Main Content

- Detection of Discontinuities
- Edge connection and edge detection
- Thresholding(门限处理)
- Region based segmentation (基于区域的分割)
  - Watershed (分水岭) algorithm

Main Content

- Point detection 点检测
- Line detection 线检测
- Edge detection 边缘检测

10.1.1 Point Detection

The most common way to find discontinuities is to use a template to detect the entire image. The template response of any point in the image is:

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

FIGURE 10.1 A general 3 × 3 mask.

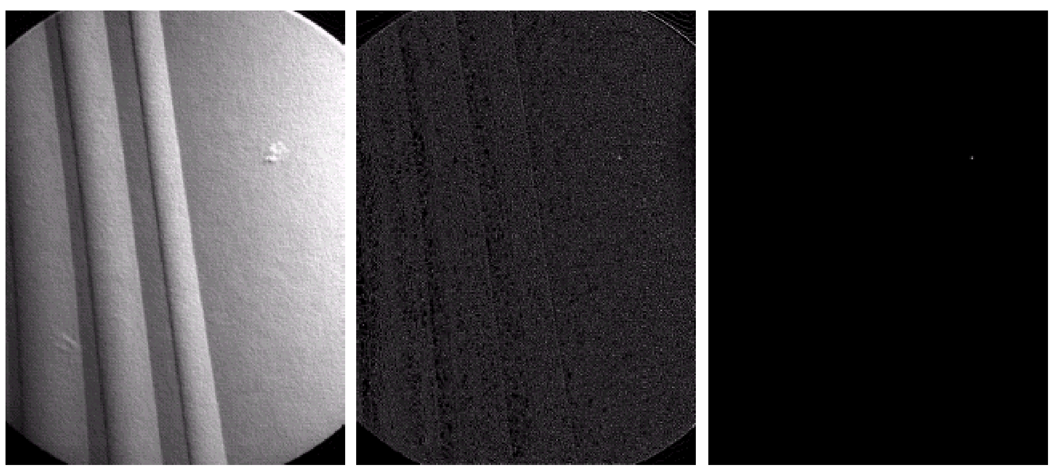
w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

10.1.1 Point Detection

The basic idea: if an outlier is very different from its surrounding peers, it can be easily detected by such a template.

$$|R| \geq T \qquad (T \text{ is a nonnegative threshold})$$

−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.)

10.1.2 Line Detection

- A set of masks can be used to detect lines
- You need thresholds!

FIGURE 10.3 Line masks.

−1	−1	−1
2	2	2
−1	−1	−1

Horizontal

−1	−1	2
−1	2	−1
2	−1	−1

+45°

−1	2	−1
−1	2	−1
−1	2	−1

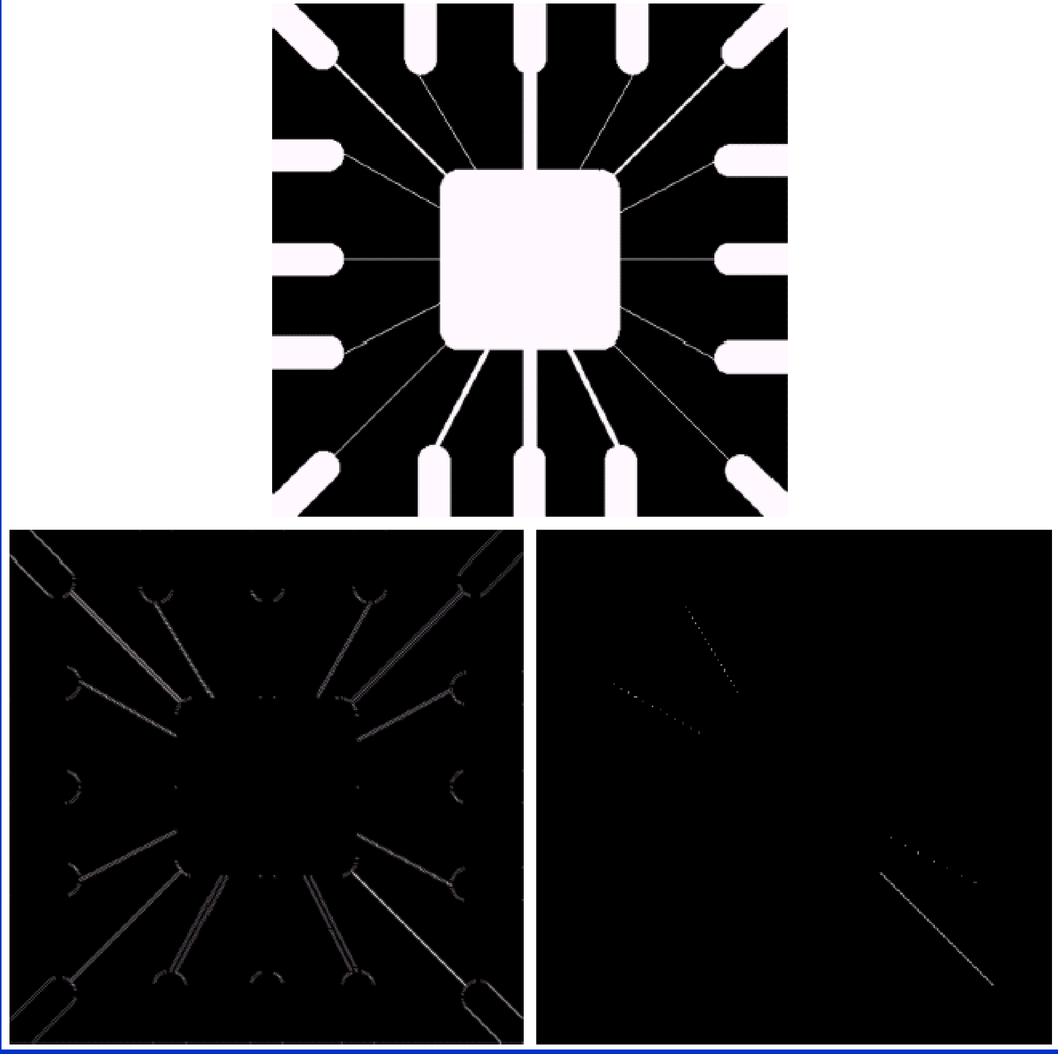
Vertical

2	−1	−1
−1	2	−1
−1	−1	2

−45°

10.1.2 Line Detection

Example : detect lines with -45 degree



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).

10.1.3 Edge detection

Fuzzy edges make it thicker and sharp edges make it thinner

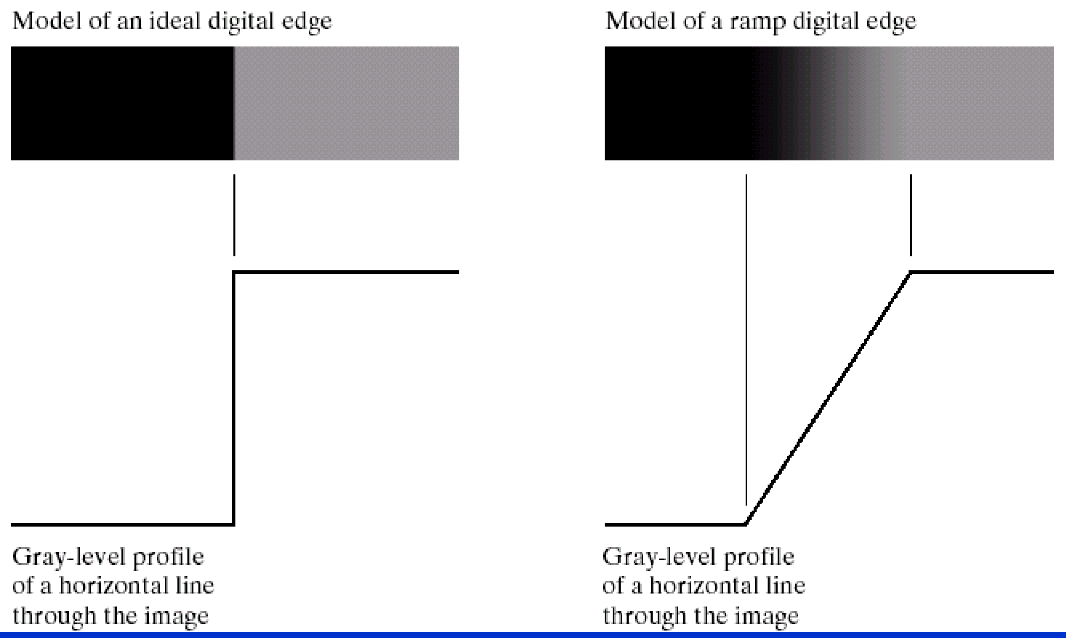
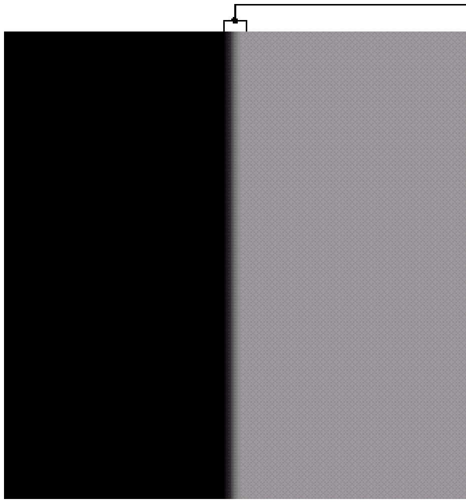


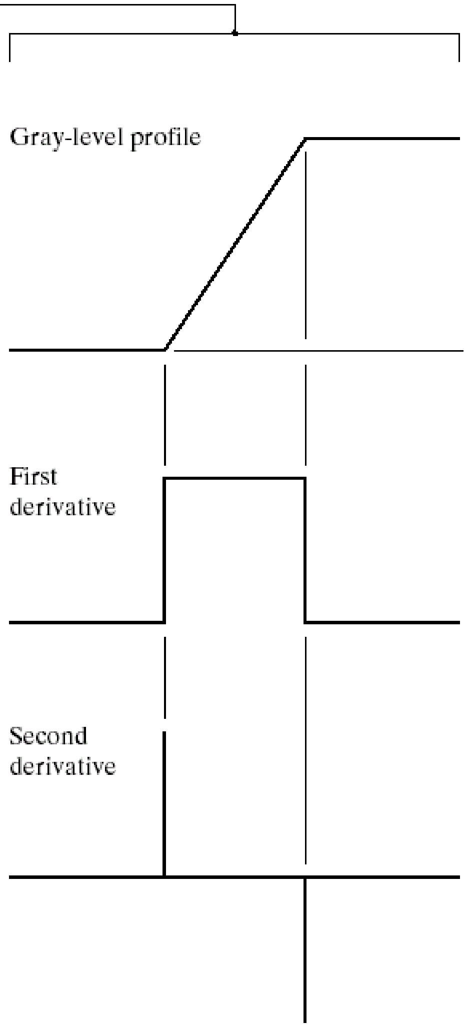
FIGURE 10.5 (a) Model of an ideal digital edge. (b) Model of a ramp edge. The slope of the ramp is proportional to the degree of blurring in the edge.

10.1.3 Edge Detection

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.





- The first derivative is used to detect whether a point in an image is a point at the edge.
- The sign of the second derivative can be used to determine whether an edge pixel is on the bright side or on the dark side.

