Image segmentation – an overview

Segmentation

- Segmentation: divides an image into its constituent regions or objects
- Segmentation algorithms based on the properties of intensity values:
- (i) **discontinuity** : Partition the image based on the abrupt change in the intensity – **edge-based**
- (ii) **similarity:** partitioning the image based on a predefined criteria – **Thresholding, region growing**
- Based on **morphology**: **Watershed algorithm**

Segmentation

- Boundaries of a region are sufficiently different from each other and from the background so that they can be differentiated based on discontinuity
- Digital images -Point, Edge, Line
- Point detection using Laplacian operator
- Edge detection - Canny, Sobel, Marr-Hildreth operator
- Line detection – Hough transform

Edge linking and boundary detection

- There may be discontinuities due to noise in the detected edges.
- Therefore edge detection is followed by edge linking to assemble to obtain meaningful boundaries
  - Local processing
  - Region processing
  - Global processing using Hough transform

Local Processing

Let S_{xy} denote the set of coordinates of a neighborhood centered at point (x, y) in an image. An edge pixel with coordinate (s,t) in S_{xy} is similar in *magnitude* to the pixel at (x, y) if

$$\left|M(s,t) - M(x,y)\right| \le E$$

An edge pixel with coordinate (s,t) in S_{xy} is similar in *angle* to the pixel at (x, y) if

$$\left|\alpha(s,t) - \alpha(x,y)\right| \le A$$

Local Processing: Steps (1)

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

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

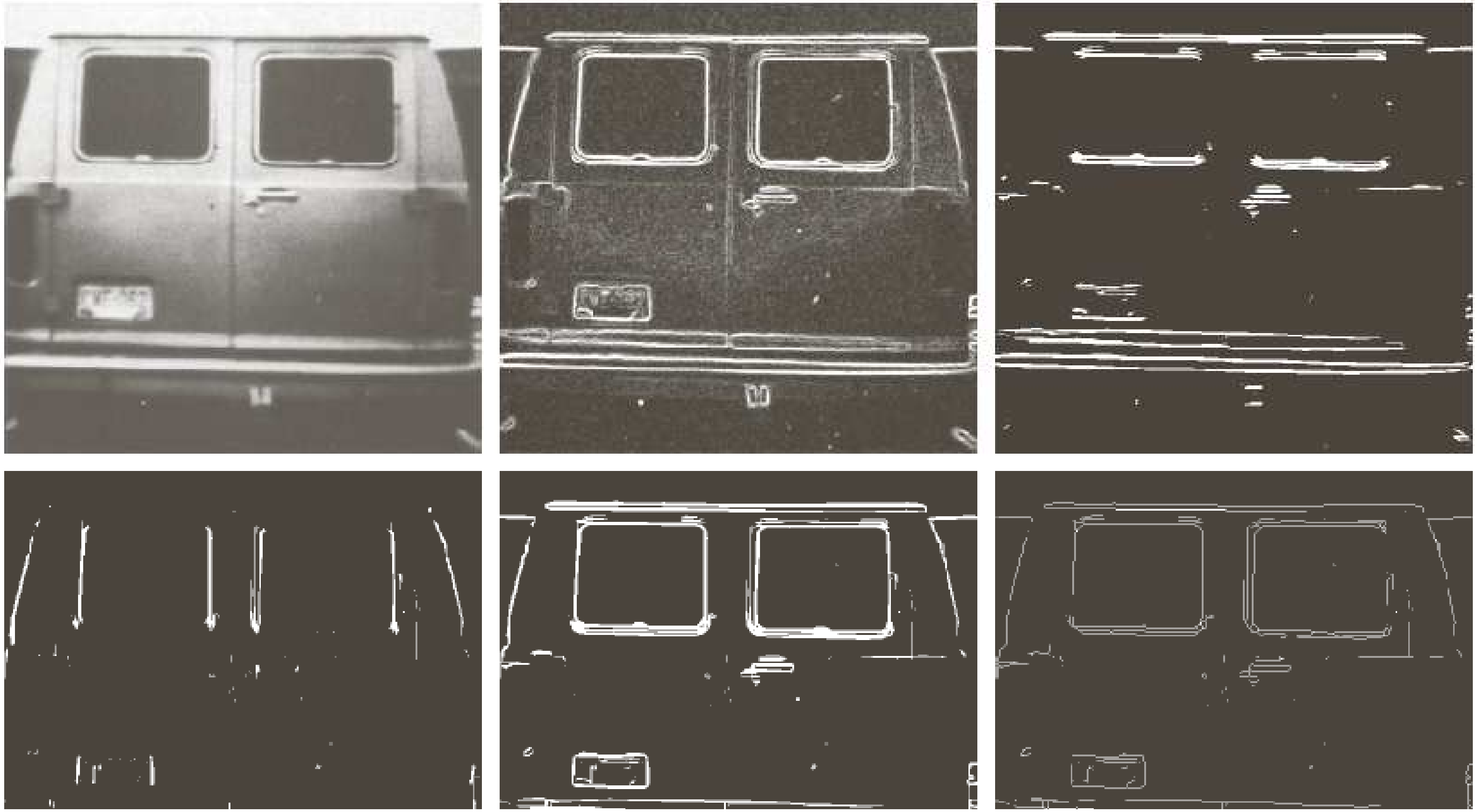
T_M : threshold $\quad A$: specified angle direction

T_A: a "band" of acceptable directions about A

Local Processing: Steps (2)

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.

