

Image Segmentation

Dr. Abdul Kayom Md Khairuzzaman
Assistant Professor
School of Electronics Engineering
VIT-AP University

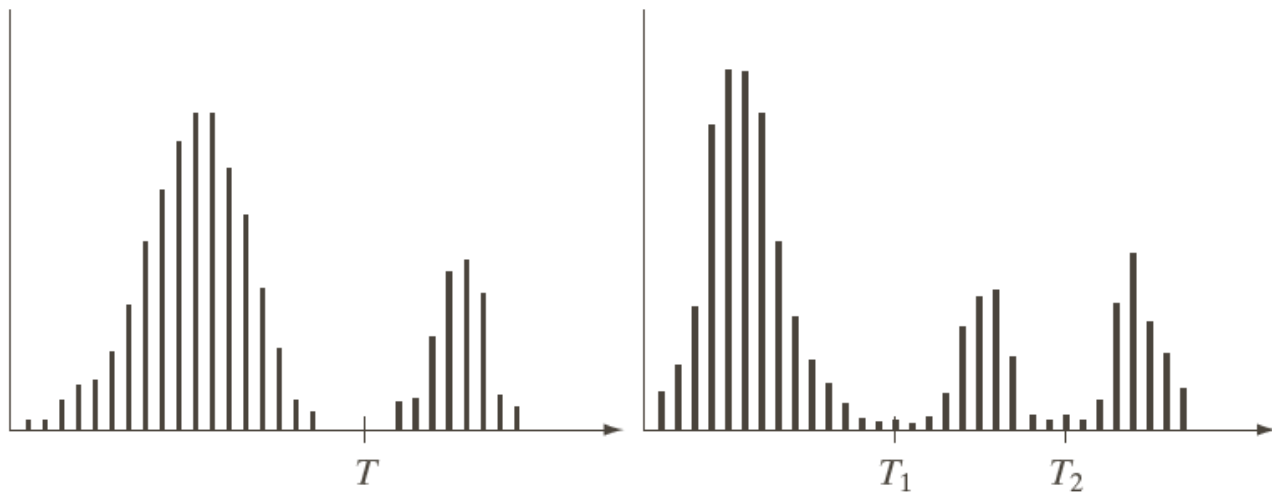
Thresholding

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

T : global thresholding

Multiple thresholding

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



a b

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

The Role of Noise in Image Thresholding

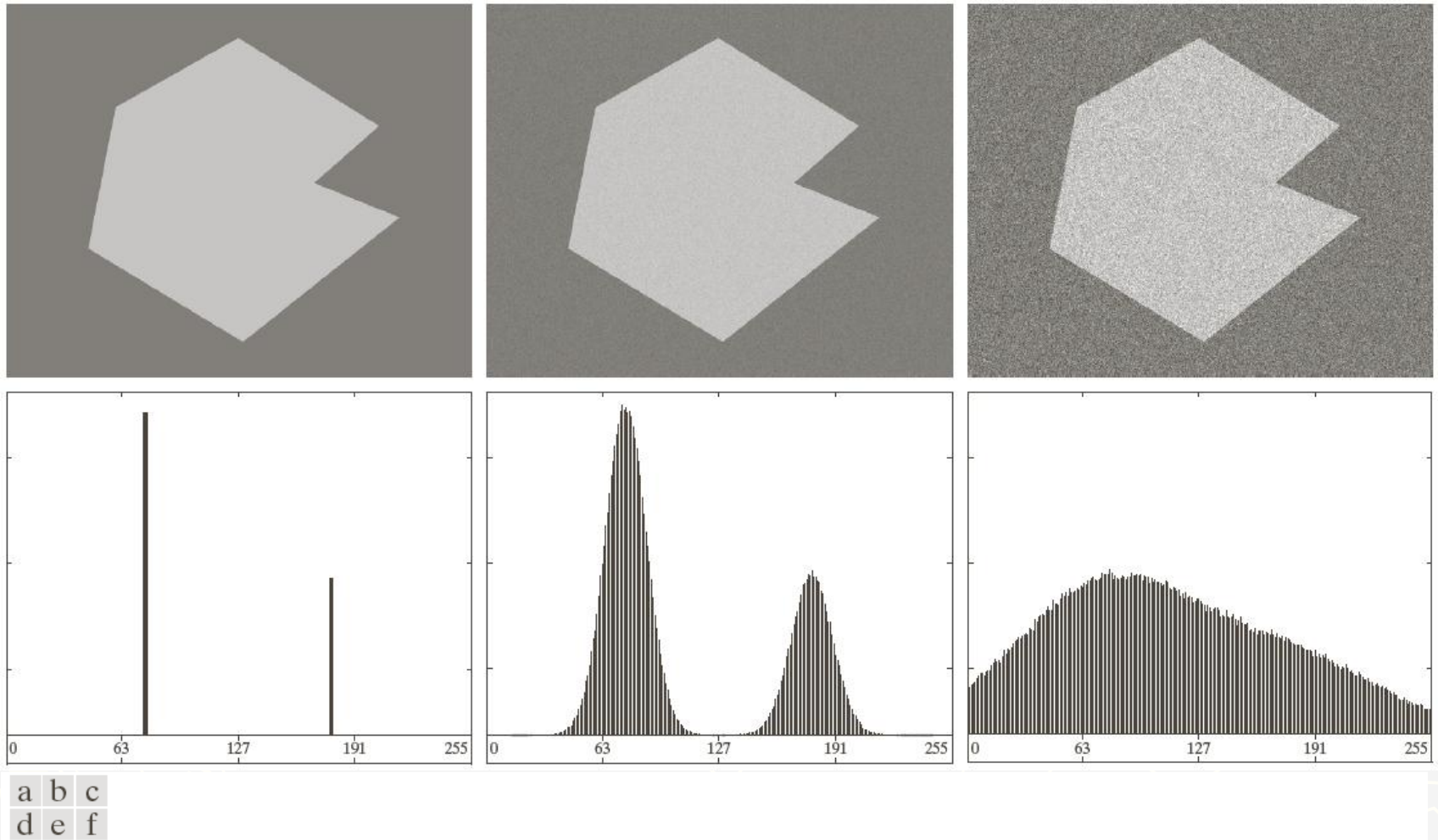


FIGURE 10.36 (a) Noiseless 8-bit image. (b) Image with additive Gaussian noise of mean 0 and standard deviation of 10 intensity levels. (c) Image with additive Gaussian noise of mean 0 and standard deviation of 50 intensity levels. (d)–(f) Corresponding histograms.