10.1.3 Edge Detection：Sensitivity to noise

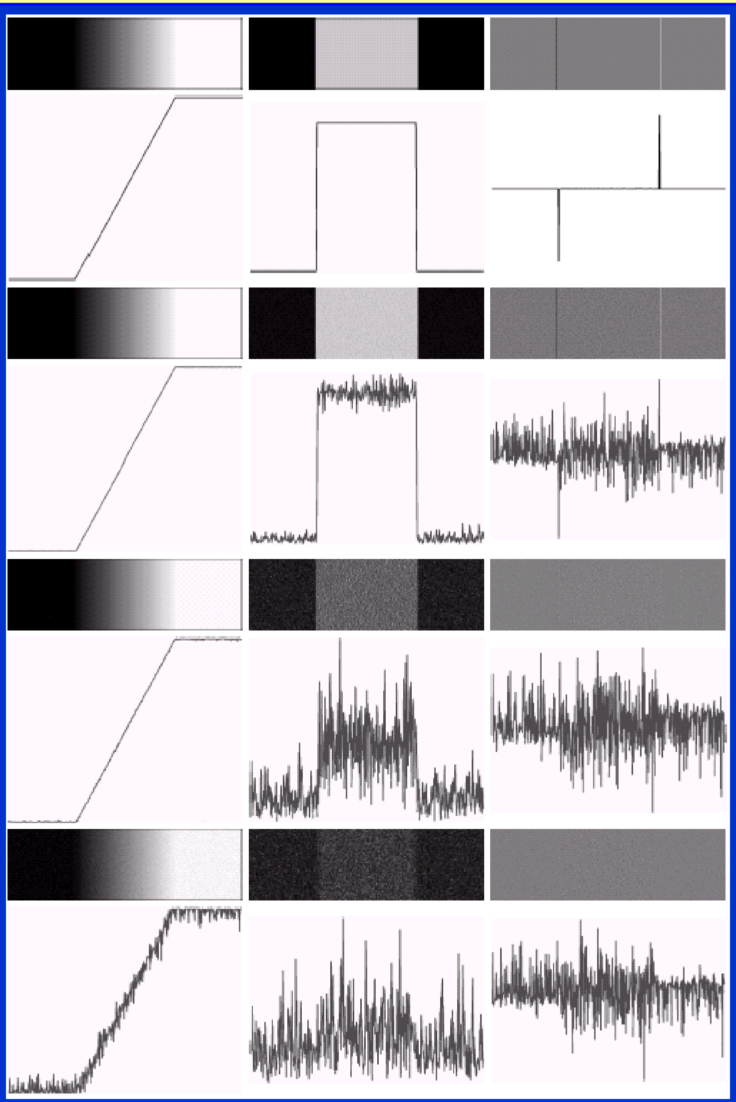


FIGURE 10.7 First column: images and gray-level profiles of a ramp edge corrupted by random Gaussian noise of mean 0 and σ = 0.0, 0.1, 1.0, and 10.0, respectively. Second column: first-derivative images and gray-level profiles. Third column: second-derivative images and gray-level profiles.

a
b
c
d

- For each edge in the image, the second derivative produces two values.
- A fictitious line connecting the positive and negative extremum of the second derivative will cross the zero near the midpoint of the edge.
- In order to classify meaningful edge points, the grayscale transformation associated with the point must be more efficient than the transformation on the background of the point.

10.1.3 Edge Detection

Gradient of image f(x,y):

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

$$\nabla f = \mathrm{mag}(\nabla \mathbf{f}) = \sqrt{G_x^2 + G_y^2}$$

$$\alpha(x, y) = \arctan\left(\frac{G_y^2}{G_x^2}\right)$$

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

Roberts Cross Gradient Operator:

$$G_x = z_9 - z_5 \qquad G_y = z_8 - z_6$$

Prewitt Operator:

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

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

Sobel Operator:

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

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

10.1.3 Edge Detection

Masks used for detecting diagonal edges

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

a b
c d

FIGURE 10.9 Prewitt and Sobel masks for detecting diagonal edges.

10.1.3 Edge Detection

Example: Gradient is used for edge detection

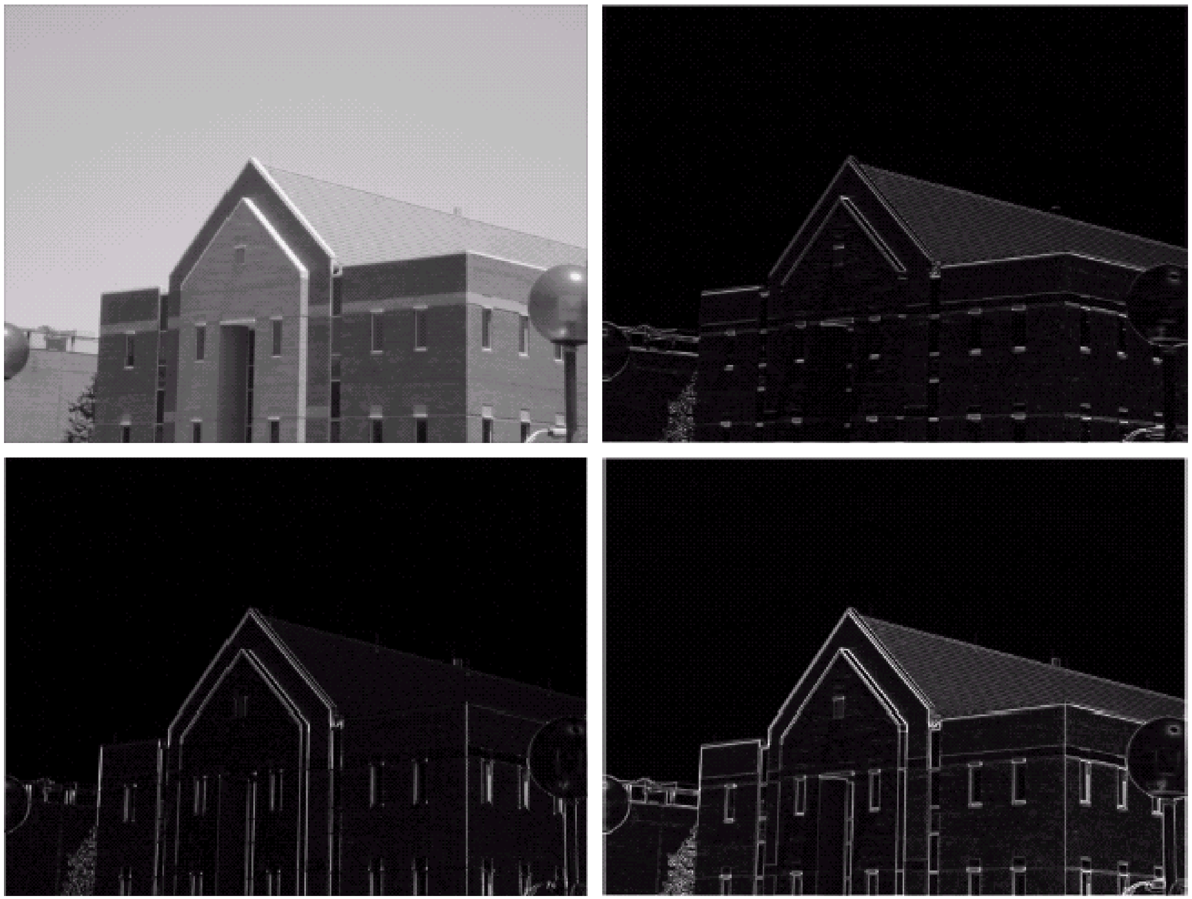
- Note: the detail of bricks is visible

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, $|G_x| + |G_y|$.

10.1.3 Edge Detection

- To get rid of the detail of bricks, a smoothing filter can be used



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.

10.1.3 Edge Detection

Diagonal edge can be detected using corresponding masks

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).

10.1.3 Edge Detection：Laplacians

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

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

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

The role of Laplacians operator in segmentation:

•The zero crossing property is used to locate the edge.

•To determine whether a pixel is on the dark side or the bright side of en edge

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

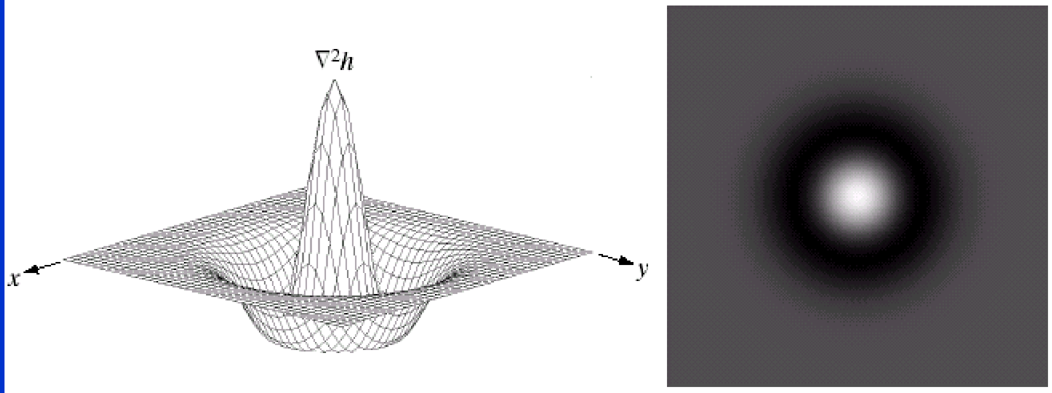
−1	−1	−1
−1	8	−1
−1	−1	−1

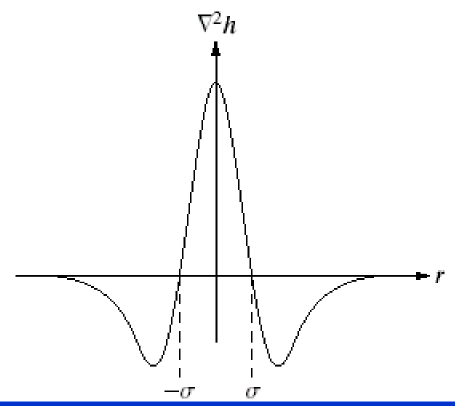
10.1.3 Edge Detection: LoG

$$h(r) = -e^{-\frac{r^2}{2\delta^2}} \qquad (r^2 = x^2 + y^2, \delta \text{ is standard deviation})$$

A gaussian Laplacians operator:

$$\nabla^2 h(r) = -\left[\frac{r^2 - \delta^2}{\delta^4}\right] e^{-\frac{r^2}{2\delta^2}}$$





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

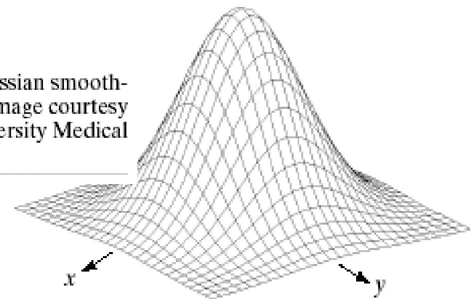
a b
c d

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).

10.1.3 Edge Detection

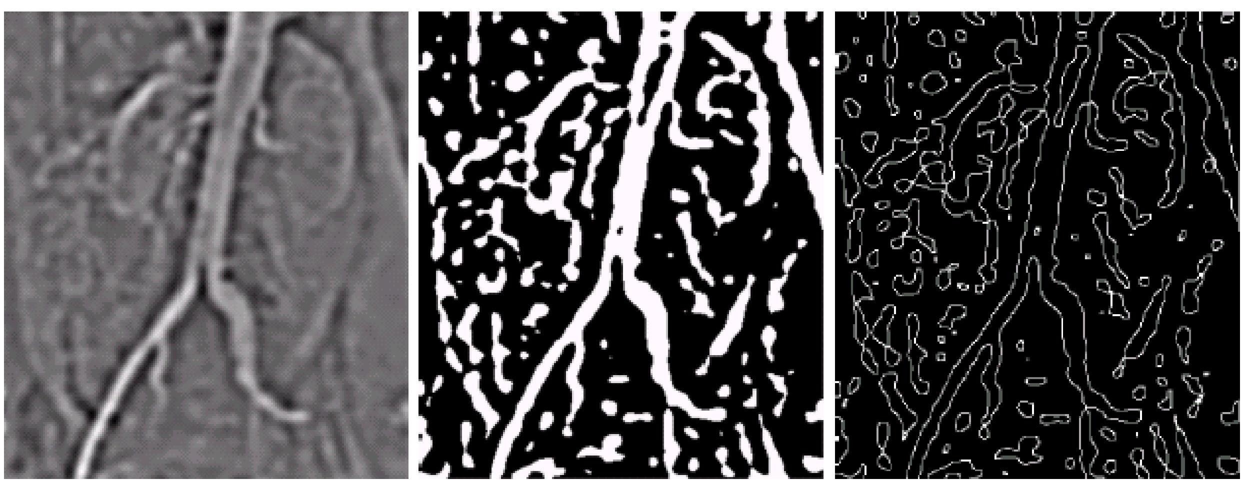
a b
c d
e f g

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.)