4. To detect gaps in any other direction, rotate g by this angle and apply the horizontal scanning procedure in step 3.



a	b	c
d	e	f

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

- The location of regions of interest in an image are known or can be determined

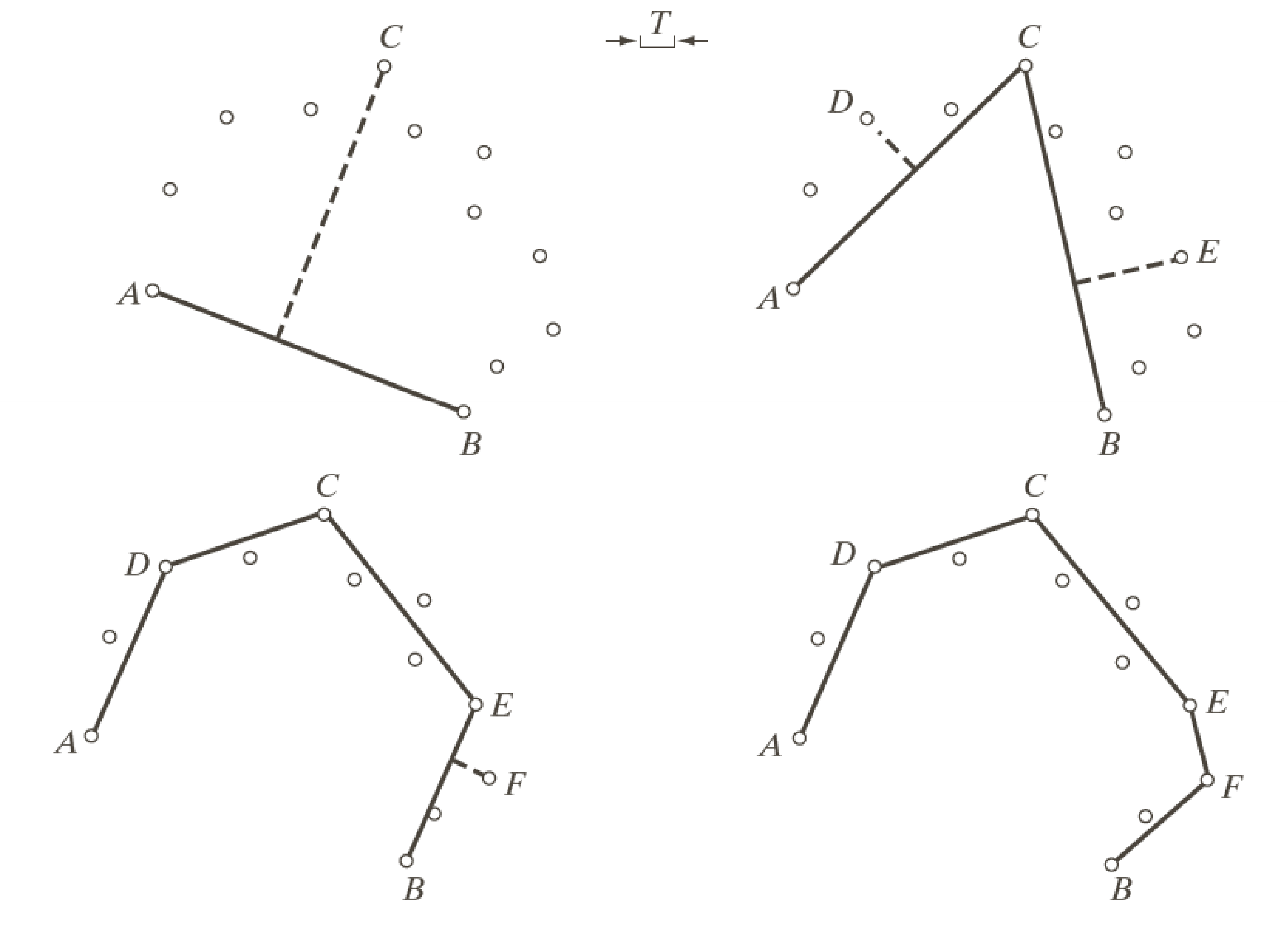
- Polygonal approximations can capture the essential shape features of a region while keeping the representation of the boundary relatively simple

- We can identify the curve as open or closed by analysing the distance between ordered points
- Open curve: a large distance between two consecutive points in the ordered sequence relative to the distance between other points
- Closed Curve: If the distance is uniform throughout

Regional Processing: Steps

- Open curve end points labelled as A and B (vertices)
- Compute the perpendicular distance from all other points in the curve to this line
- Obtain the point that yields maximum distance
- If the distance exceeds specified threshold T, corresponding point is declared as vertex (c)
- Lines from A to C and B to C are established
- Distances obtained and maximum distance is decleared as vertex
- Iterative procedure is continued untill no points statisfy the threshold test

Regional Processing: Steps



a b
c d

FIGURE 10.28
Illustration of the iterative polygonal fit algorithm.

Regional Processing: Steps

1. Let P be the sequence of ordered, distinct, 1-valued points of a binary image. Specify two starting points, A and B.
2. Specify a threshold, T, and two empty stacks, OPEN and ClOSED.
3. If the points in P correspond to a closed curve, put A into OPEN and put B into OPEN and CLOSES. If the points correspond to an open curve, put A into OPEN and B into CLOSED.
4. Compute the parameters of the line passing from the last vertex in CLOSED to the last vertex in OPEN.

Regional Processing: Steps

5. Compute the distances from the line in Step 4 to all the points in P whose sequence places them between the vertices from Step 4. Select the point, V_{max}, with the maximum distance, D_{max}
6. If $D_{max} > T$, place V_{max} at the end of the OPEN stack as a new vertex. Go to step 4.
7. Else, remove the last vertex from OPEN and insert it as the last vertex of CLOSED.
8. If OPEN is not empty, go to step 4.
9. Else, exit. The vertices in CLOSED are the vertices of the polygonal fit to the points in P.