The Role of Illumination and Reflectance

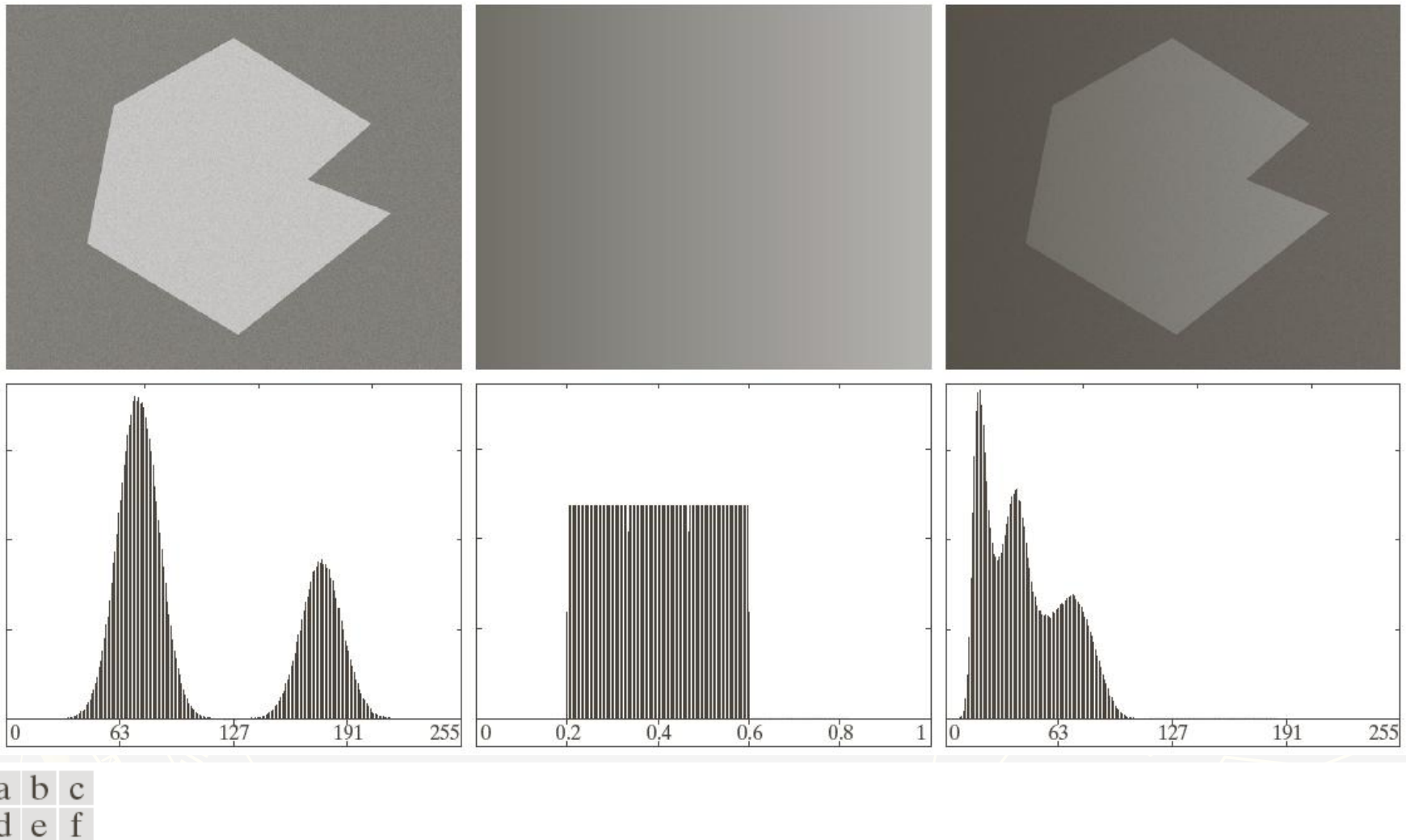


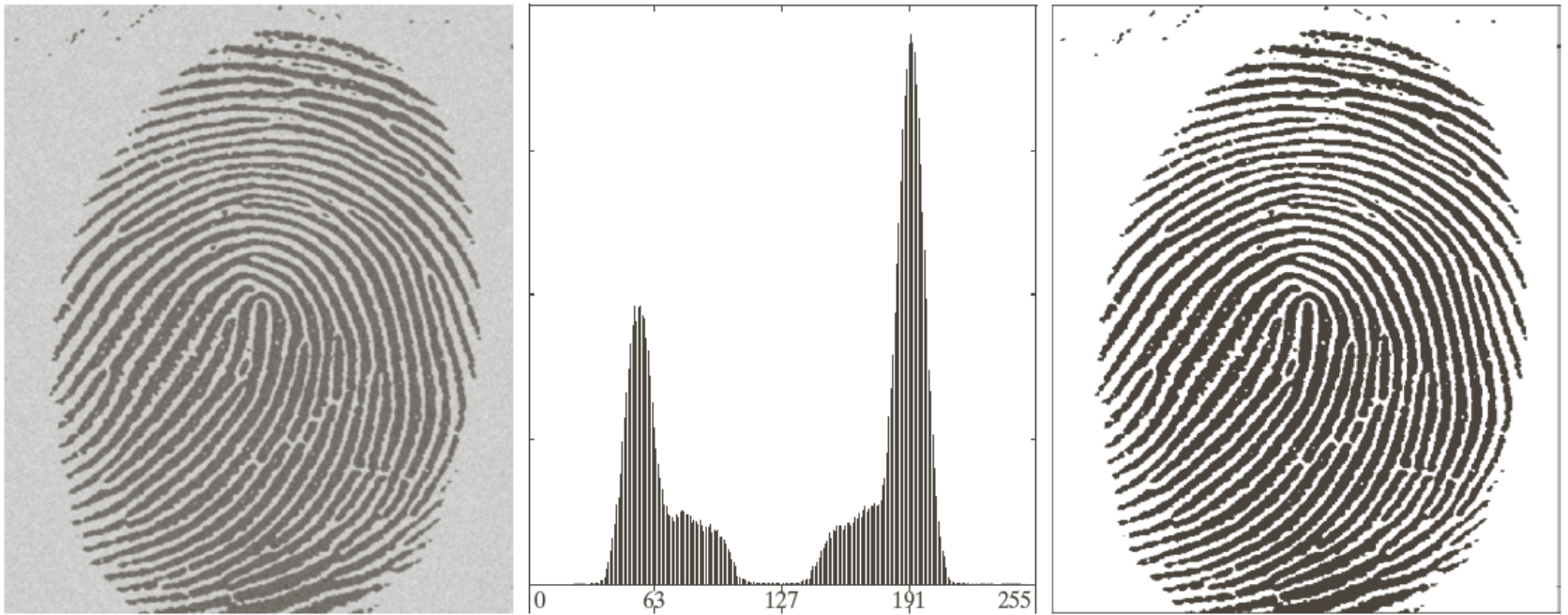
FIGURE 10.37 (a) Noisy image. (b) Intensity ramp in the range $[0.2, 0.6]$. (c) Product of (a) and (b). (d)–(f) Corresponding histograms.

