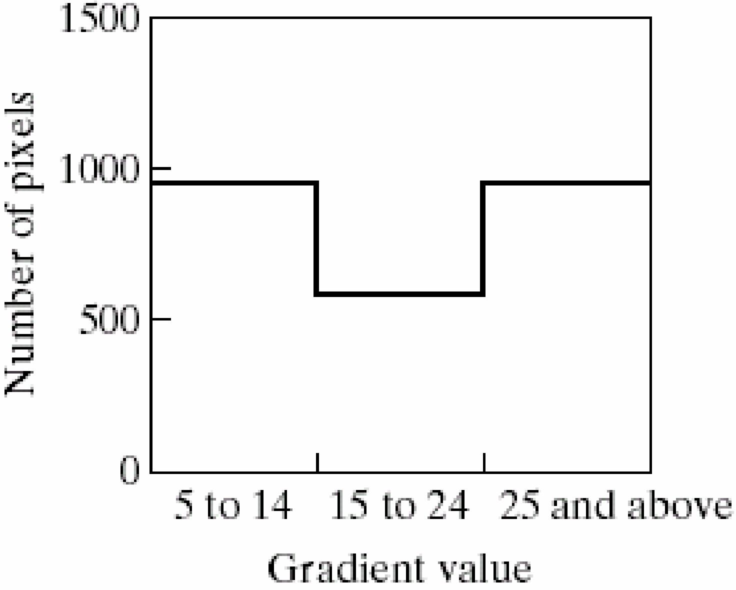
FIGURE 10.38 Histogram of pixels with gradients greater than 5. (Courtesy of IBM Corporation.)



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a b c

FIGURE 10.39 (a) Original color image shown as a monochrome picture. (b) Segmentation of pixels with colors close to facial tones. (c) Segmentation of red components.

Region Growing

- Region growing is a procedure that groups pixels or sub-regions into larger regions based on predefined criteria.
- 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 properties similar to the seed (such as specific ranges of gray level or color).

Region Growing

- The selection of similarity criteria depends not only on the problem under consideration, but also on the type of image data available.
- Another problem in region growing is the formulation of a stopping rule.

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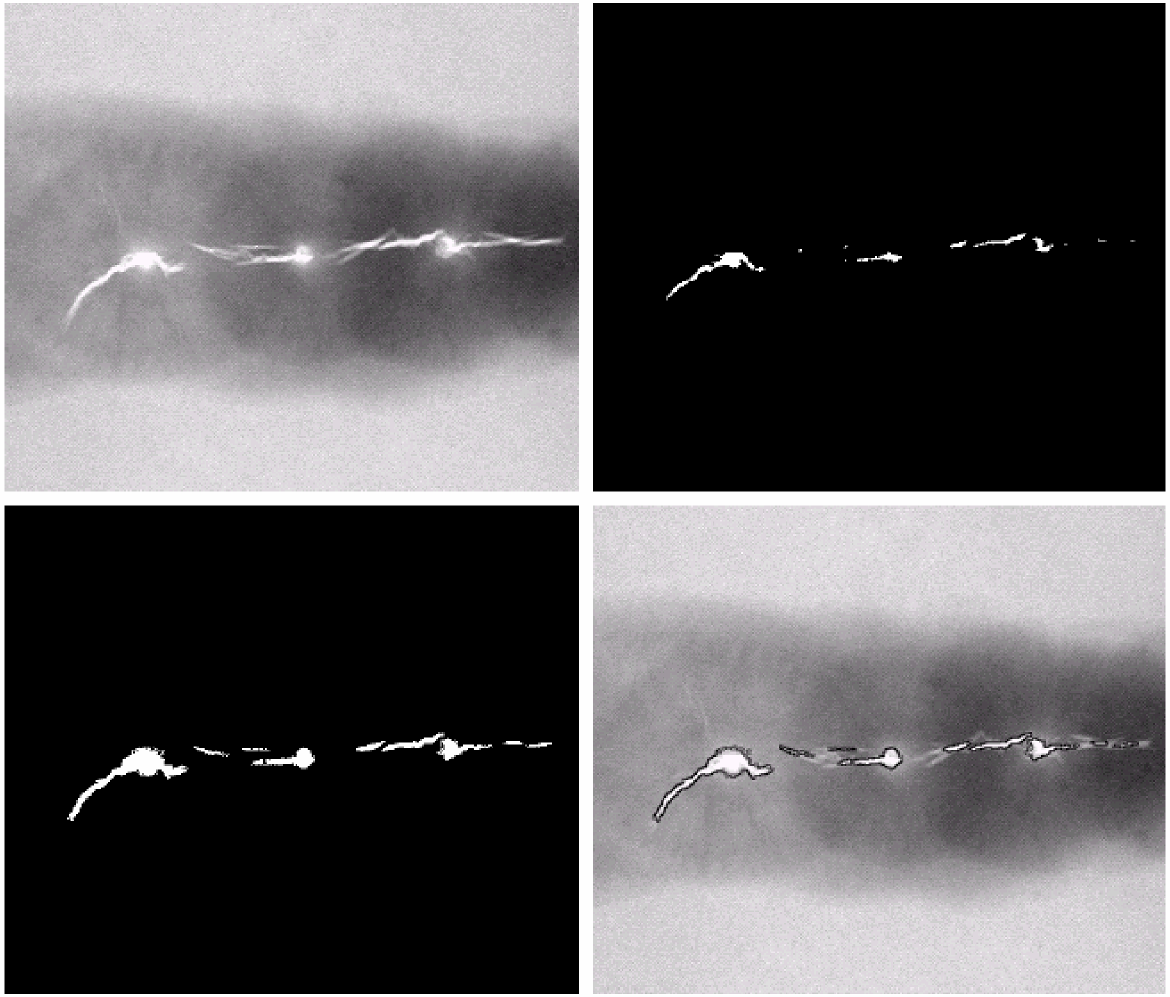
Image Segmentation