−1	−1	−1
−1	8	−1
−1	−1	−1

Application of LoG



Main Content

- Local processing
- Global processing via Hough transformation

10.2.1 Local Processing

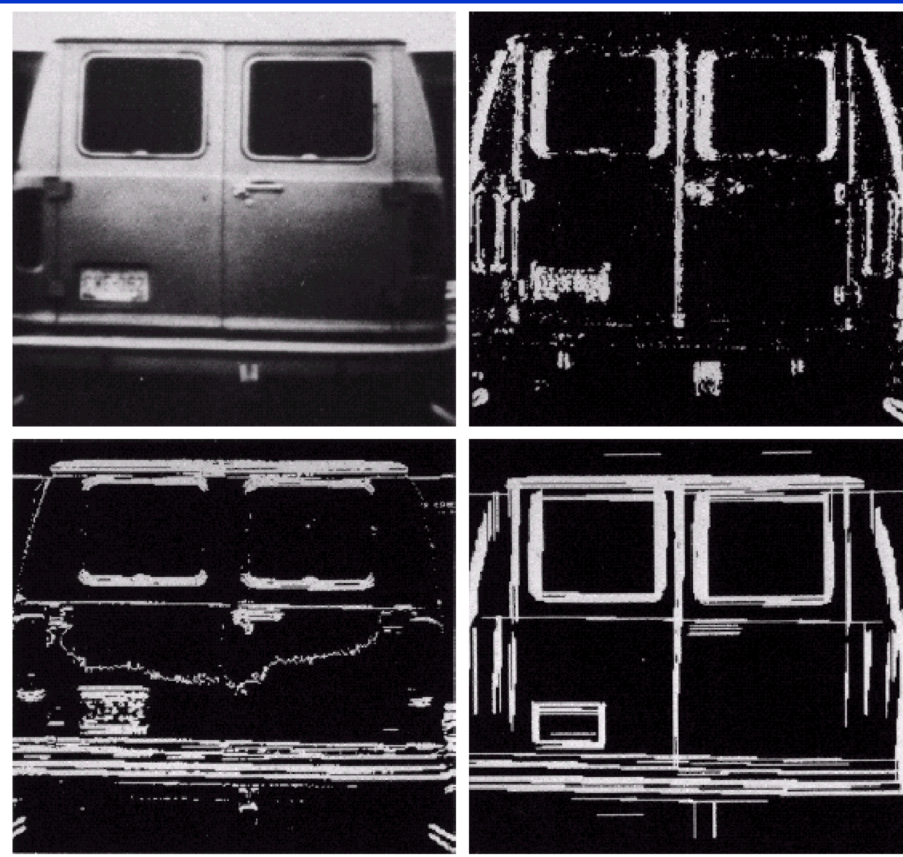
Two properties of edge similarity：

(1) Gradient intensity of edge pixels

$$\left|\nabla f(x,y)-\nabla f(x_0,y_0)\right| \le E$$

(2) The direction of the gradient vector

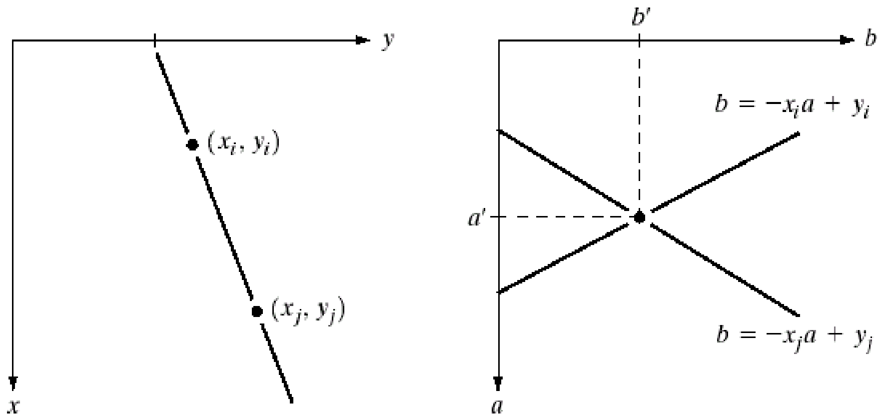
$$\left|\alpha(x,y)-\alpha(x_0,y_0)\right| \le A$$



a b
c d

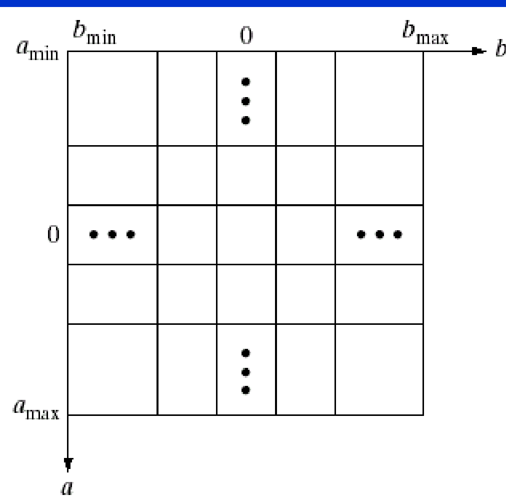
FIGURE 10.16
(a) Input image.
(b) G_y component of the gradient.
(c) G_x component of the gradient.
(d) Result of edge linking. (Courtesy of Perceptics Corporation.)

10.2.2 Global Processing via Hough Transformation(1)

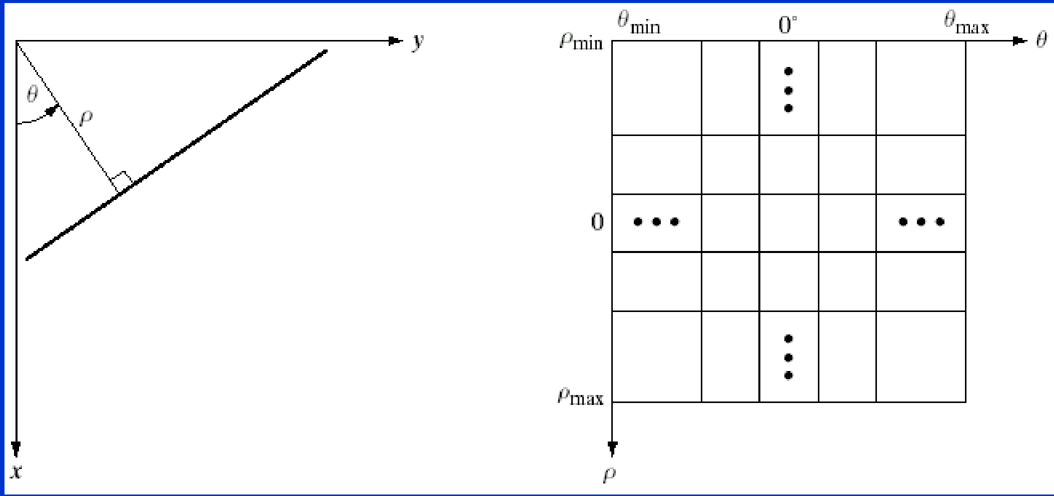


a b
FIGURE 10.17 (a) *xy*-plane. (b) Parameter space.

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



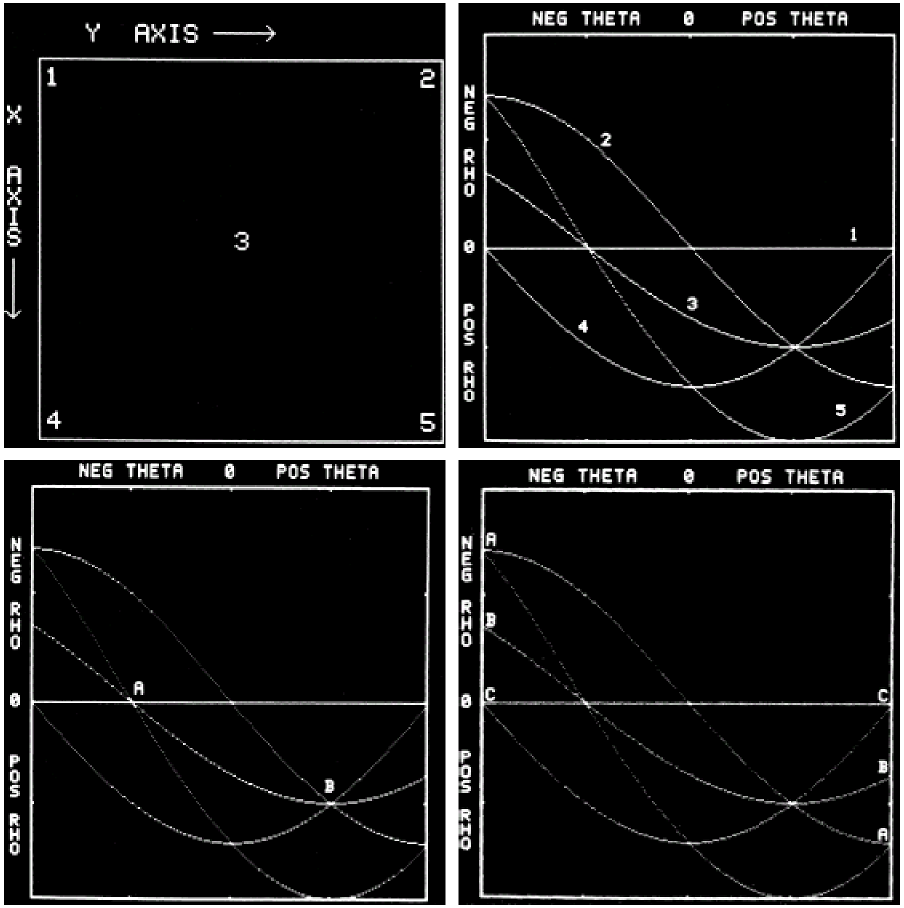
10.2.2 Global Processing via Hough Transformation(2)



a b

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

10.2.2 Global Processing via Hough Transformation(3)



a b
c d

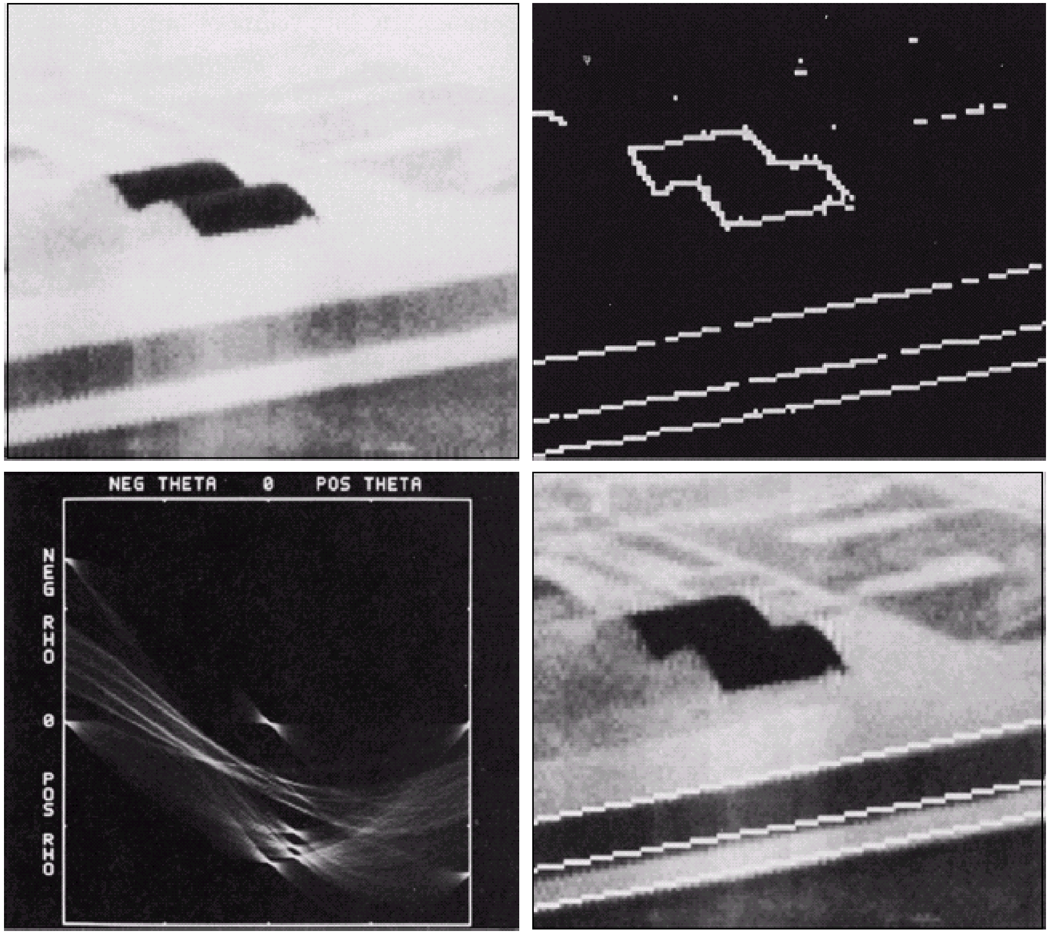
FIGURE 10.20 Illustration of the Hough transform. (Courtesy of Mr. D. R. Cate, Texas Instruments, Inc.)