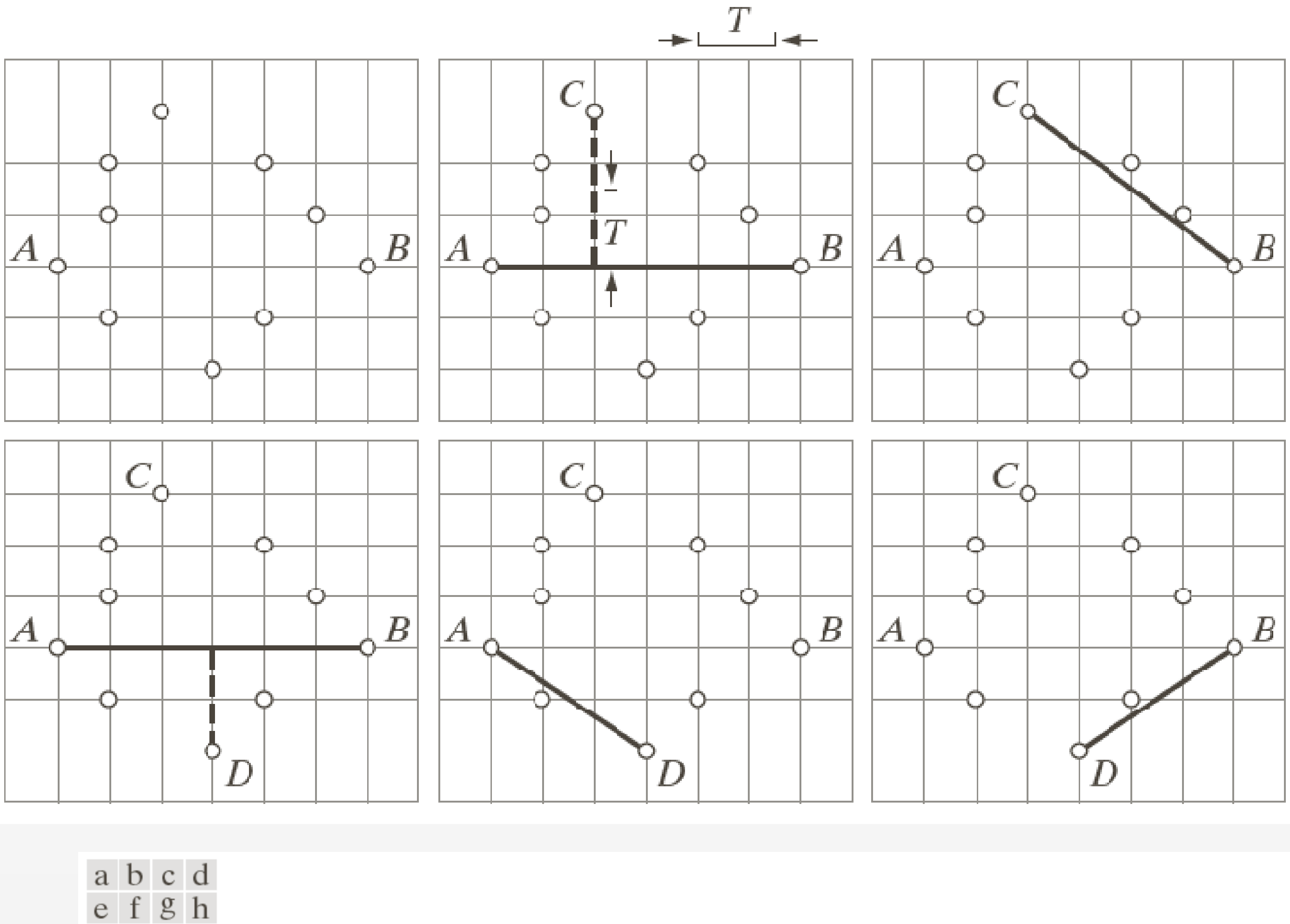
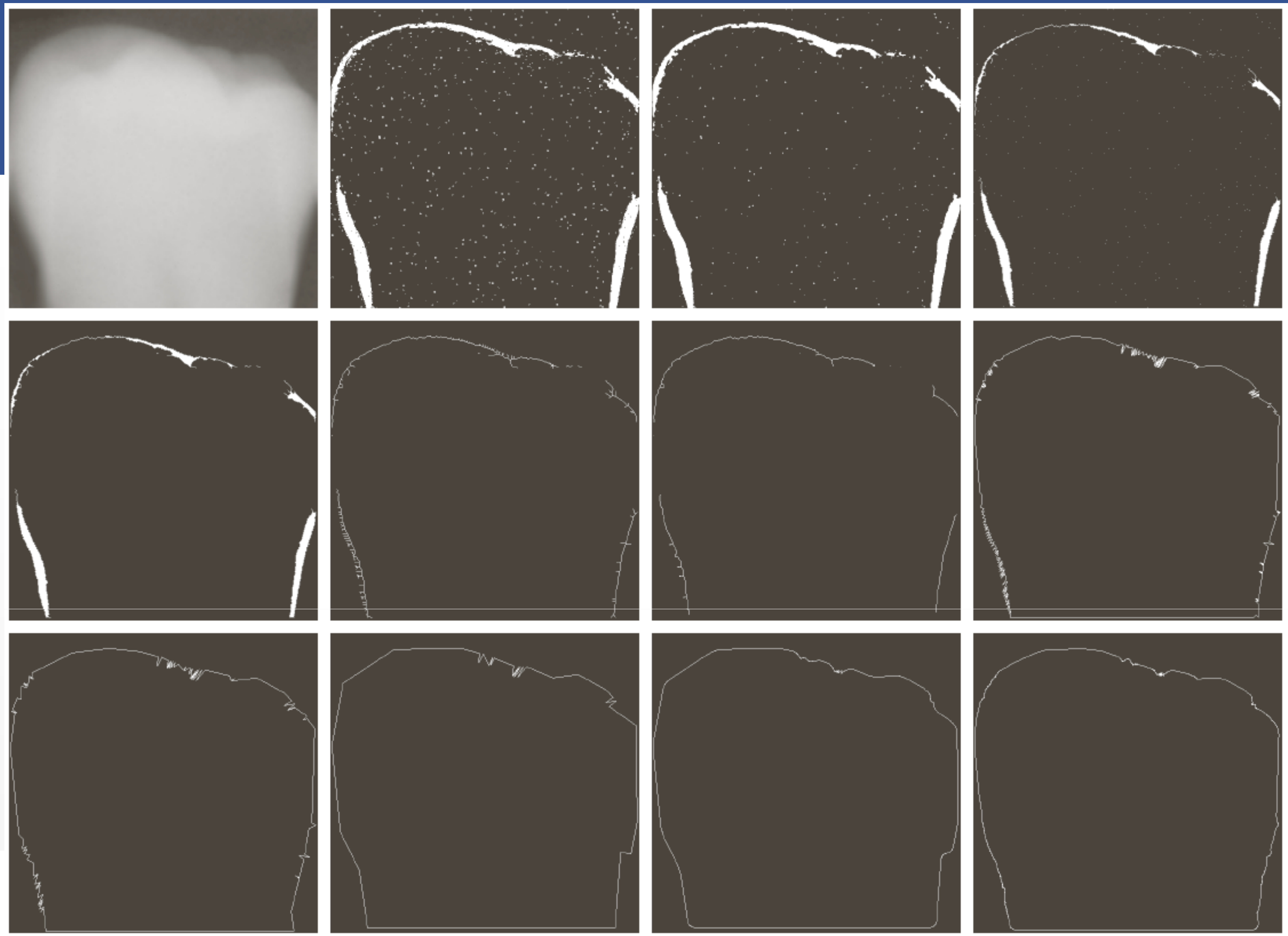


FIGURE 10.29 (a) A set of points in a clockwise path (the points labeled A and B were chosen as the starting vertices). (b) The distance from point C to the line passing through A and B is the largest of all the points between A and B and also passed the threshold test, so C is a new vertex. (d)–(g) 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.

CLOSED	OPEN	Curve segment processed	Vertex generated
B	B, A	—	A, B
B	B, A	(BA)	C
B	B, A, C	(BC)	—
B, C	B, A	(CA)	—
B, C, A	B	(AB)	D
B, C, A	B, D	(AD)	—
B, C, A, D	B	(DB)	—
B, C, A, D, B	Empty	—	—

TABLE 10.1
Step-by-step details of the mechanics in Example 10.11.