a b
c d

FIGURE 10.40 (a) Image showing defective welds. (b) Seed points. (c) Result of region growing. (d) Boundaries of segmented defective welds (in black). (Original image courtesy of X-TEK Systems, Ltd.).

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Image Segmentation

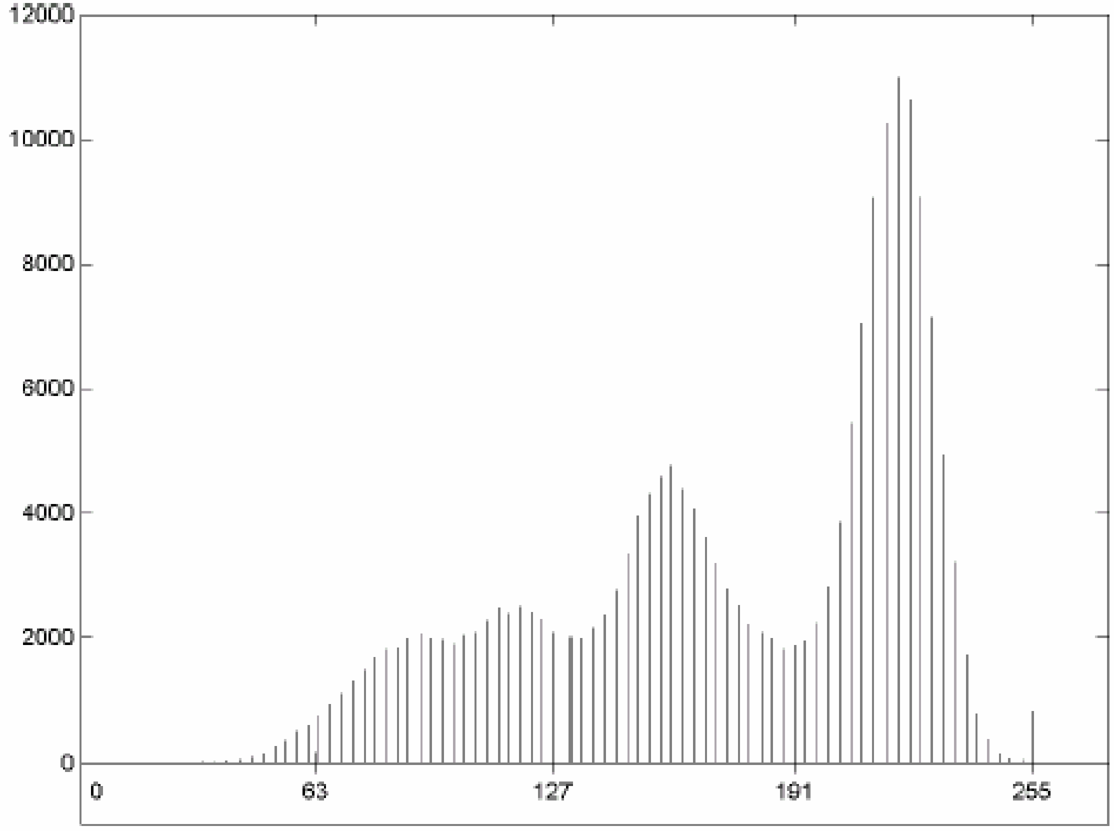
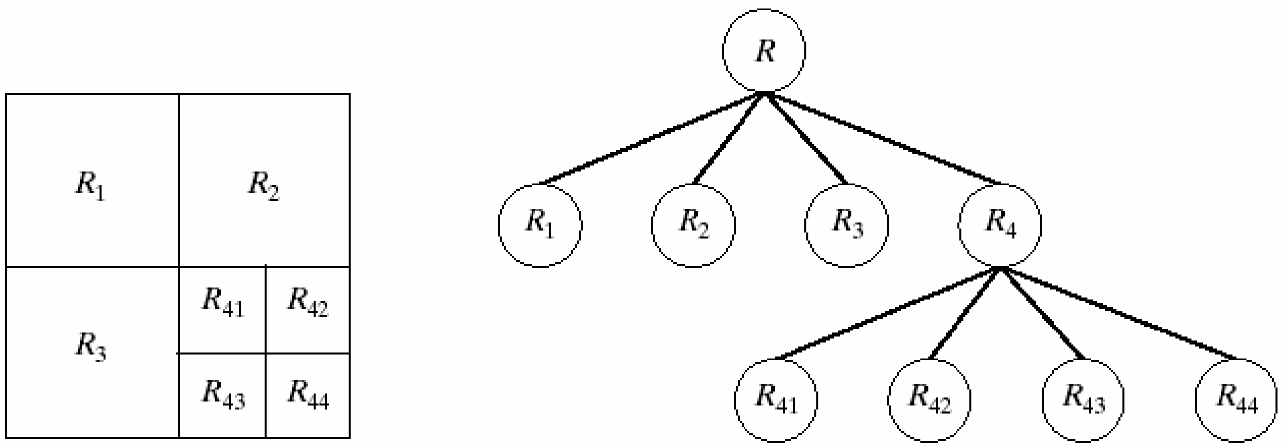