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.

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

5. 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 THRESHOLDING

Optimum Global Thresholding Using Otsu's Method

- ▶ Principle: maximizing the between-class variance

Let $\{0, 1, 2, \dots, L-1\}$ denote the L distinct intensity levels in a digital image of size $M \times N$ pixels, and let n_i denote the number of pixels with intensity i .

$$p_i = n_i / MN \quad \text{and} \quad \sum_{i=0}^{L-1} p_i = 1$$

k is a threshold value, $C_1 \rightarrow [0, k]$, $C_2 \rightarrow [k+1, L-1]$

$$P_1(k) = \sum_{i=0}^k p_i \quad \text{and} \quad P_2(k) = \sum_{i=k+1}^{L-1} p_i = 1 - P_1(k)$$

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

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

$$P_1m_1 + P_2m_2 = m_G \quad (\text{Global mean value})$$

Optimum Global Thresholding Using Otsu's Method

Between-class variance, σ_B^2 is defined as

$$\begin{aligned}\sigma_B^2 &= P_1(m_1 - m_G)^2 + P_2(m_2 - m_G)^2 \\ &= P_1P_2(m_1 - m_2)^2 \\ &= \frac{[m_GP_1 - m_1P_1]^2}{P_1(1 - P_1)} \\ &= \frac{[m_GP_1 - m]^2}{P_1(1 - P_1)}\end{aligned}$$