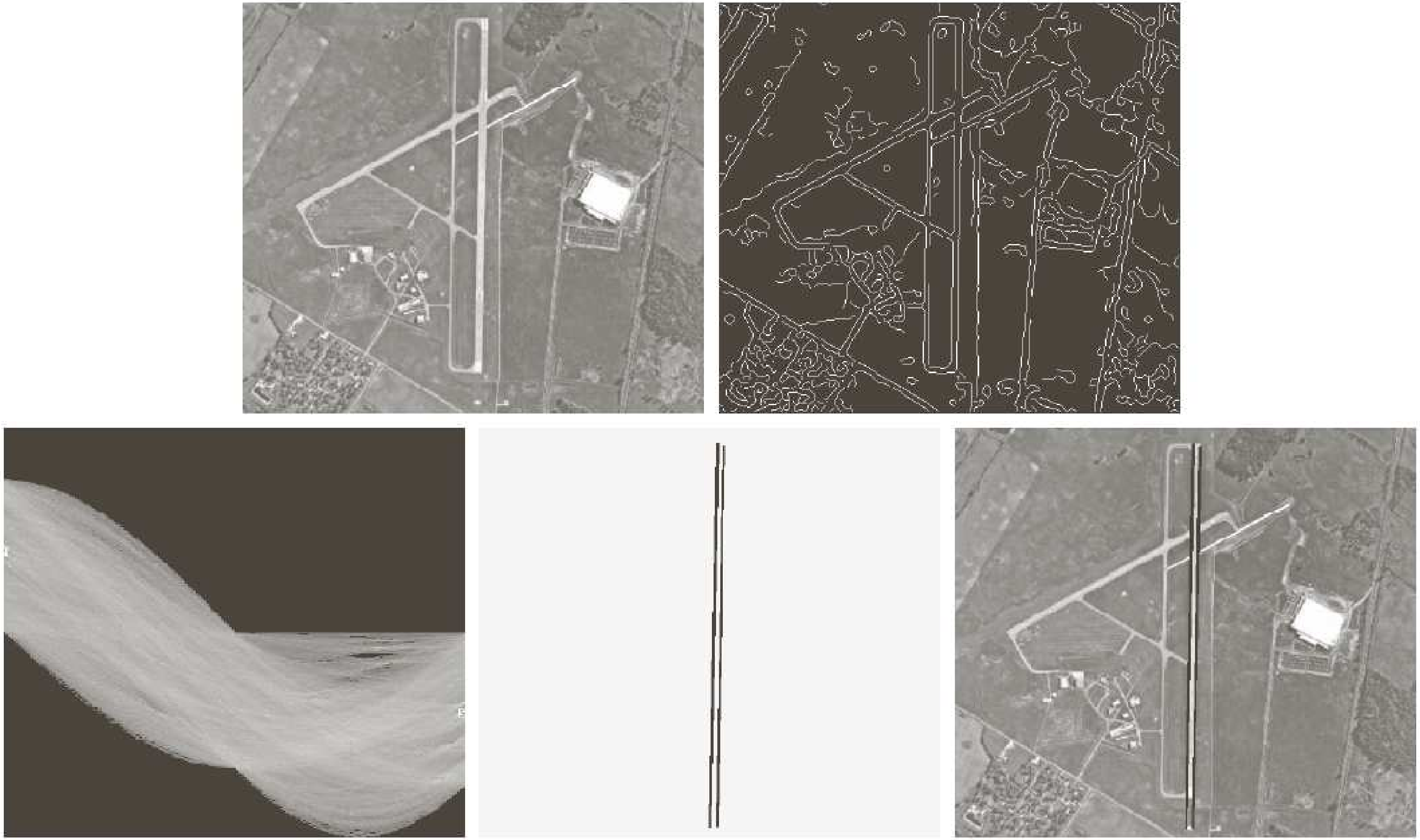


a	b	c	d
e	f	g	h
i	j	k	l

FIGURE 10.30 (a) A 550 × 566 X-ray image of a human tooth. (b) Gradient image. (c) Result of majority filtering. (d) Result of morphological shrinking. (e) Result of morphological cleaning. (f) Skeleton. (g) Spur reduction. (h)–(j) Polygonal fit using thresholds of approximately 0.5%, 1%, and 2% of image width ($T = 3$, 6, and 12). (k) Boundary in (j) smoothed with a 1-D averaging filter of size 1 × 31 (approximately 5% of image width). (l) Boundary in (h) smoothed with the same filter.

Edge-linking Based on the Hough Transform

1. Obtain a binary edge image
1. Specify subdivisions in $\rho\theta - plane$
1. Examine the counts of the accumulator cells for high pixel concentrations
1. Examine the relationship between pixels in chosen cell



a b
c d e

FIGURE 10.34 (a) A 502 × 564 aerial image of an airport. (b) Edge image obtained using Canny's algorithm. (c) Hough parameter space (the boxes highlight the points associated with long vertical lines). (d) Lines in the image plane corresponding to the points highlighted by the boxes). (e) Lines superimposed on the original image.

Thresholding

- Partitioning the image into regions based on intensity values
- Obtain the image histogram showing variation between background and foreground in the intensity levels by two different modes
- Fix up a threshold T
- $g(x,y) = 1$ (object points) if $f(x,y) > T$

  $= 0$ (background points) if $f(x,y) < T$

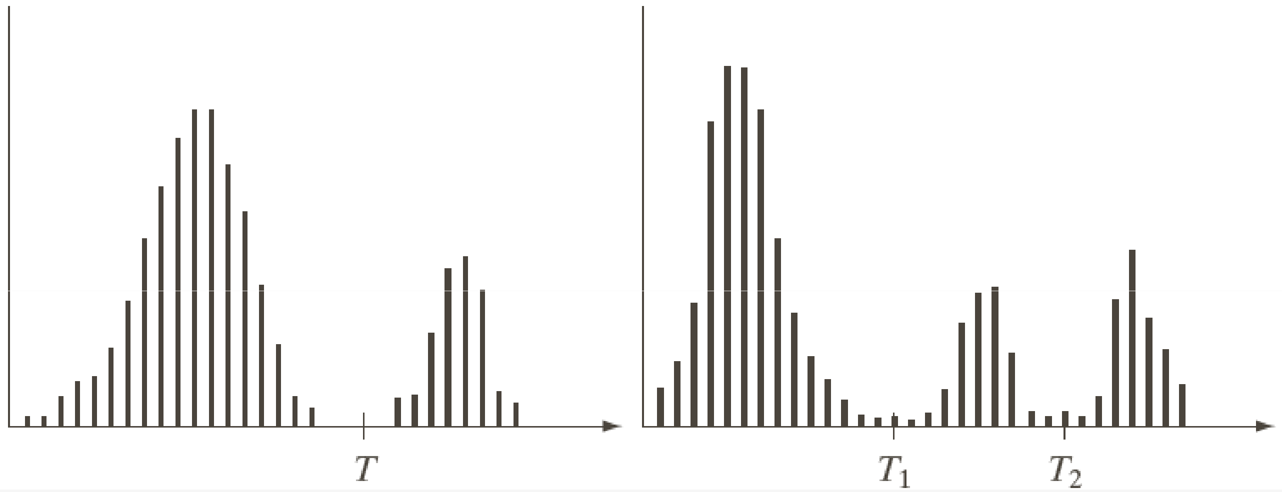
If 'T' is a constant and is applicable to entire image then it is called 'global Thresholding'. When 'T' changes it is 'variable Thresholding'