FIGURE 10.41 Histogram of Fig. 10.40(a).

a b

FIGURE 10.42
(a) Partitioned image.
(b) Corresponding quadtree.



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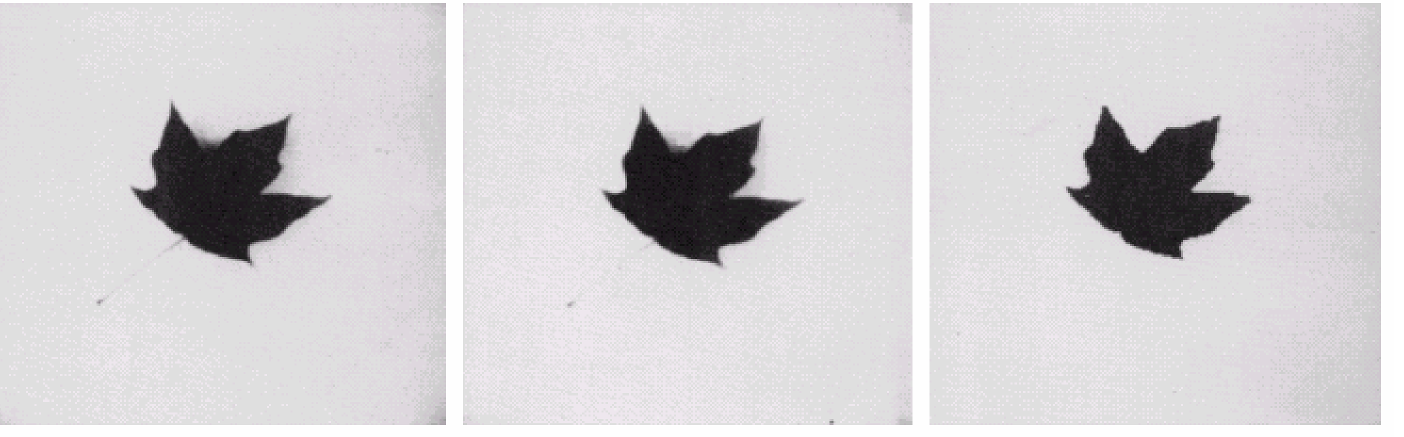

a b c

FIGURE 10.43 (a) Original image. (b) Result of split and merge procedure. (c) Result of thresholding (a).

Segmentation by Morphological Watersheds

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Image Segmentation

a b
c d

FIGURE 10.44
(a) Original image.
(b) Topographic view. (c)–(d) Two stages of flooding.

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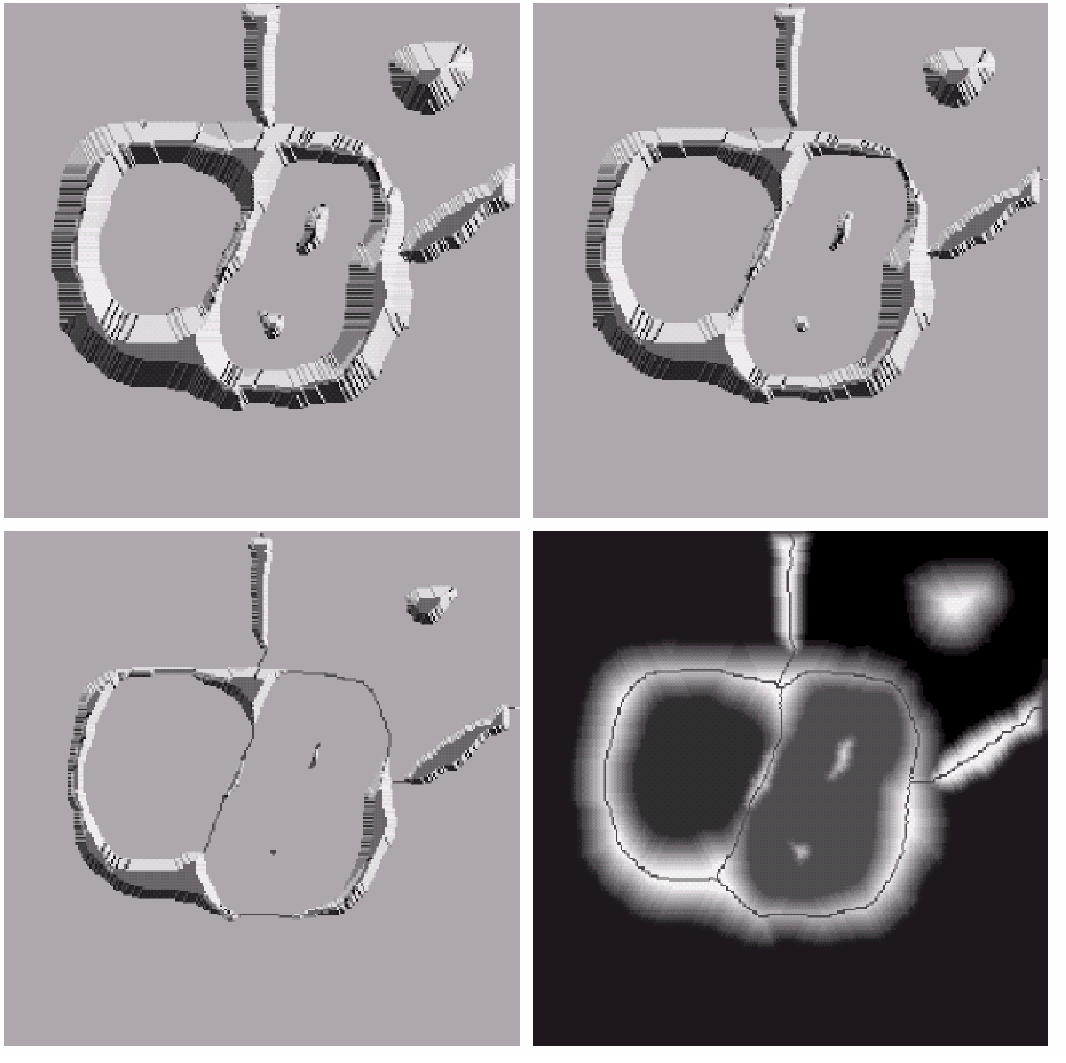
Image Segmentation