Optimum Global Thresholding Using Otsu's Method

The optimum threshold is the value, k^* , that maximizes

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

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

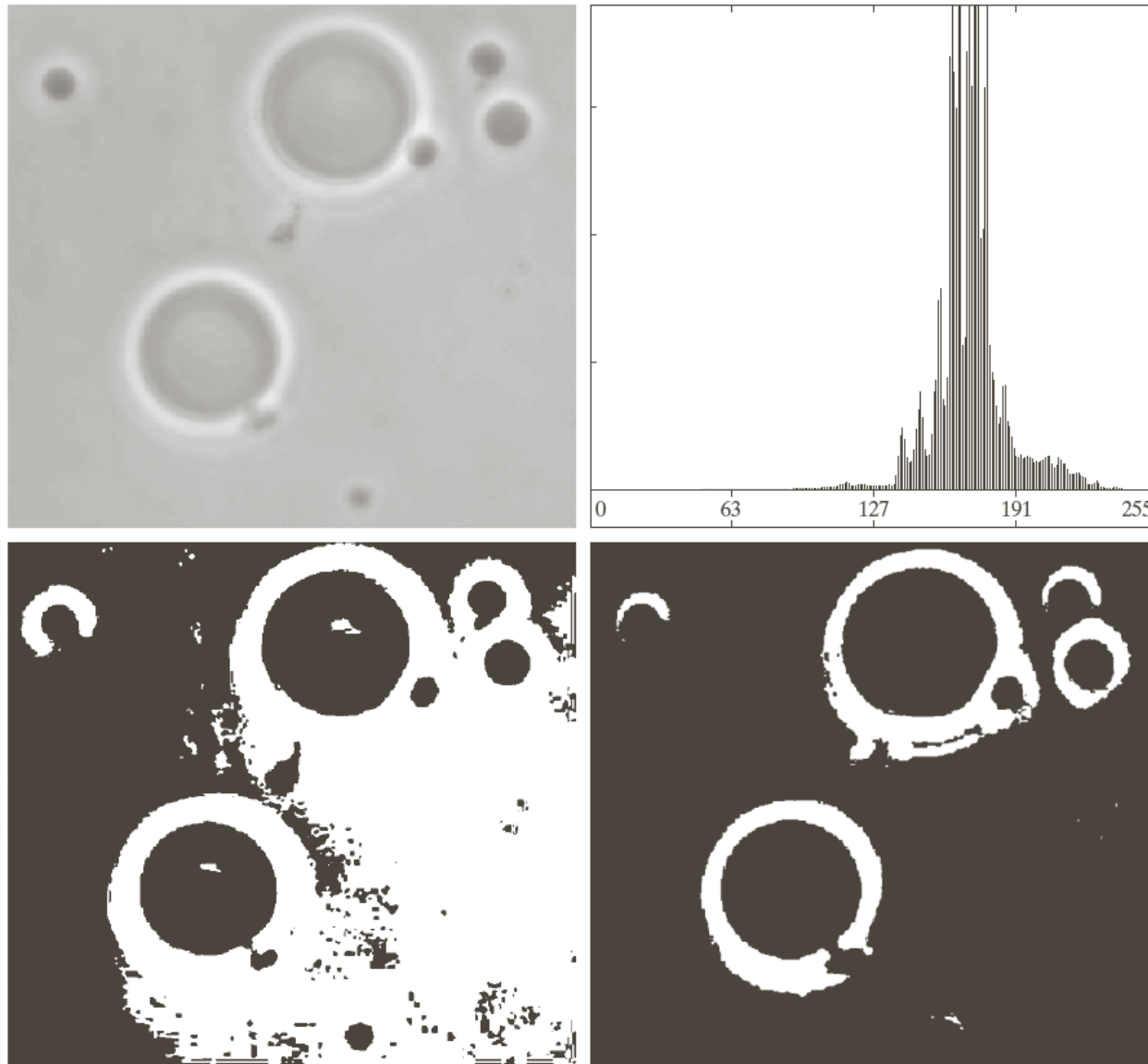
Separability measure $\eta = \frac{\sigma_B^2}{\sigma_G^2}$

Otsu's Algorithm: Summary

1. Compute the normalized histogram of the input image. Denote the components of the histogram by p_i , $i=0, 1, \dots, L-1$.
2. Compute the cumulative sums, $P_1(k)$, for $k = 0, 1, \dots, L-1$.
3. Compute the cumulative means, $m(k)$, for $k = 0, 1, \dots, L-1$.
4. Compute the global intensity mean, m_G .
5. Compute the between-class variance, for $k = 0, 1, \dots, L-1$.

Otsu's Algorithm: Summary

6. Obtain the Otsu's threshold, k^* .
7. Obtain the separability measure.



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.)

Multiple Thresholds

In the case of K classes, $C_1, C_2, \dots, C_K$, the between-class variance is

$$\sigma_B^2 = \sum_{k=1}^K P_k (m_k - m_G)^2$$

where $P_k = \sum_{i \in C_k} p_i$ and $m_k = \frac{1}{P_k} \sum_{i \in C_k} ip_i$

The optimum threshold values, $k_1^*, k_2^*, \dots, k_{K-1}^*$ that maximize

$$\sigma_B^2(k_1^*, k_2^*, \dots, k_{K-1}^*) = \max_{0 \leq k \leq L-1} \sigma_B^2(k_1, k_2, \dots, k_{K-1})$$