Multiple Thresholding

Multiple thresholding

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

Histogram



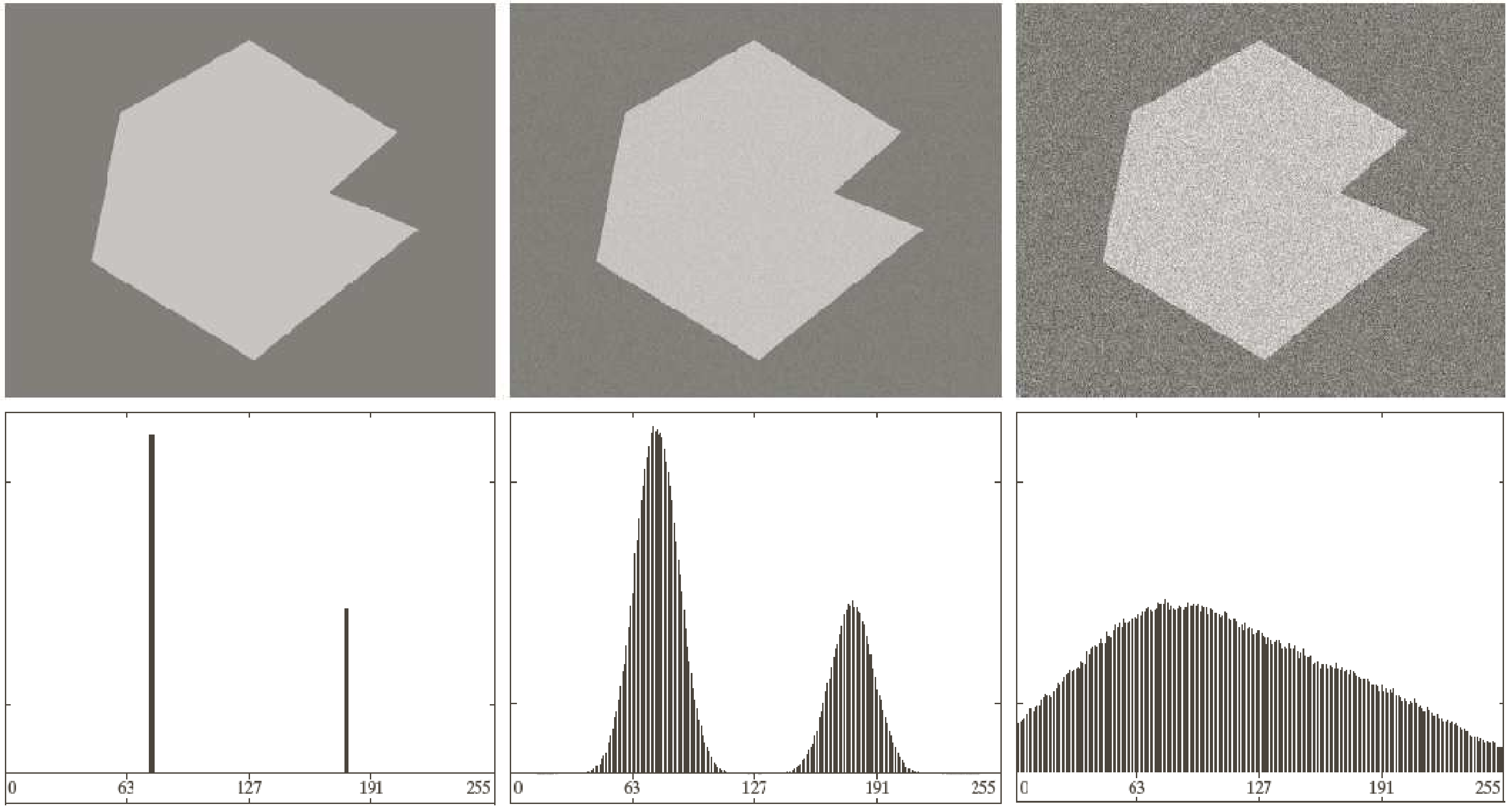
a b

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

Key Factors Affecting the properties of the valleys:

- Separation between peaks
- Noise content in the image
- Relative size of objects and background
- The uniformity of the illumination source and reflectance property