e f
g h

FIGURE 10.44 *(Continued)* (e) Result of further flooding. (f) Beginning of merging of water from two catchment basins (a short dam was built between them). (g) Longer dams. (h) Final watershed (segmentation) lines. (Courtesy of Dr. S. Beucher, CMM/Ecole des Mines de Paris.)

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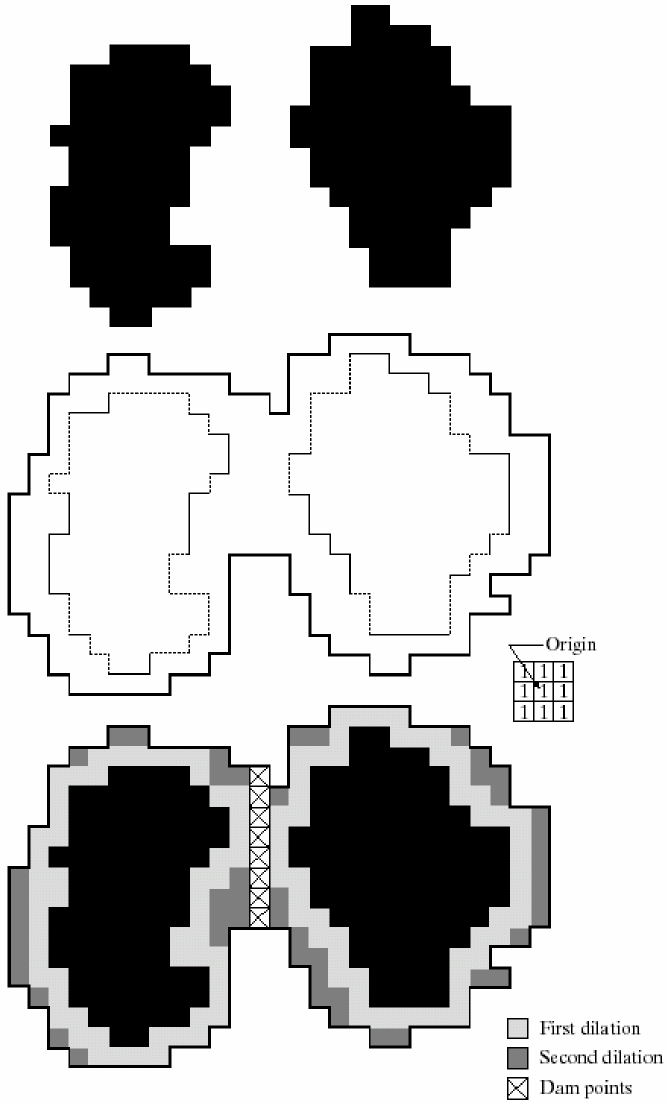

a
b c
d

FIGURE 10.45 (a) Two partially flooded catchment basins at stage $n-1$ of flooding. (b) Flooding at stage n, showing that water has spilled between basins (for clarity, water is shown in white rather than black). (c) Structuring element used for dilation. (d) Result of dilation and dam construction.