10.2.2 Global Processing via Hough Transformation(4)

Connection method based on Hough transformation:

1. The gradient of the image is calculated and the threshold is set to obtain a binary image.
2. To determine the subdivision in the $\rho\theta$ plane.
3. The number of accumulator units is checked where the pixels are highly concentrated.
4. Verify relationships between pixels in selected cells (mainly for continuity).

10.2.2 Global Processing via Hough Transformation(5)



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.)

Main Content

- Fundamentals
- Brightness effect
- Basic global threshold
- Basic adaptive threshold
- Optimal global and adaptive thresholds

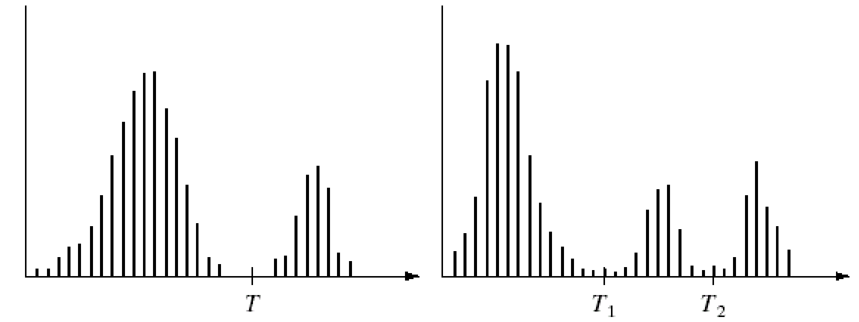
10.3.1 Fundamentals

- Threshold processing is regarded as an operation involving the following formal function T.

$$T = T[x, y, p(x, y), f(x, y)]$$

Here *f(x,y) is the grayscale of* (x,y), *p(x,y)* is the local property of this point.

- If T depends only on f(x,y), the threshold is called the global.
- If T depends on f(x,y) and p(x,y), the threshold is local.
- If T depends on coordinates x and y, the threshold is adaptive.



a b

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

10.3.2 Brightness Effect

$$f(x,y) = i(x,y)r(x,y)$$

$$z(x,y) = \ln f(x,y)$$

$$= \ln i(x,y) + \ln r(x,y)$$

$$= i'(x,y) + r'(x,y)$$

$i(x,y)$: brightness

$r(x,y)$: reflection

Convolution of histograms!

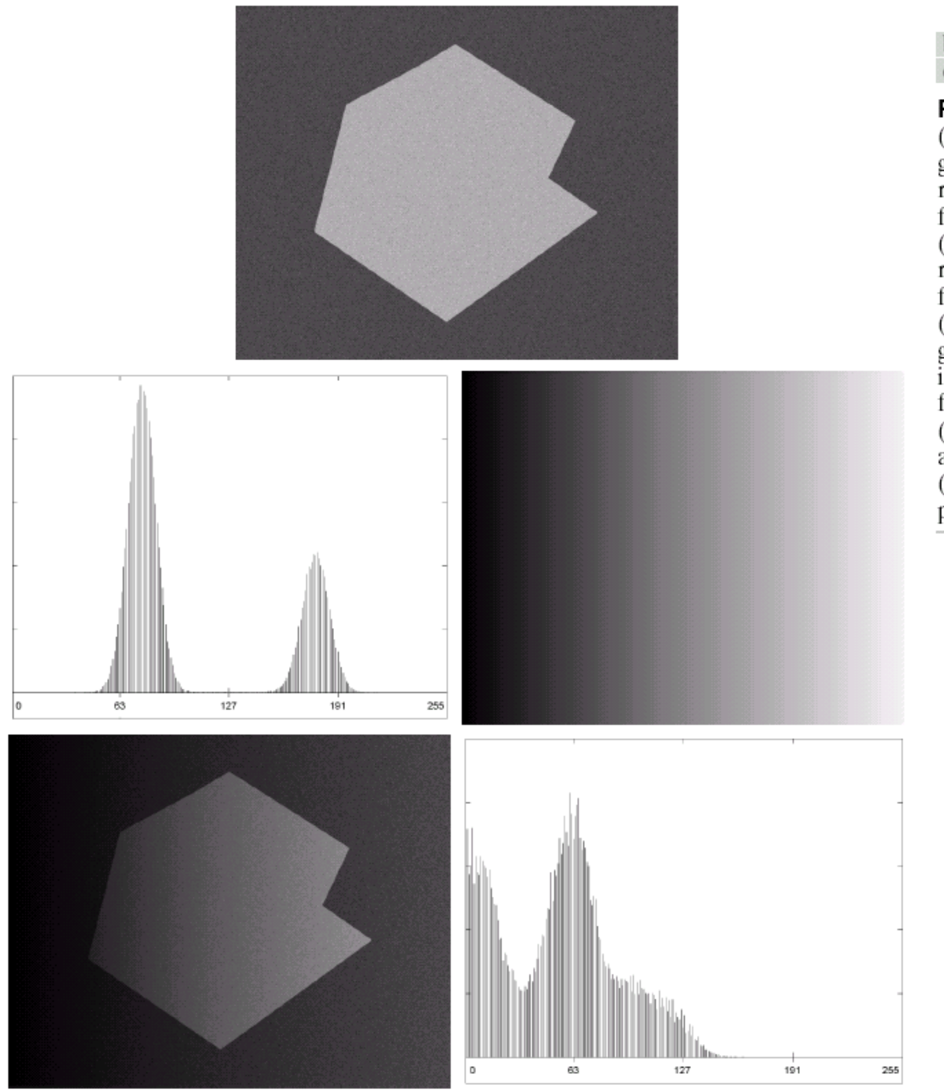


FIGURE 10.27 (a) Computer generated reflectance function. (b) Histogram of reflectance function. (c) Computer generated illumination function. (d) Product of (a) and (c). (e) Histogram of product image.

10.3.3 Basic Global Threshold(1)

Simple operation

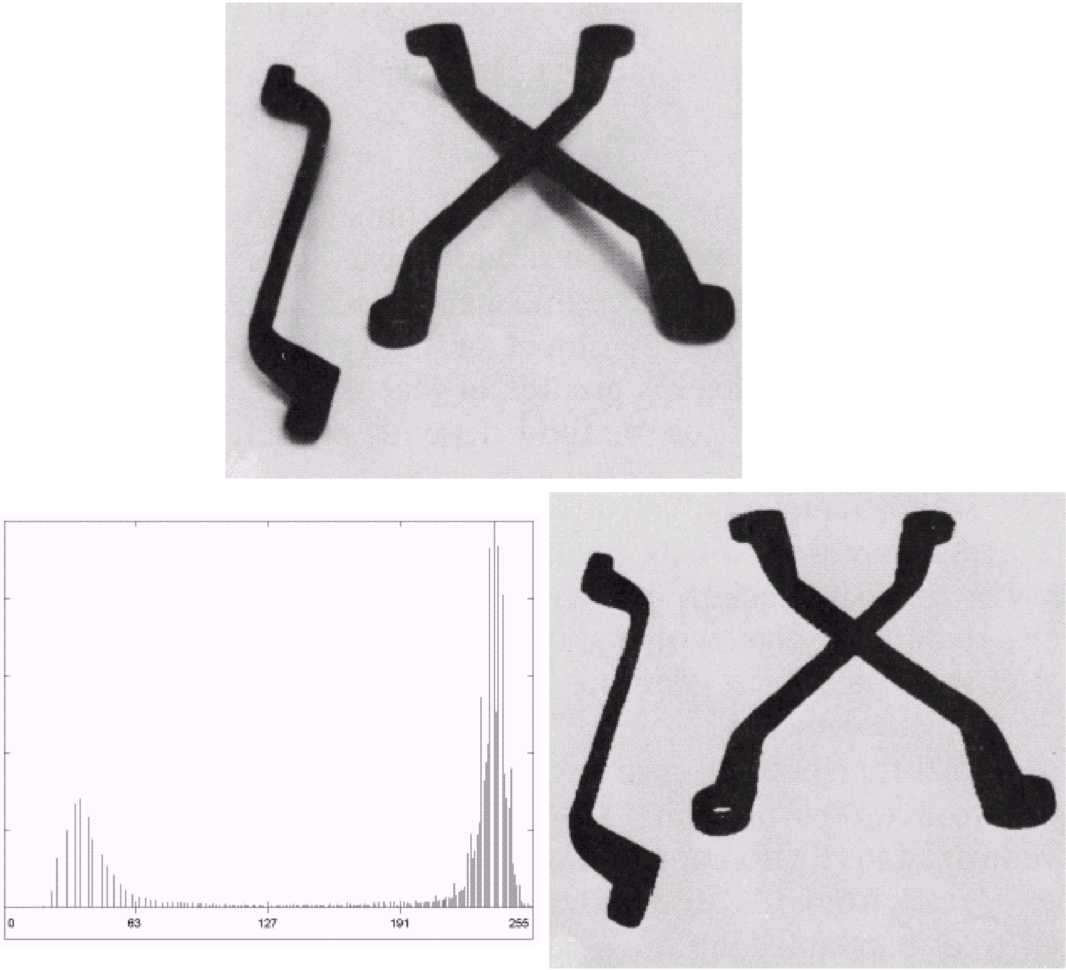


FIGURE 10.28 (a) Original image. (b) Image histogram. (c) Result of global thresholding with T midway between the maximum and minimum gray levels.

10.3.3 Basic Global Threshold(2)

1. Select an initial value of T.
2. Segment the image with T. This produces two sets of pixels: G_1 with a gray value greater than T, and G_2 with a gray value less than or equal to T.
3. Calculates the average grayscale μ_1 and μ_2 for all pixels in the region G_1 and G_2.
4. Calculate the new threshold:

$$T = \frac{\mu_1 + \mu_2}{2}$$

5. Repeat steps 2 through 4 until the difference between the T values obtained by successive iterations is less than the parameter T_0 defined in advance.

10.3.3 Basic Adaptive Threshold(1)

Example

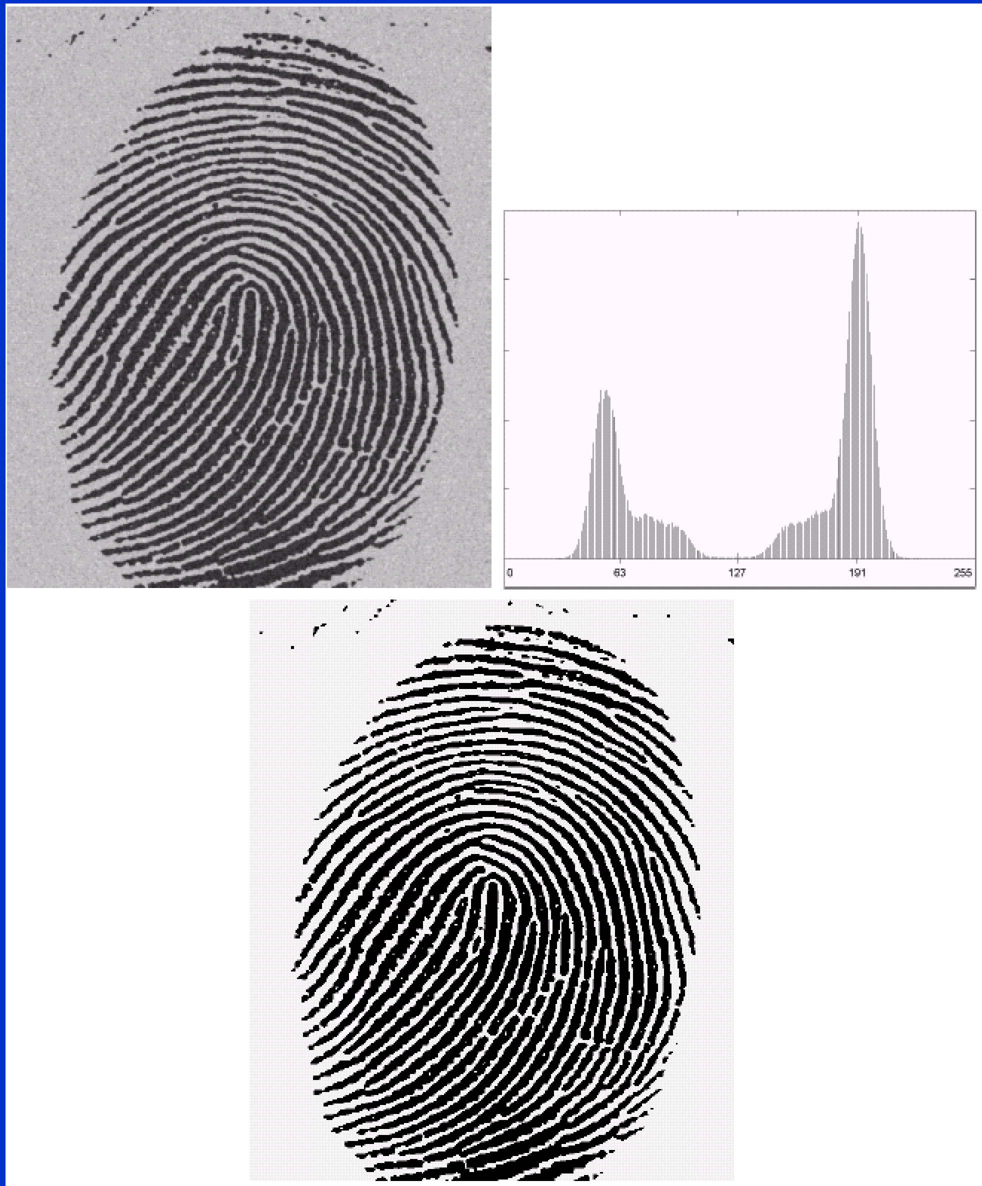


FIGURE 10.29 (a) Original image. (b) Image histogram. (c) Result of segmentation with the threshold estimated by iteration. (Original courtesy of the National Institute of Standards and Technology.)

