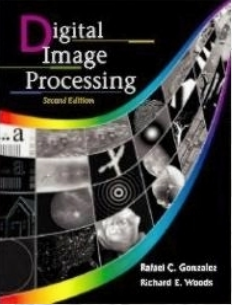


Chapter 11

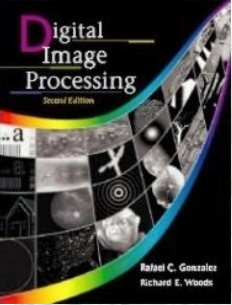
Representation & Description

- Image segmented into regions, how to represent and describe these regions?
 - 1) In terms of its external characteristics (boundary)
 - 2) In terms of its internal characteristics (pixels in the region)



11.1 Representation – Chain code

- **Chain codes** are used to represent a **boundary** as a connected sequence of straight line segments of specified length and direction.
- The representation is based on 4- or 8- connectivity.
- Chain code is generated by following a boundary in clockwise direction and assigning a direction to the segments connecting every pair of pixels.
- Disadvantages of chain codes:
 - 1) The chain code is quite long
 - 2) Any small disturbance along the boundary due to noise cause change in the code that may not related to the shape of the boundary.

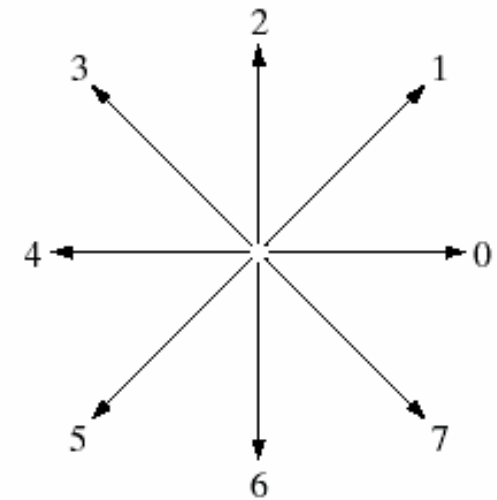
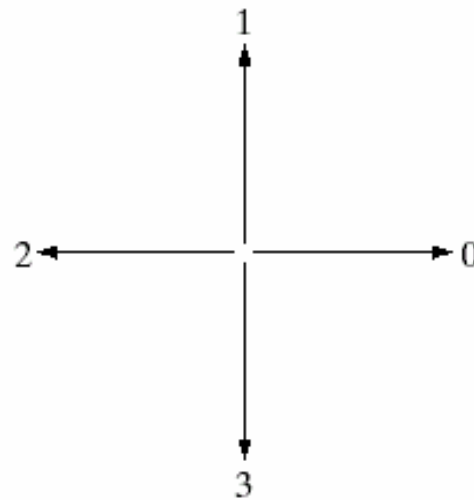


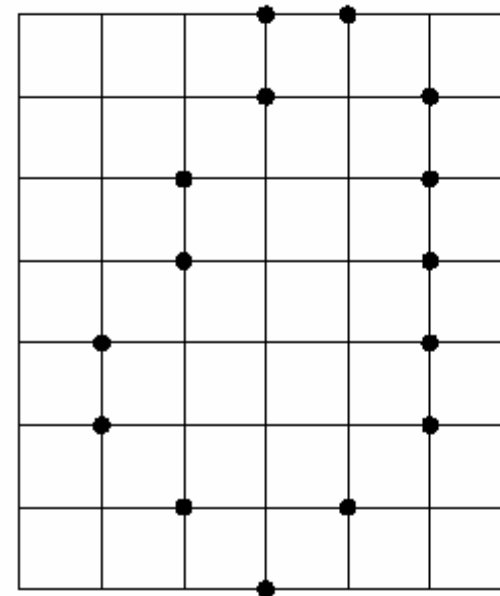
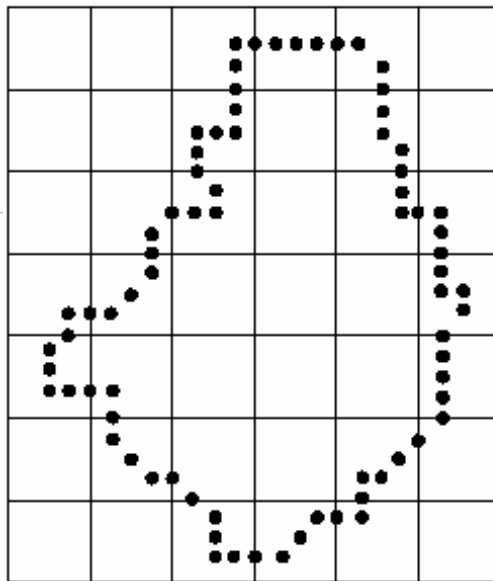
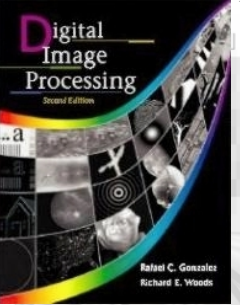
11.1 Representation – Chain code