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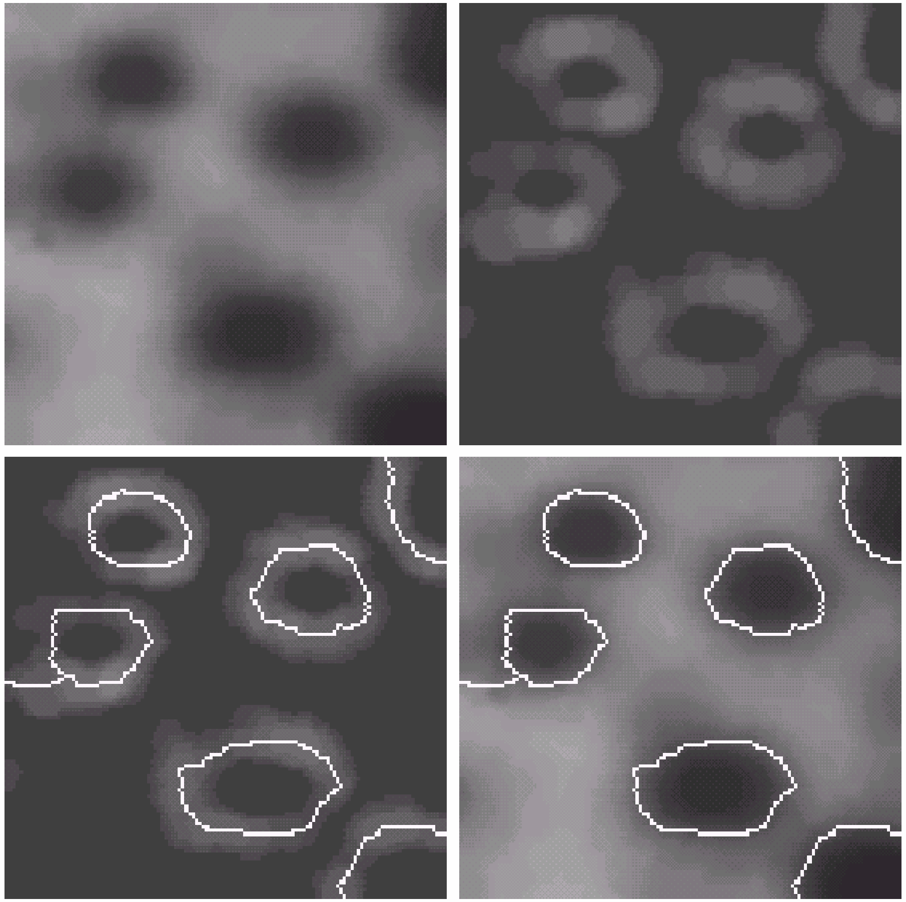

a b
c d

FIGURE 10.46 (a) Image of blobs. (b) Image gradient. (c) Watershed lines. (d) Watershed lines superimposed on original image. (Courtesy of Dr. S. Beucher, CMM/Ecole des Mines de Paris.)

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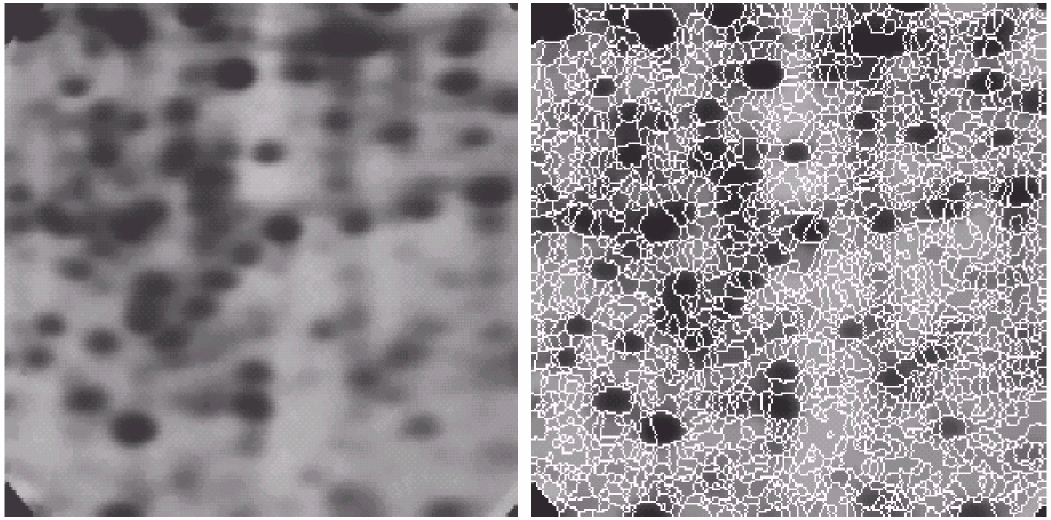

a b

FIGURE 10.47
(a) Electrophoresis image. (b) Result of applying the watershed segmentation algorithm to the gradient image. Oversegmentation is evident. (Courtesy of Dr. S. Beucher, CMM/Ecole des Mines de Paris.)