10.3.3 Basic Adaptive Threshold(2)

To obtain a good threshold, the input image can be divided into many small blocks

a b
c d

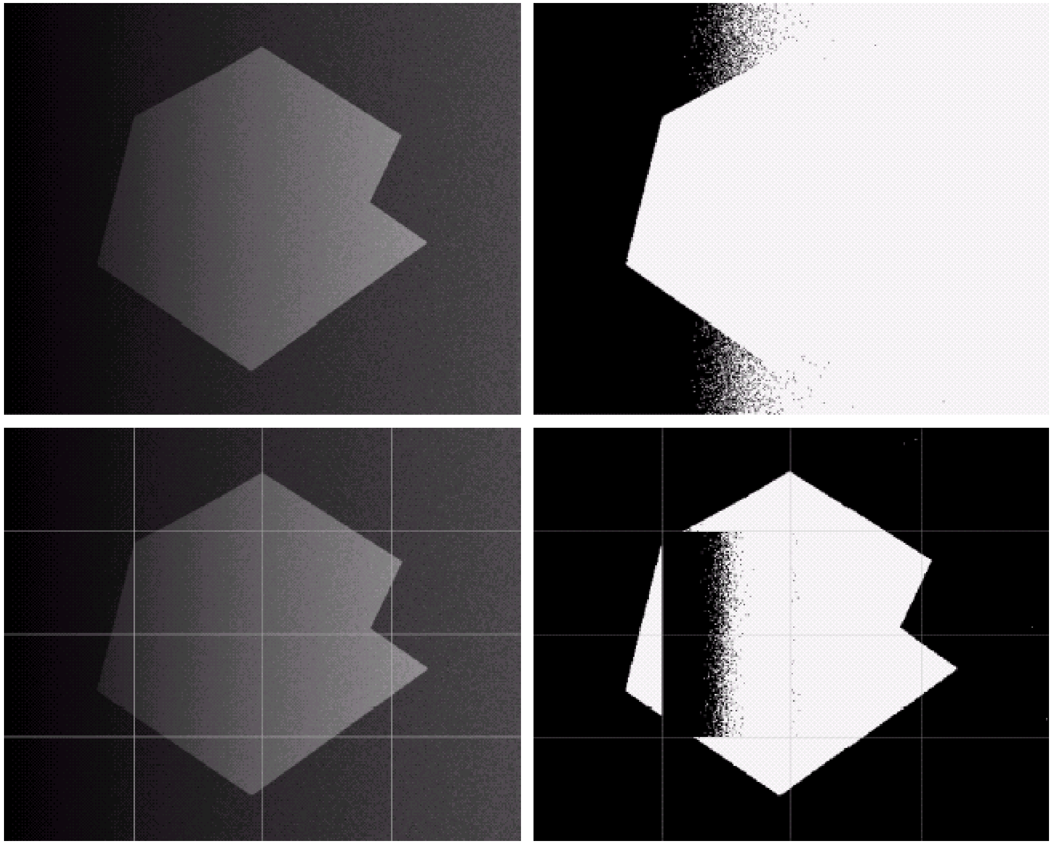
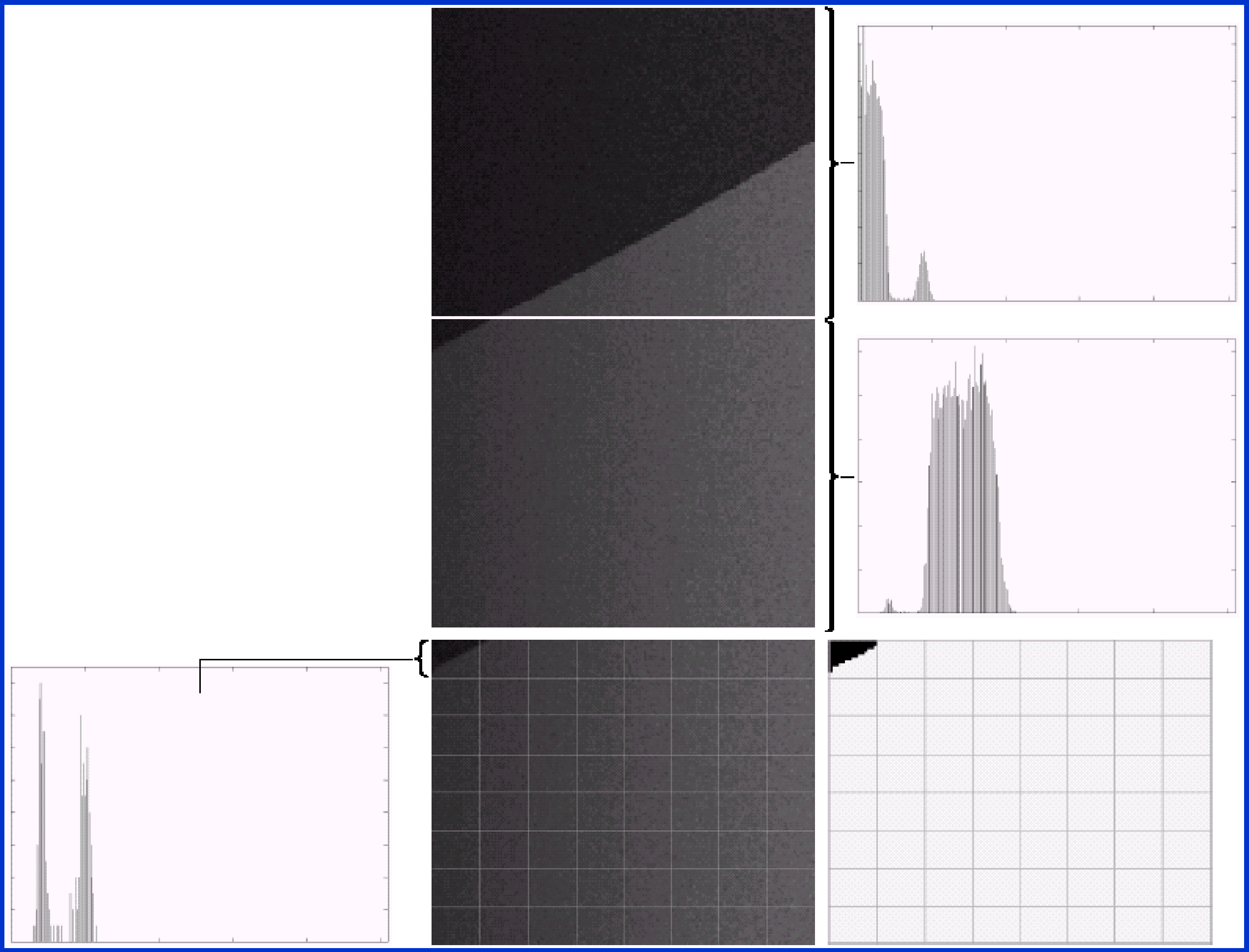


FIGURE 10.30 (a) Original image. (b) Result of global thresholding. (c) Image subdivided into individual subimages. (d) Result of adaptive thresholding.

10.3.3 Basic Adaptive Threshold(3)

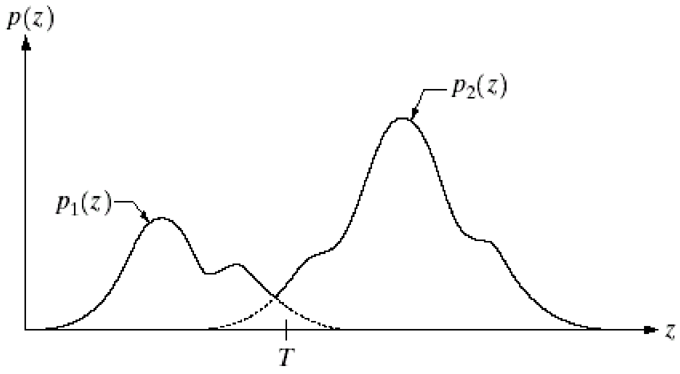


	a	b
		c
e	d	f

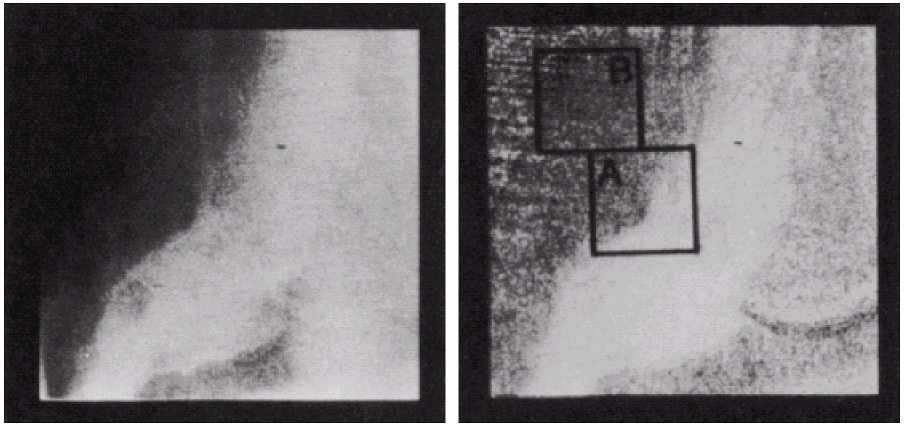
FIGURE 10.31 (a) Properly and improperly segmented subimages from Fig. 10.30. (b)–(c) Corresponding histograms. (d) Further subdivision of the improperly segmented subimage. (e) Histogram of small subimage at top, left. (f) Result of adaptively segmenting (d).