The Role of Noise in Image Thresholding



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

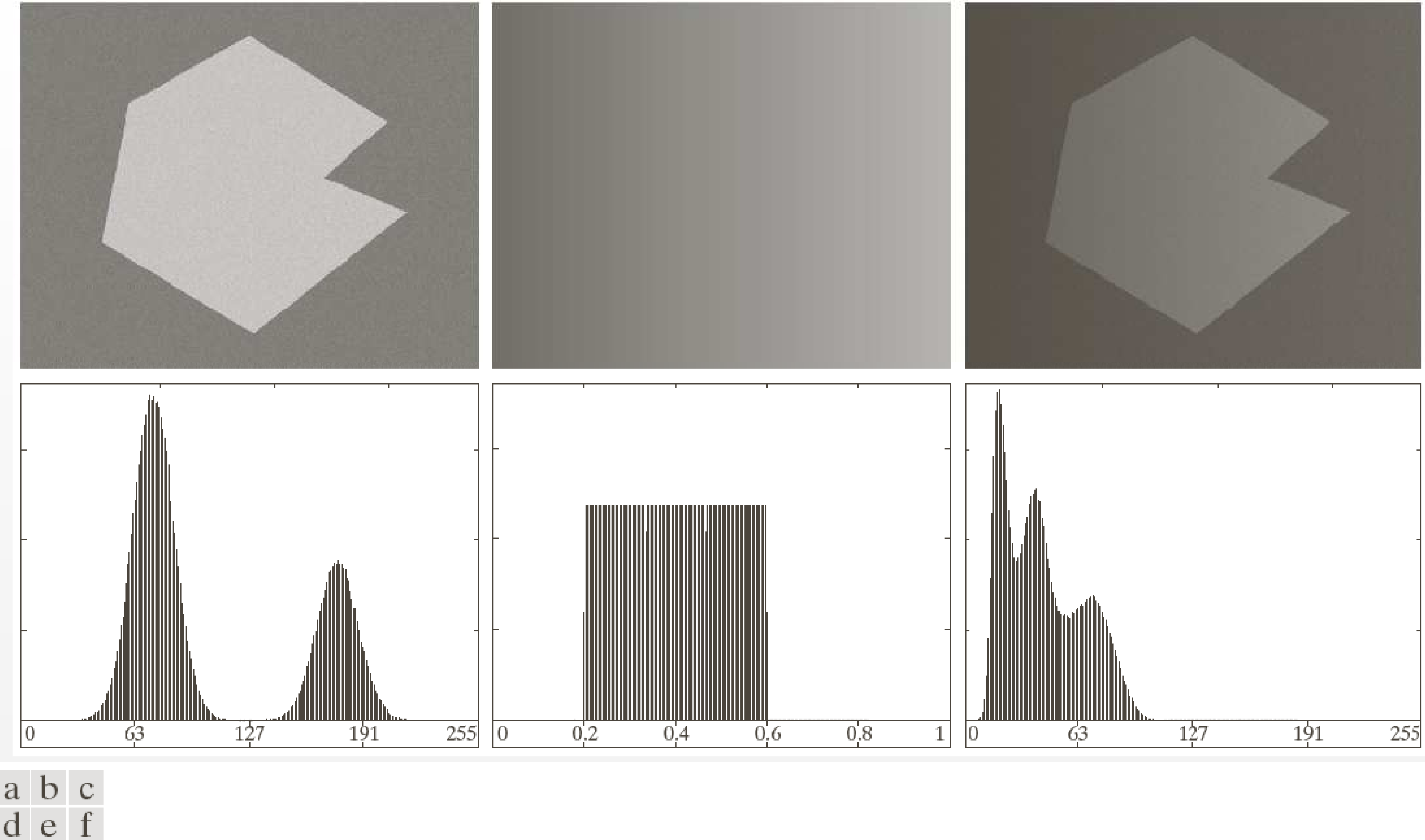


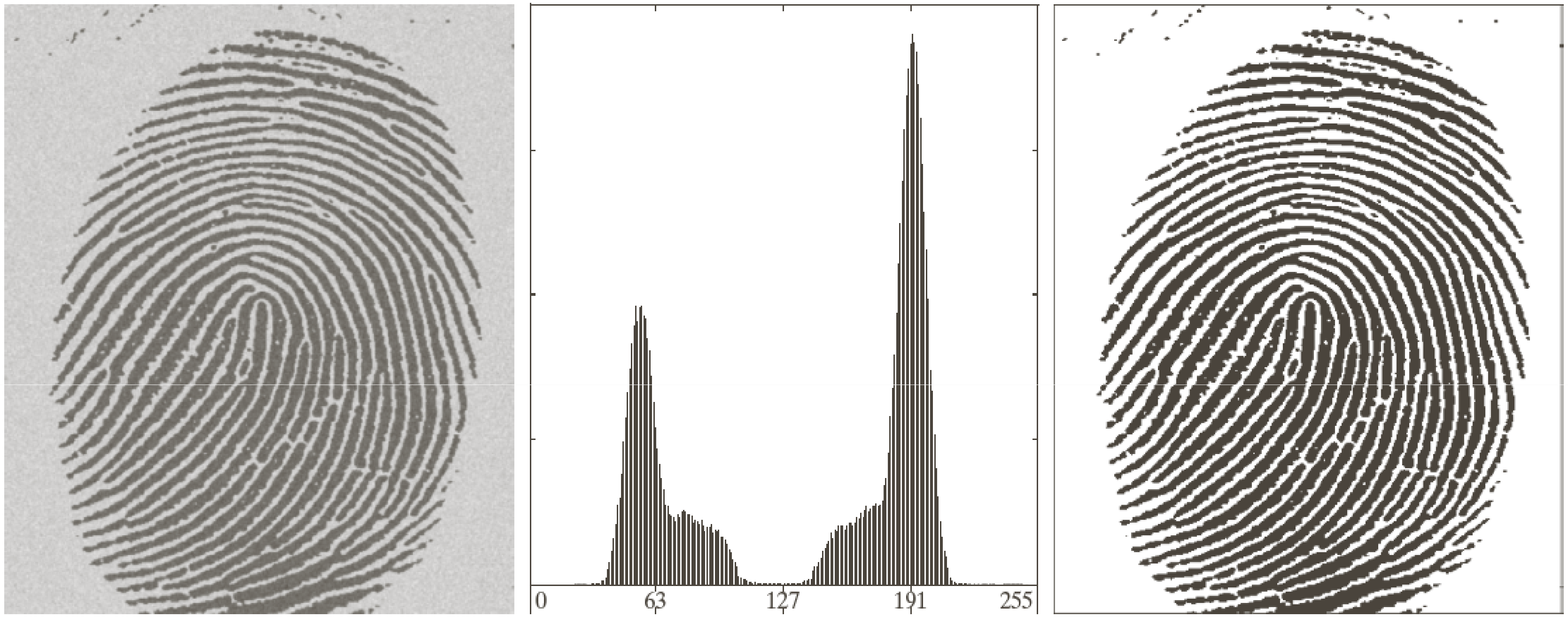
FIGURE 10.37 (a) Noisy image. (b) Intensity ramp in the range [0.2, 0.6]. (c) Product of (a) and (b). (d)–(f) Corresponding histograms.

Basic Global Thresholding

1. Select an initial estimate for the global threshold, T.
2. Segment the image using T. It will produce two groups of pixels: G1 consisting of all pixels with intensity values > T and G2 consisting of pixels with values $\leq$ T.
3. Compute the average intensity values m1 and m2 for the pixels in G1 and G2, respectively.
4. Compute a new threshold value.

$$T = \frac{1}{2}\left(m1 + m2\right)$$

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



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.)

Otsu's method – optimum global thresholding

- Uses Statistical decision theory
- Minimizes the average error incurred in assigning pixels to two or more groups called classes by the following solutions
    - PDF of the intensity levels of each class
    - Probability that each class occurs in given application

Otsu's method – optimum global thresholding

- Optimum because it increases the between-class variance
- It is based on the computation performed on histogram of an image
- {0,1,2,... L-1} denote the possible intensity levels
- MxN size of the image
- Normalized histogram $p_i = \frac{n_i}{MN}$
- Define a threshold $T(k) = k$, $0 < k < L-1$
- Divide the image into two classes C1 and C2
- C1 – containing pixels with intensity values [0,k]
- C2 – containing pixels with intensity values [k+1, L-1]

Otsu's method – optimum global thresholding

- Compute the probability of pixels in class 1

$$P_1(k) = \sum_{i=0}^{k} p_i$$

$$P_2(k) = \sum_{i=k+1}^{L-1} p_i = 1 - P_1(k)$$

- Mean intensity value of the pixels assigned to class C1

$$m_1(k) = \sum_{i=0}^{k} iP(i|C_1)$$

- Using Bayes rule

$$m_1(k) = \sum_{i=0}^{k} iP(C_1|i)P(i)/P(C_1)$$

$$= \frac{1}{P_1(k)} \sum_{i=0}^{k} iP_i$$

- Cumulative mean (average intensity) up to level k is given by $m(k) = \sum_{i=0}^{k} ip_i$

Optimum Global Thresholding Using Otsu's Method

The mean intensity value of the pixels assigned to class C_1 is

$$m_1(k) = \sum_{i=0}^{k} iP(i / C_1) = \frac{1}{P_1(k)} \sum_{i=0}^{k} ip_i$$

The mean intensity value of the pixels assigned to class C_2 is

$$m_2(k) = \sum_{i=k+1}^{L-1} iP(i / C_2) = \frac{1}{P_2(k)} \sum_{i=k+1}^{L-1} ip_i$$

$$P_1 m_1 + P_2 m_2 = m_G \quad \text{(Global mean value)}$$

Otsu's method

- Average intensity of the entire image (the global mean) is given by

$$m_G = \sum_{i=0}^{L-1} i p_i$$

- To evaluate the goodness of the threshold at the level 'k' use the normalized dimensionless metric

$$\eta = \frac{\sigma_B^2}{\sigma_G^2}$$

Otsu

- Where σ_B is the between class variance and σ_G is the global variance, that is, intensity variance of all the pixels in the image.