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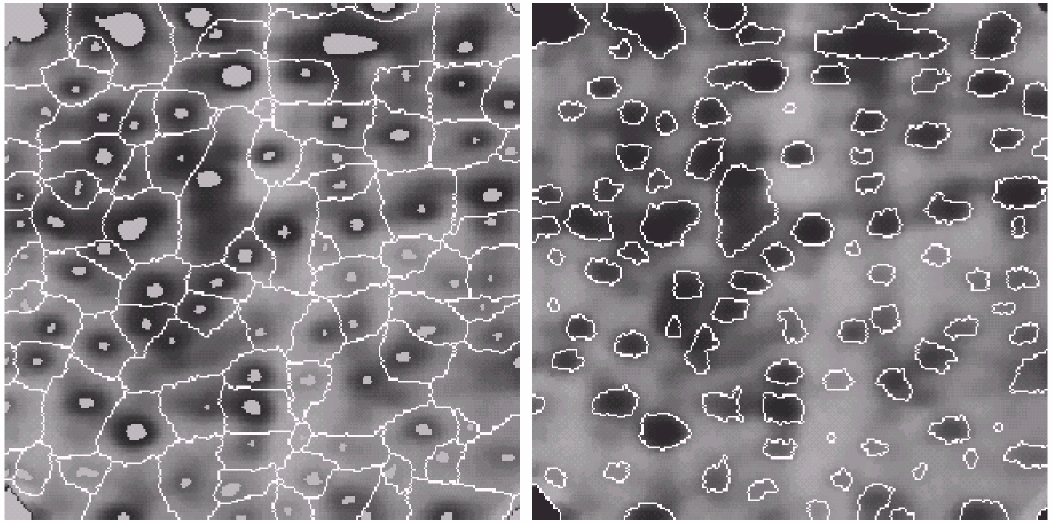
Image Segmentation



a b

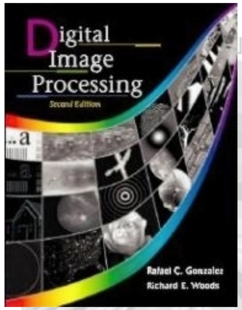
FIGURE 10.48 (a) Image showing internal markers (light gray regions) and external markers (watershed lines). (b) Result of segmentation. Note the improvement over Fig. 10.47(b). (Courtesy of Dr. S. Beucher, CMM/Ecole des Mines de Paris.)

Spatial Techniques
Basic approach

- One of the simplest approaches for detecting changes between two image frames $f(x,y,t_i)$ and $f(x,y,t_j)$ tken at time t_i and t_j, respectively, is to compare the two images pixel by pixel.
- A difference image between two image taken at times t_i and t_j may be defined as

$$d_{i,j}(x,y)=\begin{cases}1 & \text{if } \left|f(x,y,t_i)-f(x,y,t_j)\right|>T\\ 0 & \text{otherwise}\end{cases}$$

- This approach is applicable only if the two images are registered spatially and if the illumination is relatively constant within the bounds established by T.



Accumulative differences

- Consider a sequence of image frames $f(x,y,t_1)$, $f(x,y,t_2),\ldots, f(x,y,t_n)$ and let $f(x,y,t_1)$ be the reference image.
- An *accumulative difference image* (ADI) is formed by comparing this reference image with every subsequent image in the sequence.
- A counter for each pixel location in the accumulative images is incremented every time a difference occurs at that pixel location between the reference and an image in the sequence.
- Often useful is consideration of three types of accumulative difference images: *absolute*, *positive*, and *negative* ADIs.

Accumulative differences

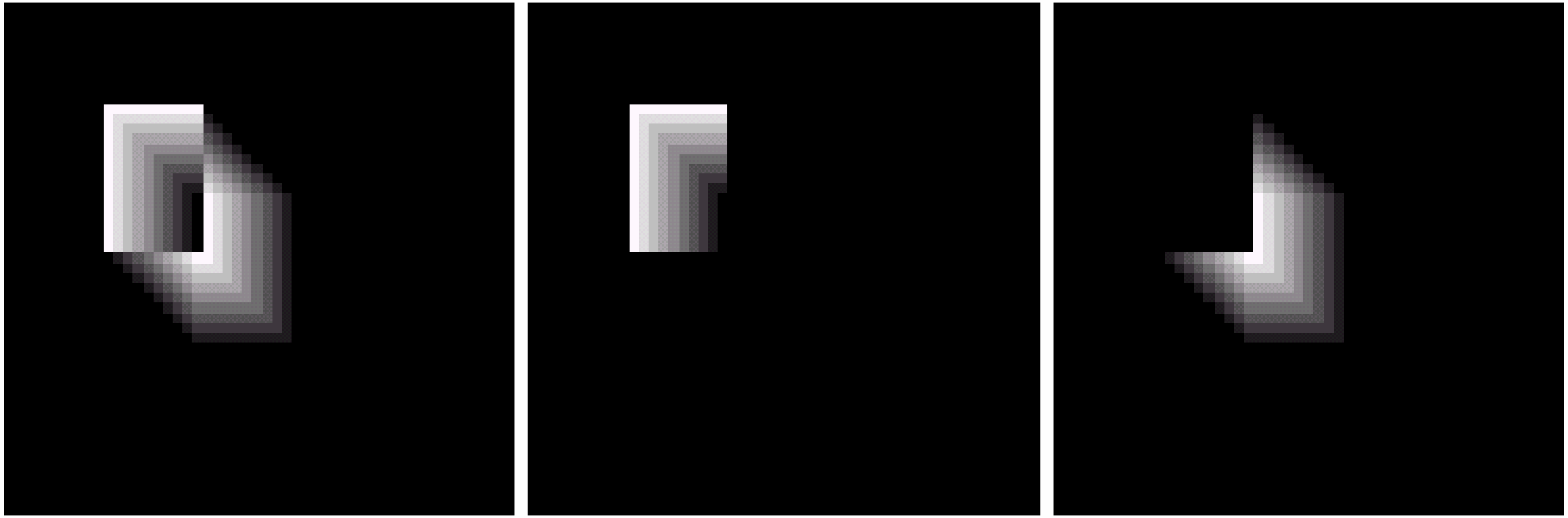
$$A_k(x,y)=\begin{cases} A_{k-1}(x,y)+1 & if\,\left|R(x,y)-f(x,y,k)\right|>T \\ A_{k-1}(x,y) & otherwise \end{cases}$$