10.3.5 Optimal Global and Adaptive Thresholds(1)

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



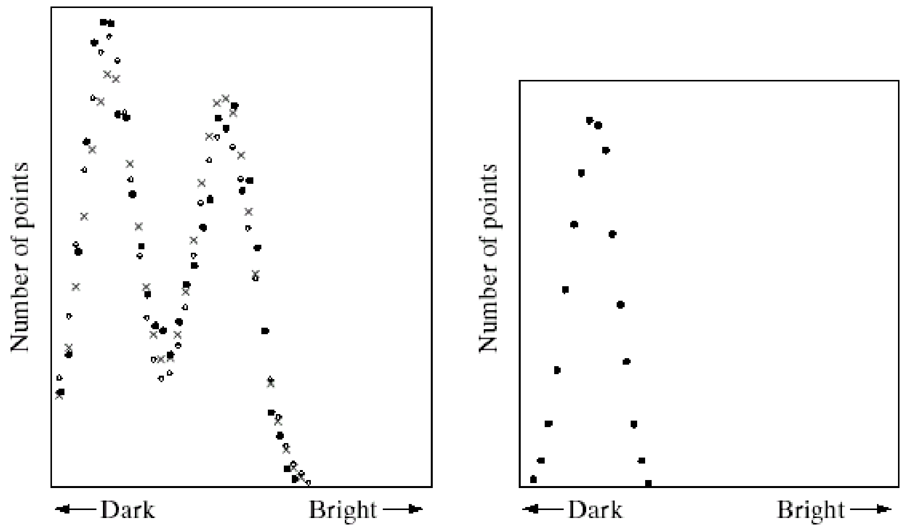
10.3.5 Optimal Global and Adaptive Thresholds(2)



a b

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

10.3.5 Optimal Global and Adaptive Thresholds(3)

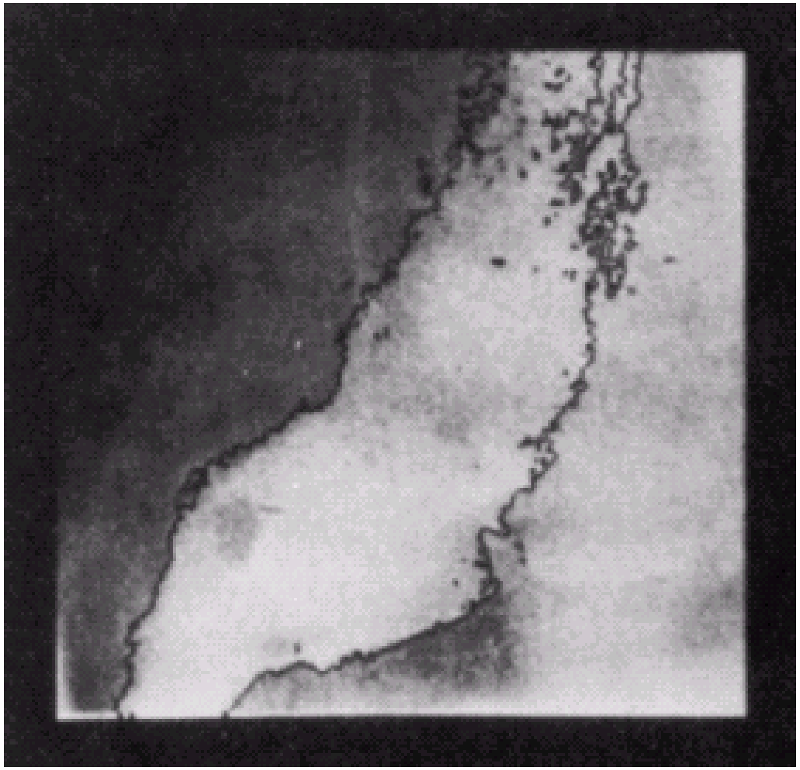


a b

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

10.3.5 Optimal Global and Adaptive Thresholds(4)

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



10.4 Region Based Segmentation

Basic content:

- Basic formulation
- Region growing
- Region Splitting and Merging

• In sections 10.1 and 10.2 , we find boundaries between regions based on discontinuities in gray levels to partition an image into regions.

• In section 10.3 segmentation was accomplished via thresholds based on the distribution of pixel properties, such as gray-level values or color.

• In this section we discuss segmentation techniques that are based on finding the regions directly.

10.4.1 Basic Formulation

Let R represent the entire image region. We may view 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 region, $i = 1, 2, \ldots, n$.

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

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

(e) $P(R_i \cup R_j) = \text{FALSE}$ for $i \neq j$.

Here, $P(R_i)$ is a logical predicate defined over the points in set R_i and $\varnothing$ is the null set.

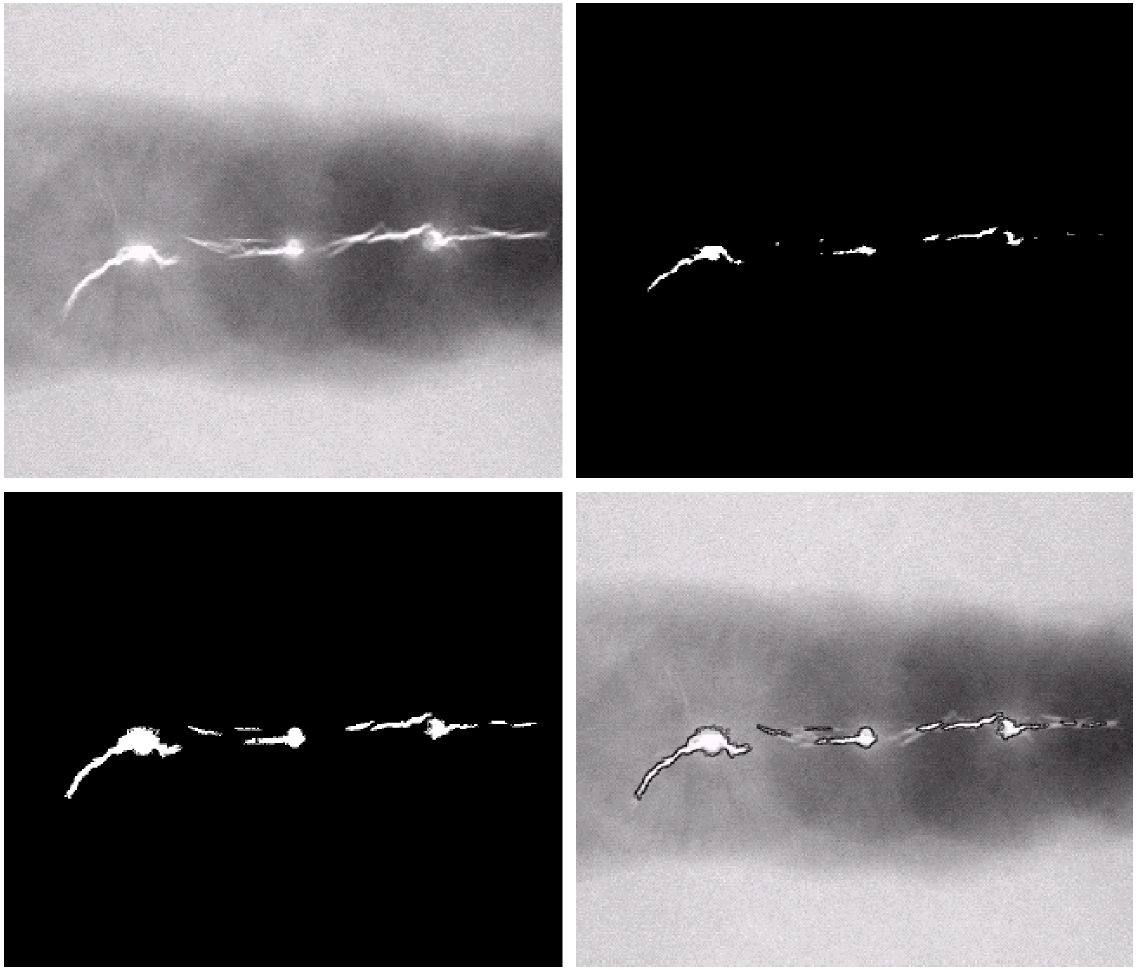
10.4.2 Region Growing

- *Region growing* is a procedure that groups pixels or subregions 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.
- If the result of these computations shows clusters of values, the pixels whose properties place them near the centroid of these clusters can be used as seeds.
- The selection of similarity criteria depends not only on the problem under consideration, but also on the type of image data available.

10.4.2 Region Growing

- Another problem in region growing is the formulation of a stopping rule.

- Example 10.16 Application of region growing in weld inspection.



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.).

10.4.2 Region Growing

- First to determine the initial seed points.
- The next step is to choose criteria for region growing.

(1) the absolute gray-level difference represents the difference between 255 and the location of the highest gray level value in the dark weld region.

(2) To be included in one of the regions, the pixel had to be 8-connected to at least one pixel in that region.

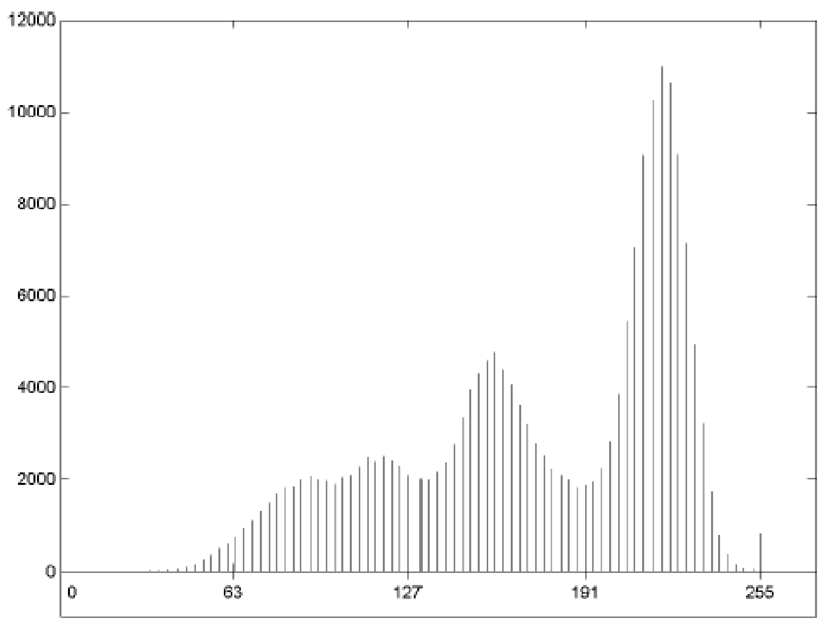


FIGURE 10.41 Histogram of Fig. 10.40(a).

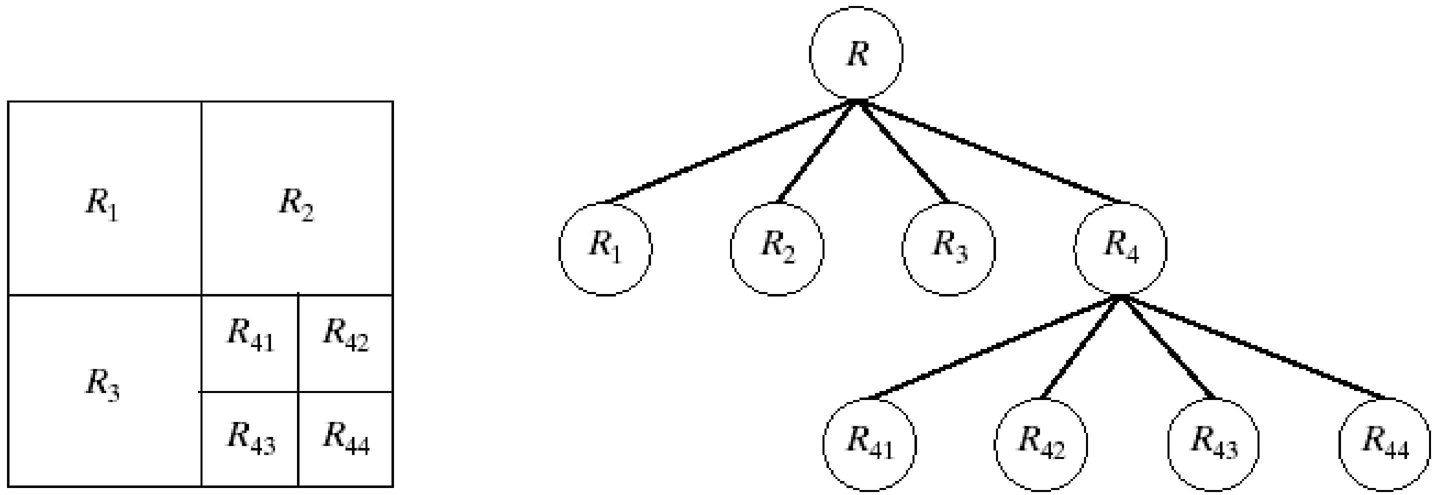
10.4.3 Region Splitting and Merging

- Another way to grow regions is to subdivide an image initially into a set of arbitrary, disjointed regions and then merge and/or split.

- *Quadtree* (四叉树) is illustrated in Fig.10.42

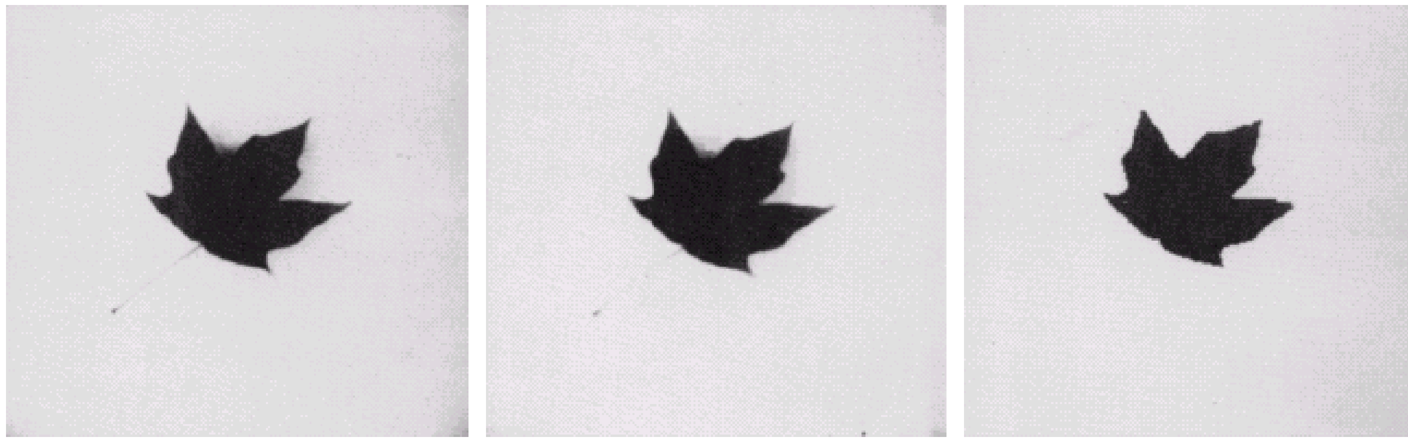
a b

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



10.4.3 Region Splitting and Merging

- Example 10.17 Split and merge



a b c

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

The image (c) was obtained by thresholding (a), with a threshold placed midway between the two principal peaks of the histogram.