$$\sigma_G^2 = \sum_{i=0}^{L-1} (i - m_G)^2 p_i$$

$$\sigma_B^2 = P_1(m_1 - m_G)^2 + P_2(m_2 - m_G)^2$$

$$= P_1 P_2 (m_1 - m_2)^2$$

$$= \frac{(m_G P_1 - m)^2}{P_1(1 - P_1)}$$

- The problem is to find an optimum threshold that maximizes the between class variance
- If the image has only one class then the separability is zero
- Eta and between class variance are measures of separability

$$\eta = \frac{\sigma_B^2(k)}{\sigma_G^2}$$

$$\sigma_B^2(k) = \frac{(m_G P_1(k) - m(k))^2}{P_1(k)(1 - P_1(k))}$$

$$\sigma_B^2(k^*) = \max_{0 \le k \le L-1} \sigma_B^2(k)$$

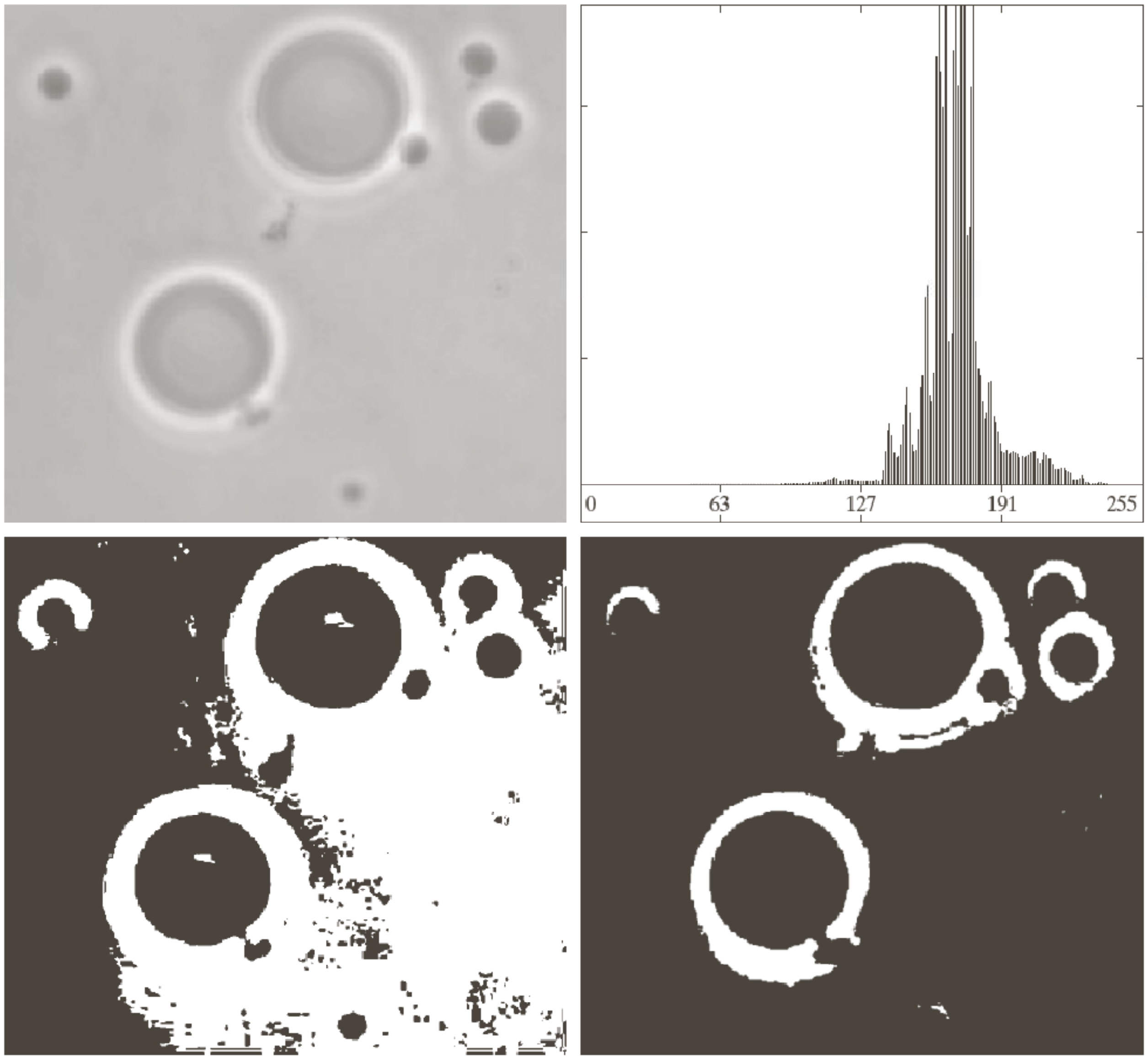
- Once k^* is found the input image can be segmented as