$$P_k(x,y)=\begin{cases} P_{k-1}(x,y)+1 & if\,\left[R(x,y)-f(x,y,k)\right]>T \\ P_{k-1}(x,y) & otherwise \end{cases}$$

$$N_k(x,y)=\begin{cases} N_{k-1}(x,y)+1 & if\,\left[R(x,y)-f(x,y,k)\right]<-T \\ N_{k-1}(x,y) & otherwise \end{cases}$$

It is understood that these ADIs start out with all zero values (counts).

The direction and speed of the moving object can be determined from The entries in the absolute and negative ADIs.



a b c

FIGURE 10.49 ADIs of a rectangular object moving in a southeasterly direction. (a) Absolute ADI. (b) Positive ADI. (c) Negative ADI.

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Image Segmentation

a b c

FIGURE 10.50 Building a static reference image. (a) and (b) Two frames in a sequence. (c) Eastbound automobile subtracted from (a) and the background restored from the corresponding area in (b). (Jain and Jain.)

Frequency Domain Techniques

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Image Segmentation

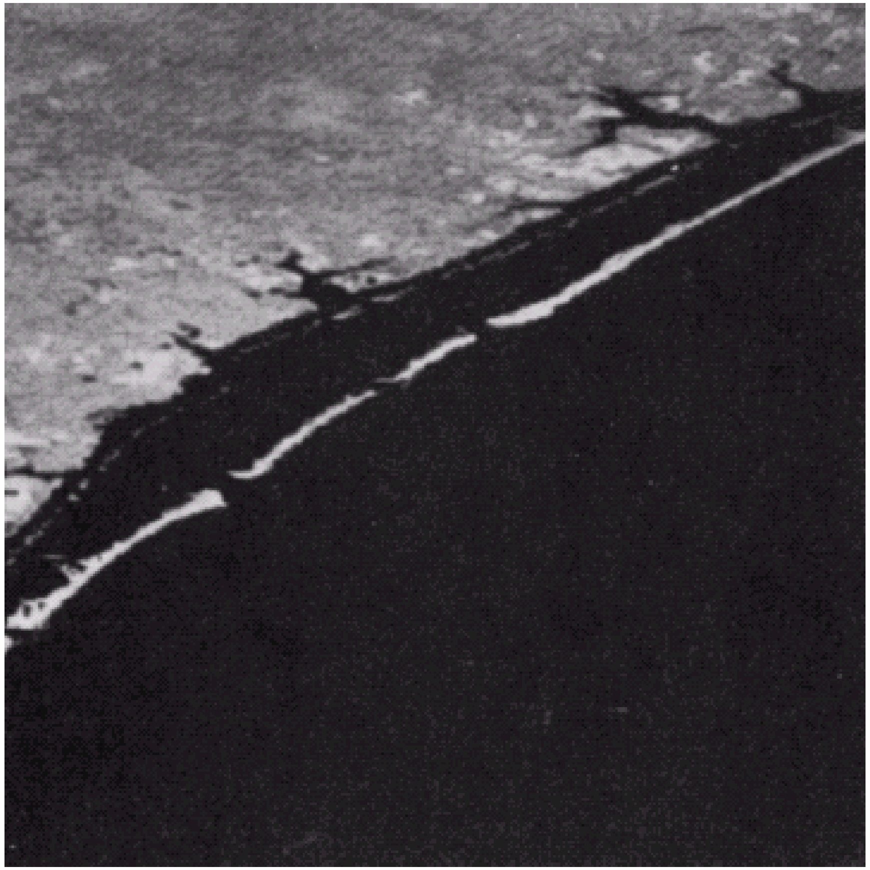

FIGURE 10.51 LANDSAT frame. (Cowart, Snyder, and Ruedger.)