The shading were erroneously eliminated by the thresholding procedure.

10.5 Segmentation by Morphological Watersheds(分水岭)

- Morphological watersheds often produces more stable segmentation results, including continuous segmentation boundaries.
- This approach also provides a simple framework for incorporating knowledge-based constraints in the segmentation process.

10.5.1 Basic concepts

- *Catchment basin* 汇水盆 or *watershed* 分水岭 of the minimum： points at which a drop of water ,if placed at the location of any of those points, would fall with certainty to a single minimum.
- *Divide lines* or *watershed lines*: points at which water would be equally likely to fall to more than one such minimum.

10.5.1 Basic concepts

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

10.5.1 Basic concepts

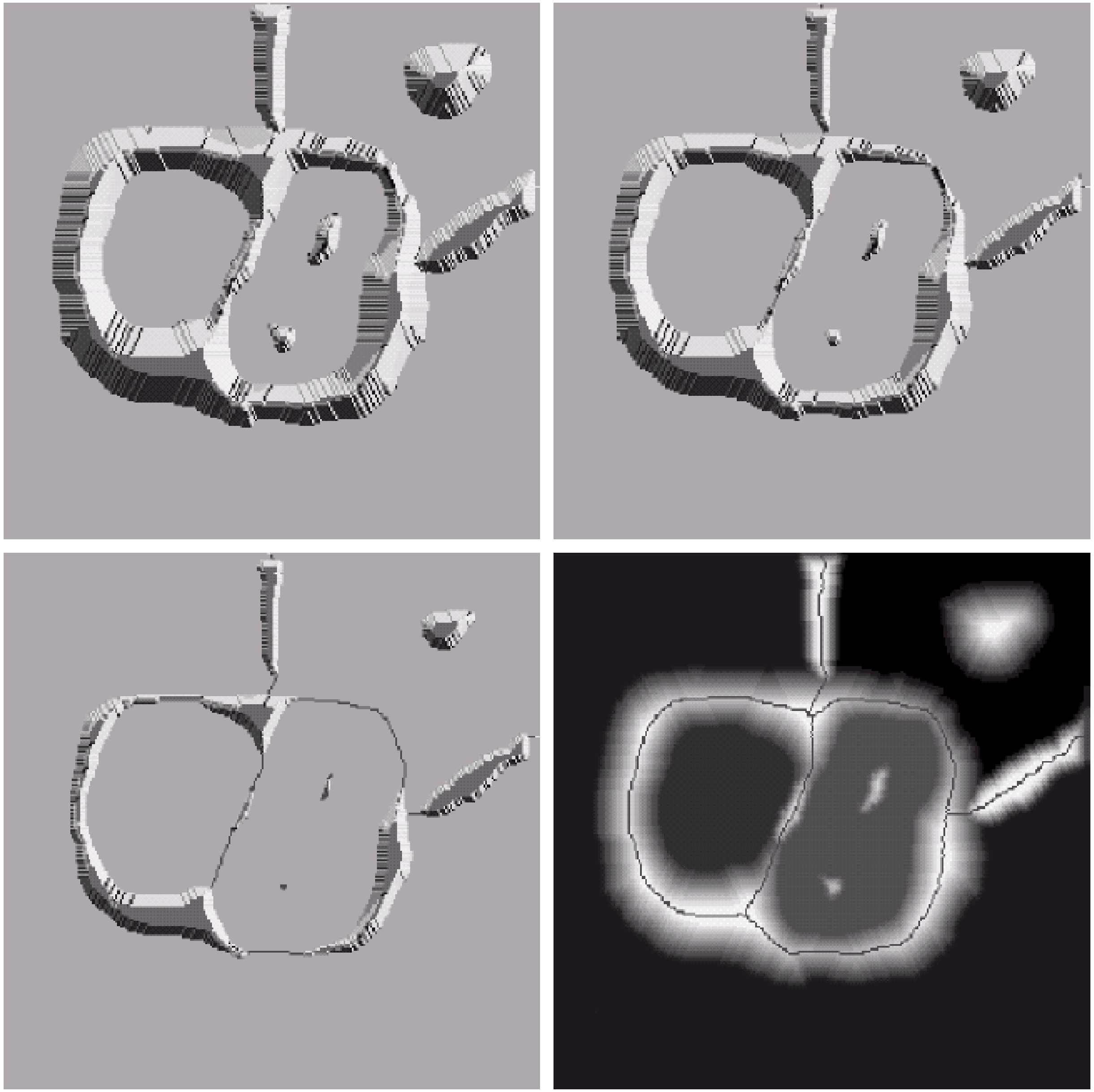
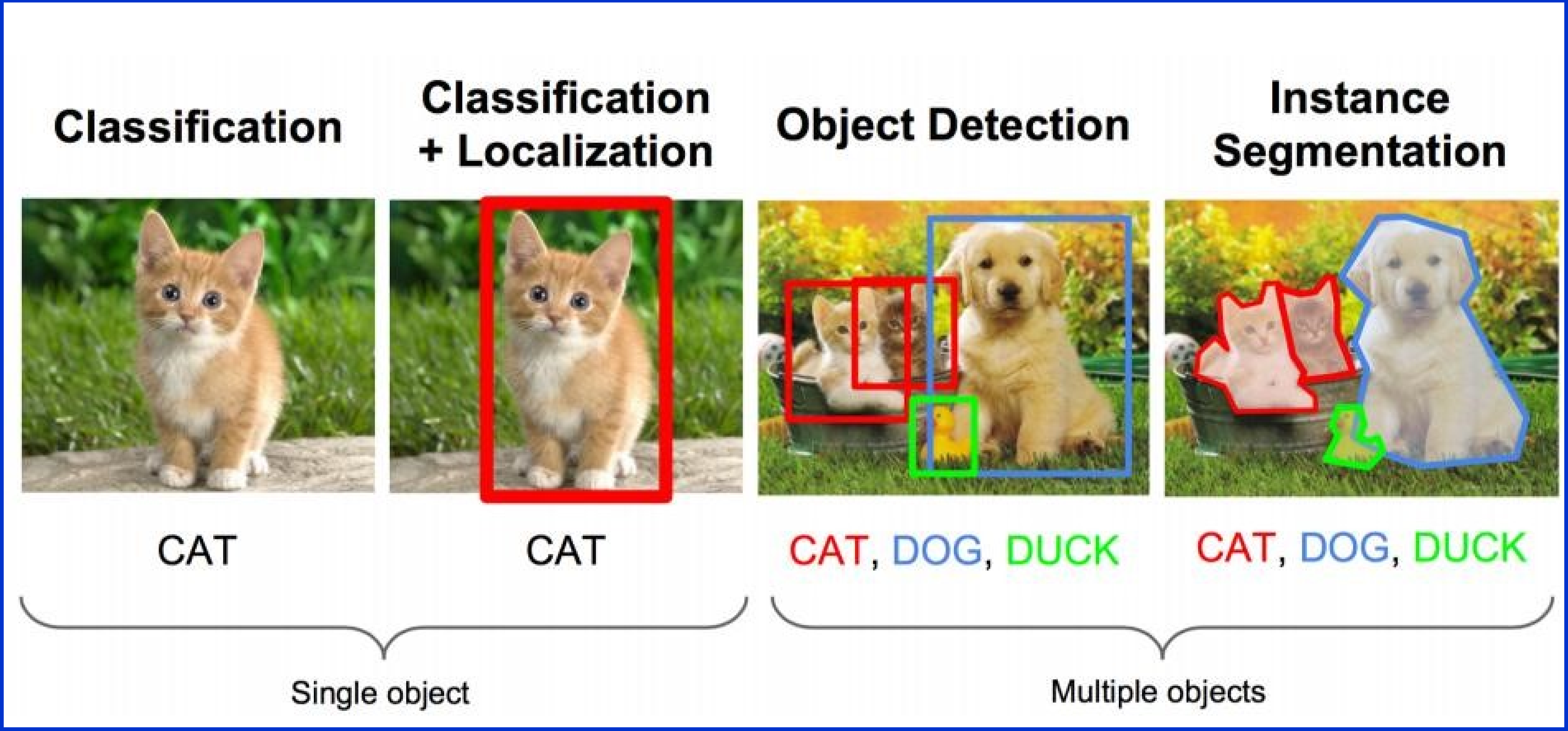


FIGURE 10.44 *(Continued)* (e) Result of further flooding. (f) Beginning of merging of water from two catchment basins (a short dam was built between them). (g) Longer dams. (h) Final watershed (segmentation) lines. (Courtesy of Dr. S. Beucher, CMM/Ecole des Mines de Paris.)

10.5.1 Basic concepts

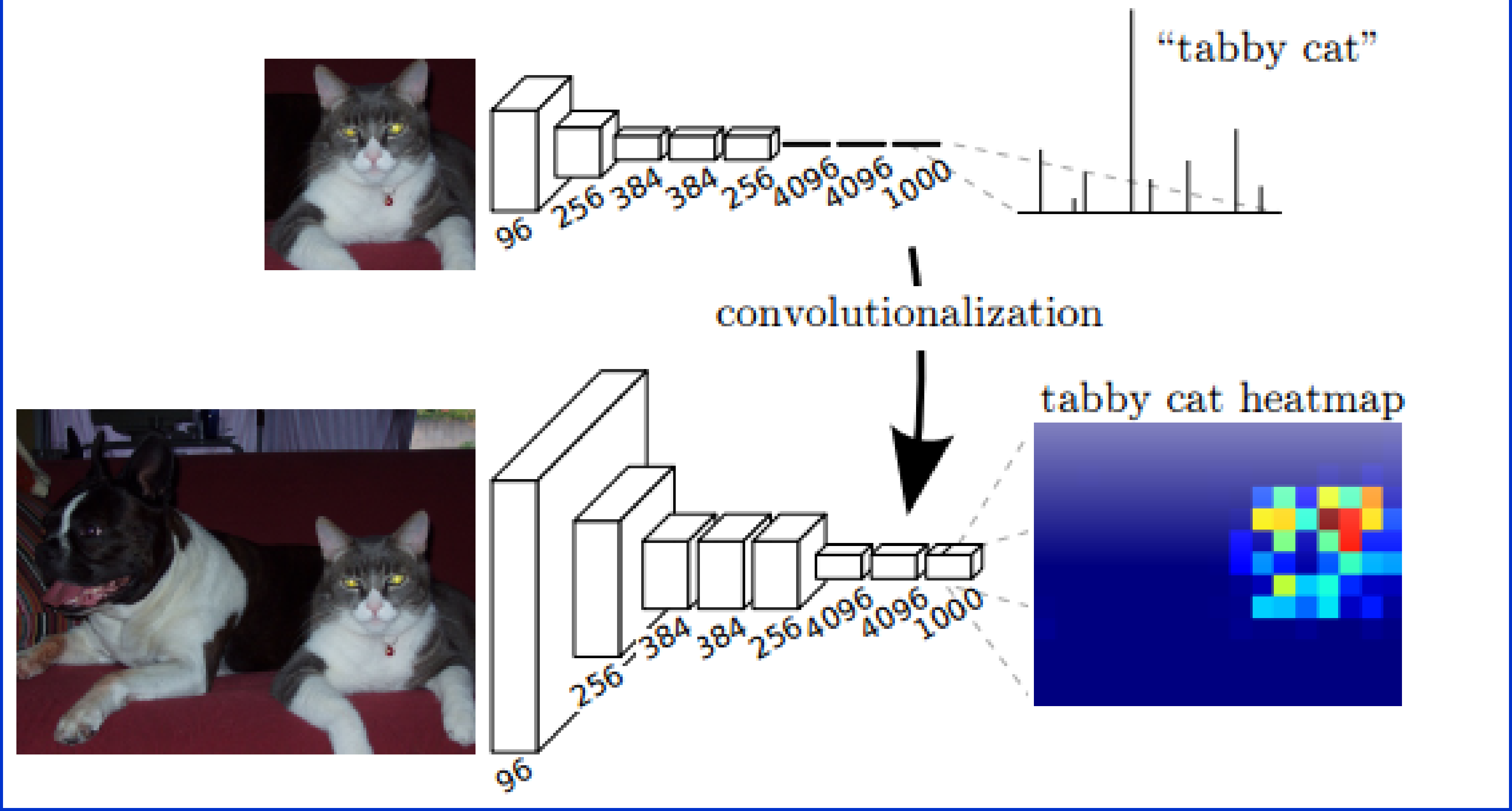
- One of the principal applications of watershed segmentation is in the extraction of nearly uniform objects form the background.
- Regions characterized by small variations in gray levels have small gradient values,
- In practice, we often see watershed segmentation applied to the gradient of an image.