$$g(x,y) = 1 \quad if\ f(x,y) > k^*$$

$$= 0 \quad if\ f(x,y) \le k^*$$

Otsu's method - steps

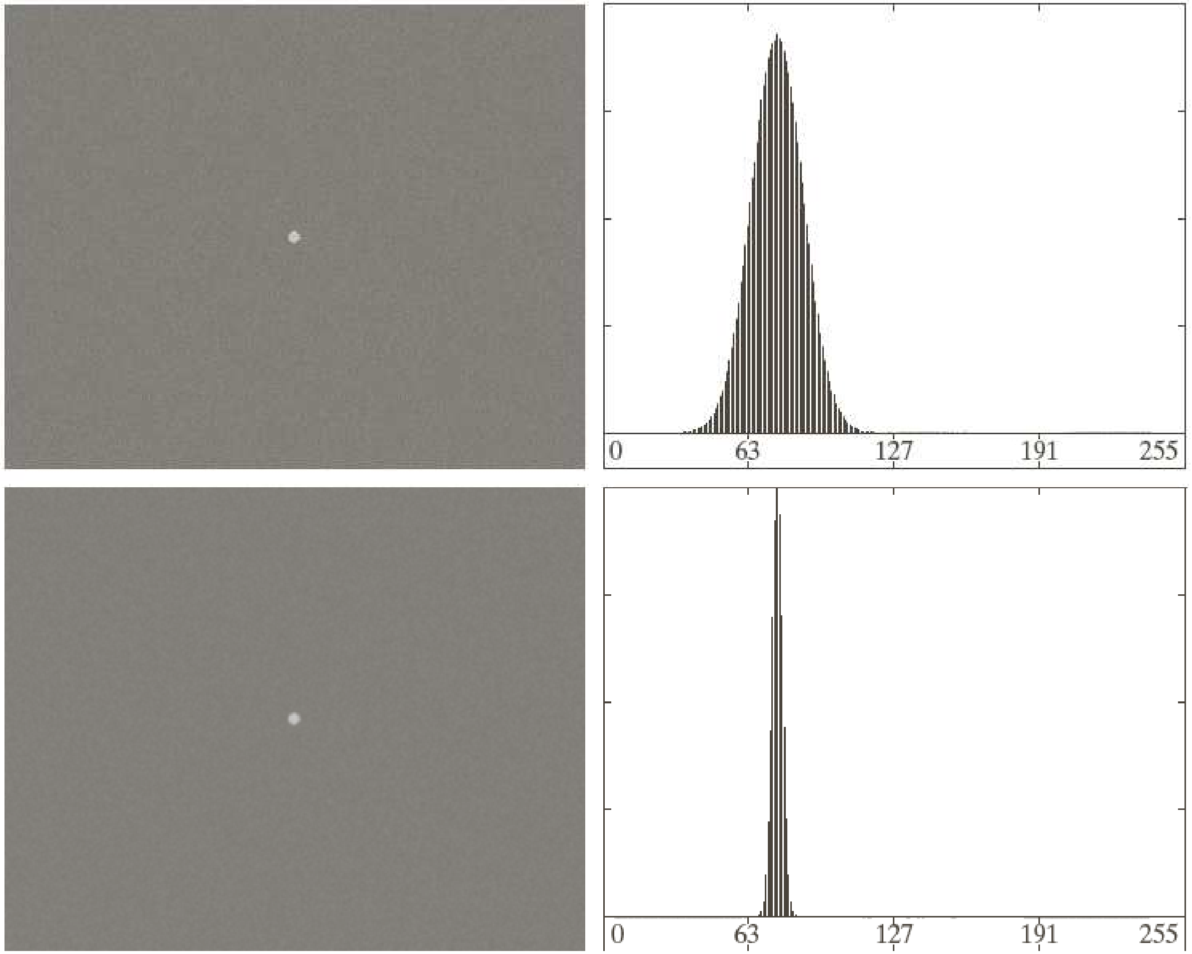
- Compute the normalized histogram of the input image
- Compute the cumulative sum
- Compute the cumulative means
- Compute the global intensity mean
- Compute the between class variance
- Obtain the Otsu's threshold k* as the value σ^2 for which between class variance is maximized
- Obtain the separability measure η^2 by evaluating at k=k*



a b
c d

FIGURE 10.39
(a) Original image.
(b) Histogram (high peaks were clipped to highlight details in the lower values).
(c) Segmentation result using the basic global algorithm from Section 10.3.2.
(d) Result obtained using Otsu's method.
(Original image courtesy of Professor Daniel A. Hammer, the University of Pennsylvania.)

Using Edges to Improve Global Thresholding

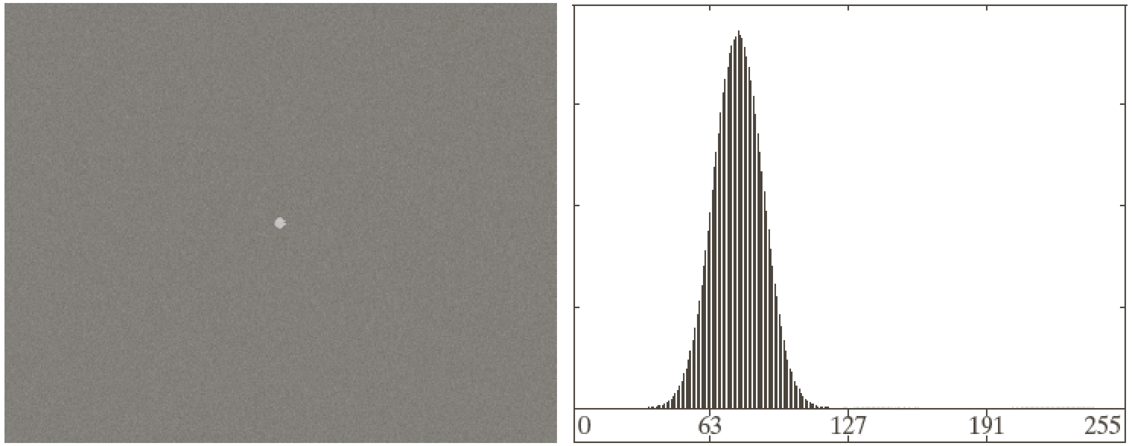


a b c
d e f

FIGURE 10.41 (a) Noisy image 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. Thresholding failed in both cases.

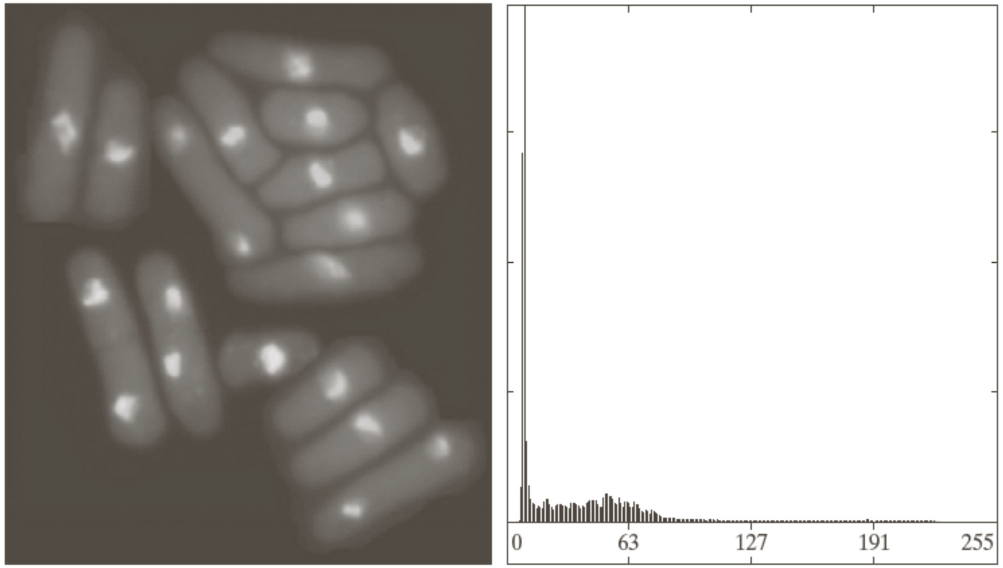
Using Edges to Improve Global Thresholding

1. Compute an edge image as either the magnitude of the gradient, or absolute value of the Laplacian of f(x,y)
2. Specify a threshold value T
3. Threshold the image and produce a binary image, which is used as a mask image; and select pixels from f(x,y) corresponding to “strong” edge pixels
4. Compute a histogram using only the chosen pixels in f(x,y)
5. Use the histogram from step 4 to segment f(x,y) globally



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.



a	b	c
d	e	f

FIGURE 10.43 (a) Image of yeast cells. (b) Histogram of (a). (c) Segmentation of (a) with Otsu's method using the histogram in (b). (d) Thresholded absolute Laplacian. (e) Histogram of the nonzero pixels in the product of (a) and (d). (f) Original image thresholded using Otsu's method based on the histogram in (e). (Original image courtesy of Professor Susan L. Forsburg, University of Southern California.)