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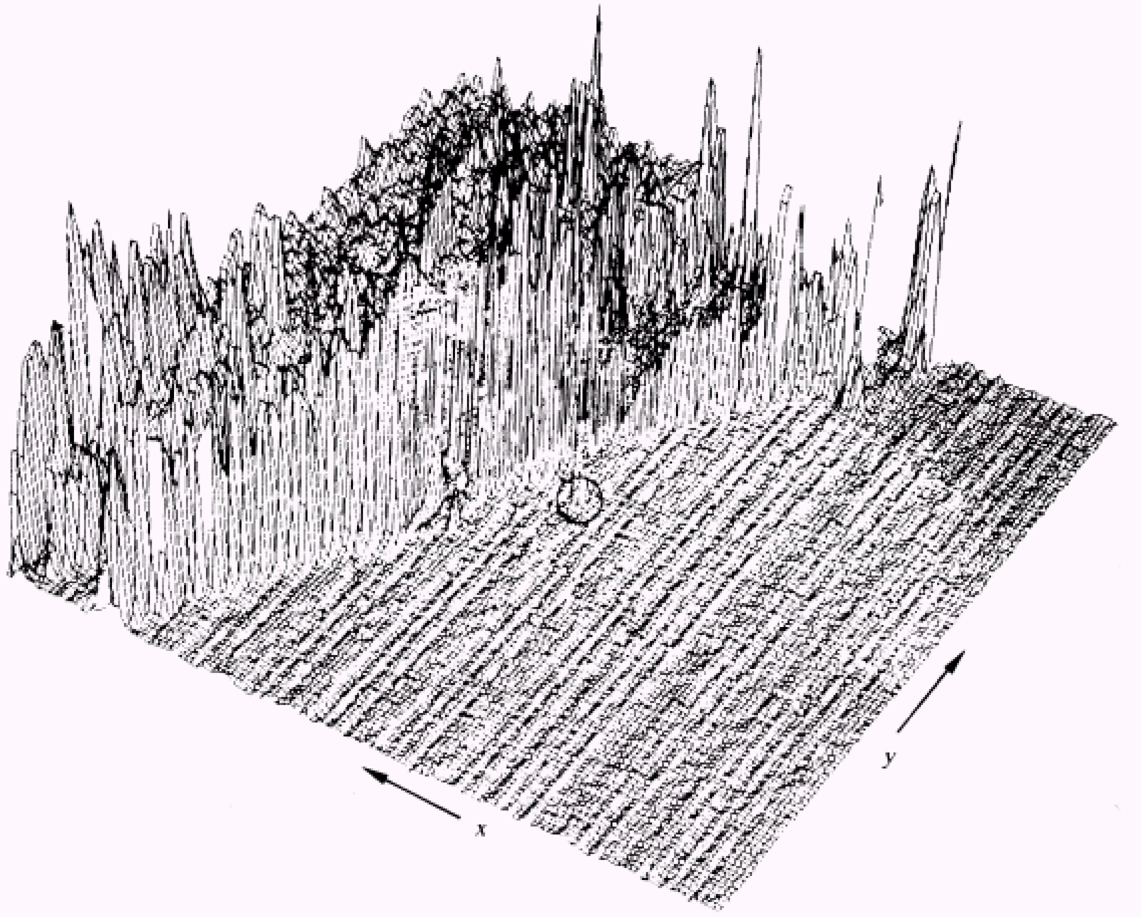

FIGURE 10.52 Intensity plot of the image in Fig. 10.51, with the target circled. (Rajala, Riddle, and Snyder.)

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Image Segmentation

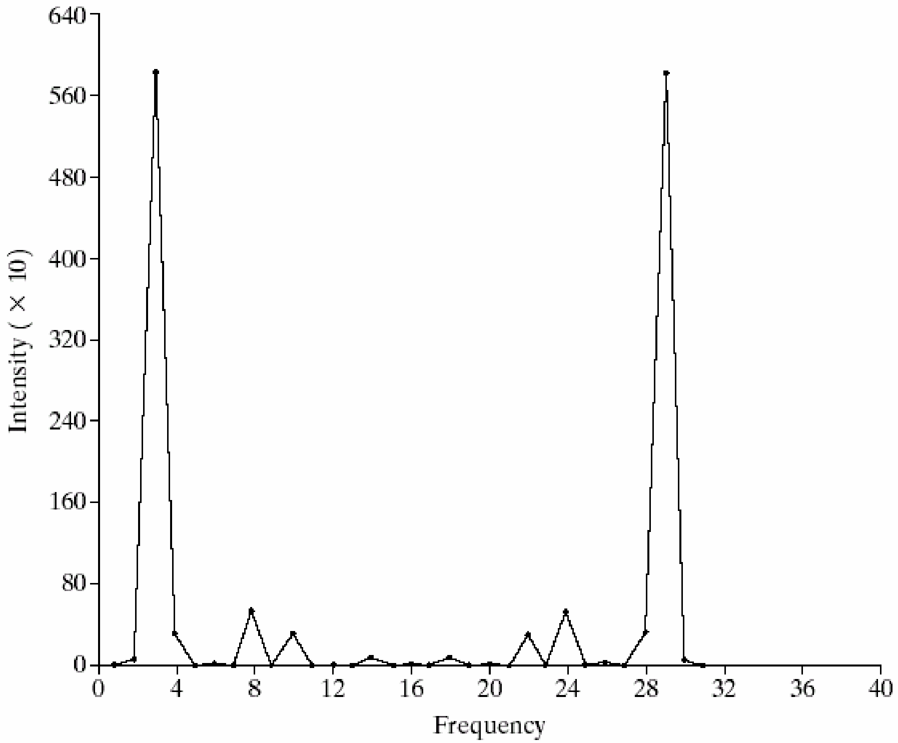

FIGURE 10.53 Spectrum of Eq. (10.6-8) showing a peak at $u_1 = 3$. (Rajala, Riddle, and Snyder.)

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FIGURE 10.54 Spectrum of Eq. (10.6-9) showing a peak at $u_2 = 4$. (Rajala, Riddle, and Snyder.)