The Evolution of Object Detection Tasks



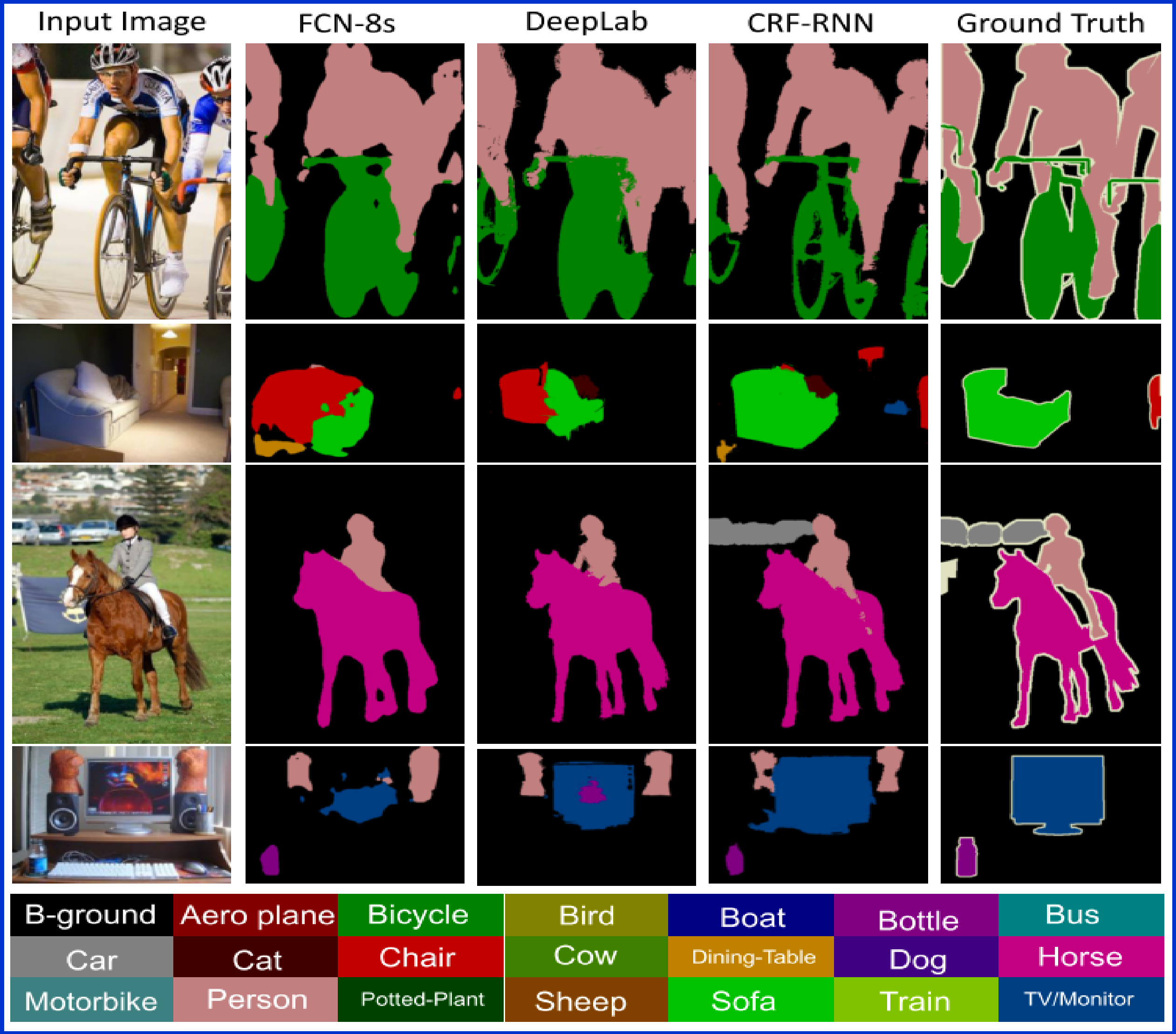
10.6 object segmentation

1. FCN (Fully Convolutional Networks for Semantic Segmentation)[1]



10.6 object segmentation

1. FCN (Fully Convolutional Networks for Semantic Segmentation)[1]



10.6 object segmentation

2. Mask R-CNN[2]

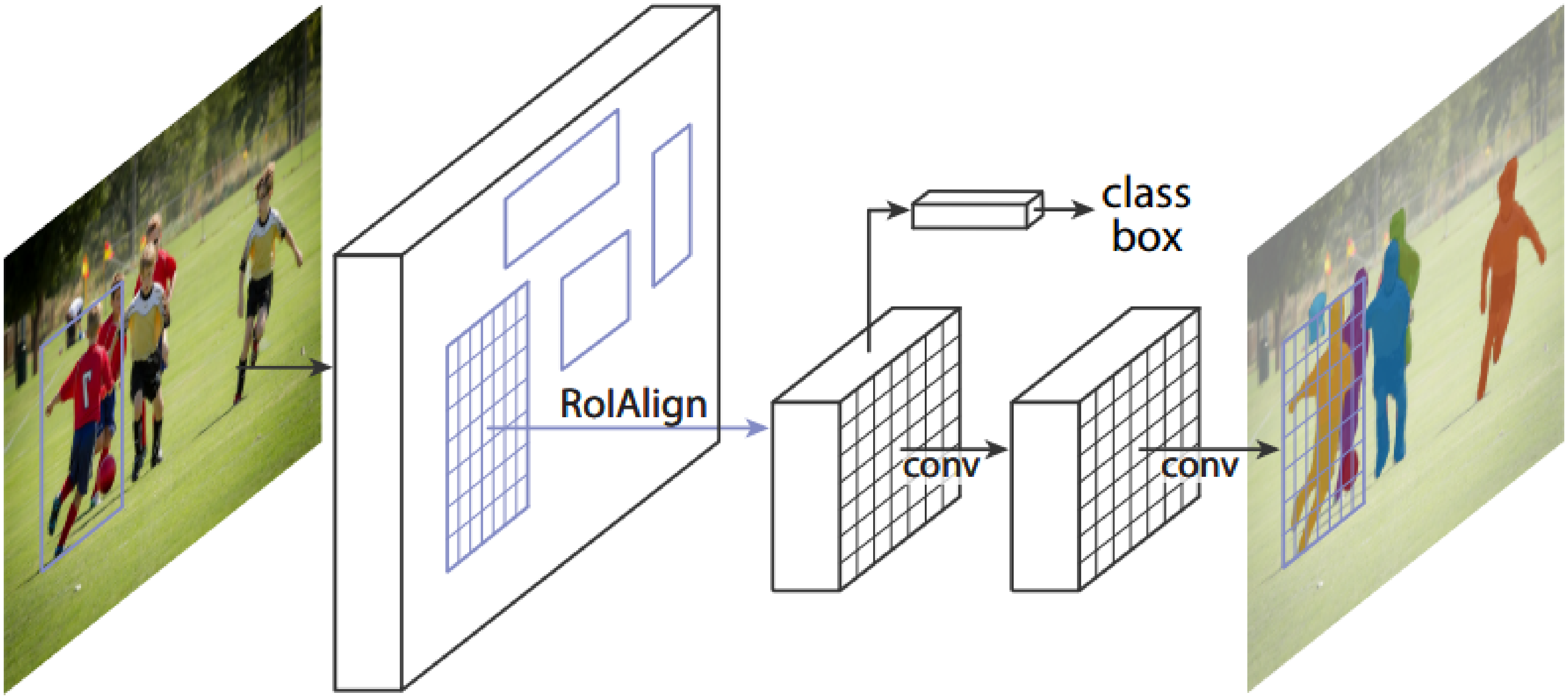


Figure 1. The **Mask R-CNN** framework for instance segmentation.

10.6 object segmentation

2. Mask R-CNN[2]

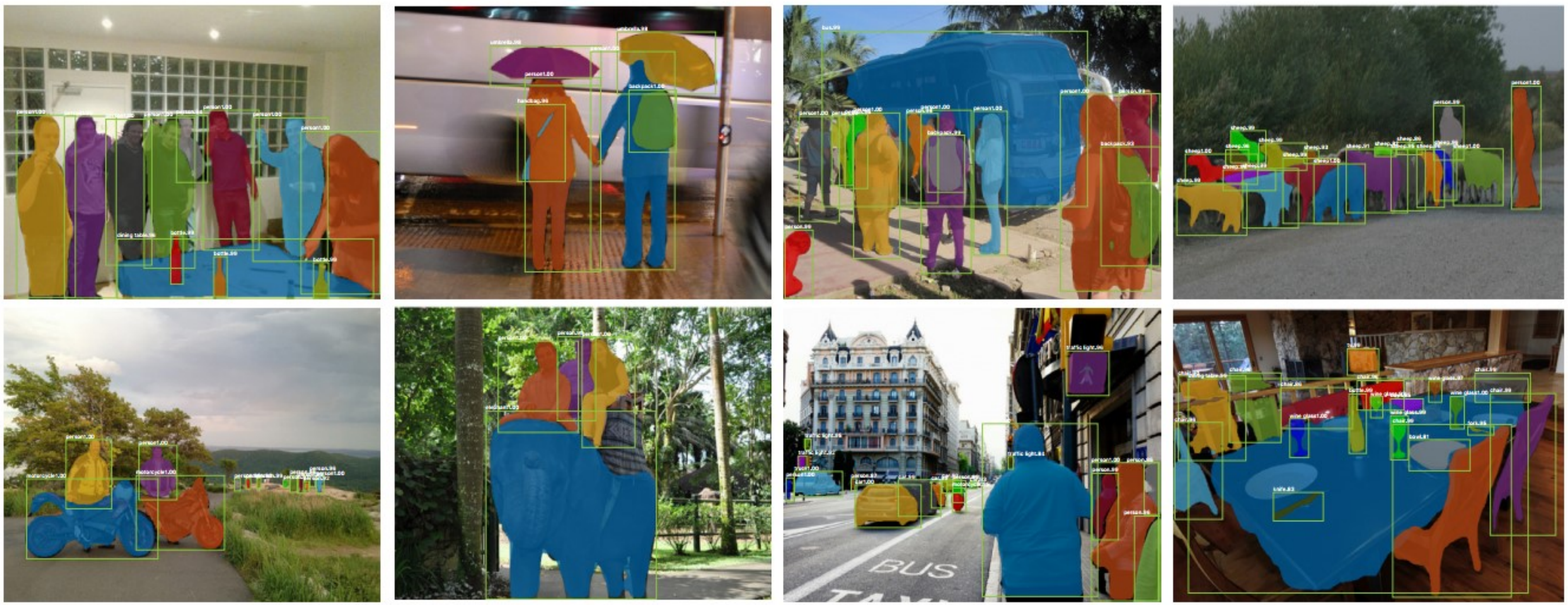


Figure 2. **Mask R-CNN** results on the COCO test set. These results are based on ResNet-101 [19], achieving a *mask* AP of 35.7 and running at 5 fps. Masks are shown in color, and bounding box, category, and confidences are also shown.

10.6 object segmentation

What has deep networks leant

Visualization of hidden neurons in deep networks

10.6 object segmentation

What has deep networks leant

Deep networks have arranged concepts in a map with similar concepts in proximal areas

10.6 object segmentation

1. Long J, Shelhamer E, Darrell T. Fully convolutional networks for semantic segmentation[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2015: 3431-3440.

2. He K, Gkioxari G, Dollár P, et al. Mask r-cnn[C]//Computer Vision (ICCV), 2017 IEEE International Conference on. IEEE, 2017: 2980-2988.