a b

FIGURE 11.1

Direction numbers for (a) 4-directional chain code, and (b) 8-directional chain code.

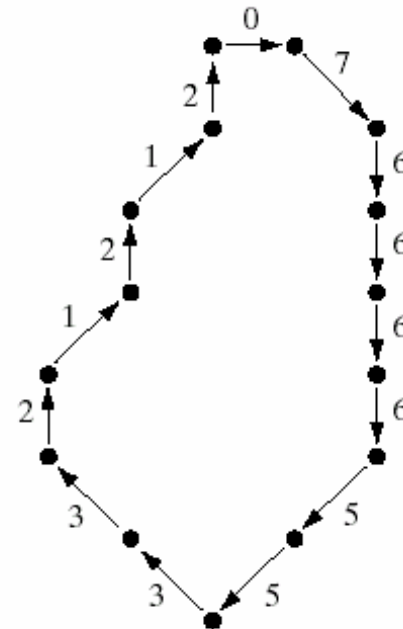
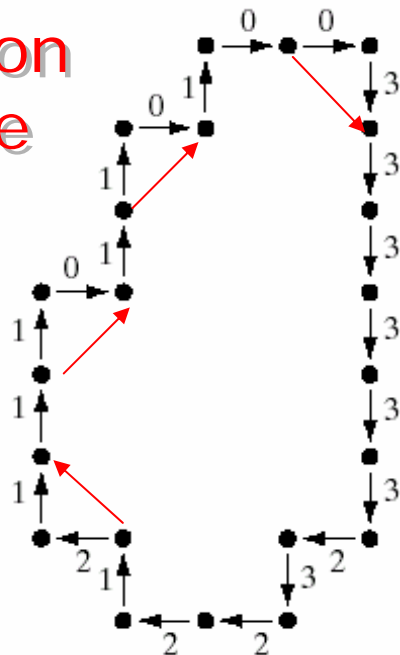


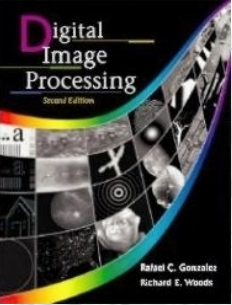


a	b
c	d

FIGURE 11.2
 (a) Digital boundary with resampling grid superimposed.
 (b) Result of resampling.
 (c) 4-directional chain code.
 (d) 8-directional chain code.

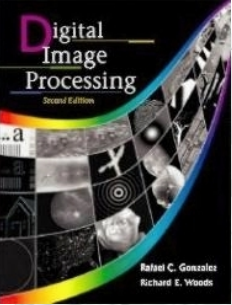
11.1 Representation – chain code





11.1 Representation – Chain code

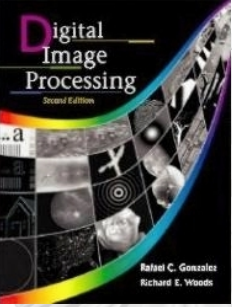
- The chain code of a boundary depends on the ***starting point***.
- ***Normalize*** the chain code by using the first difference of the chain code.
- ***Example***: the chain code is 10103322, the first difference is 3133030 or **3**3133030, the 1st “3” is obtained by connecting the last and the first element of the chain.
- ***Size normalization*** can be obtained by alternating the size of the sampling grid.



11.1 Representation - Polygon approximation

- **Minimum perimeter polygons**

- Enclose the boundary by a set of concatenated cells (Fig. 11.3).
- The enclosure has two walls corresponding to the inside and outside boundaries of the strip of cell.
- Think of the object boundary as a **rubber band** contained within the wall.
- The rubber band shrinks and produces a polygon of minimum perimeter that fit the geometry established by the cell strip.

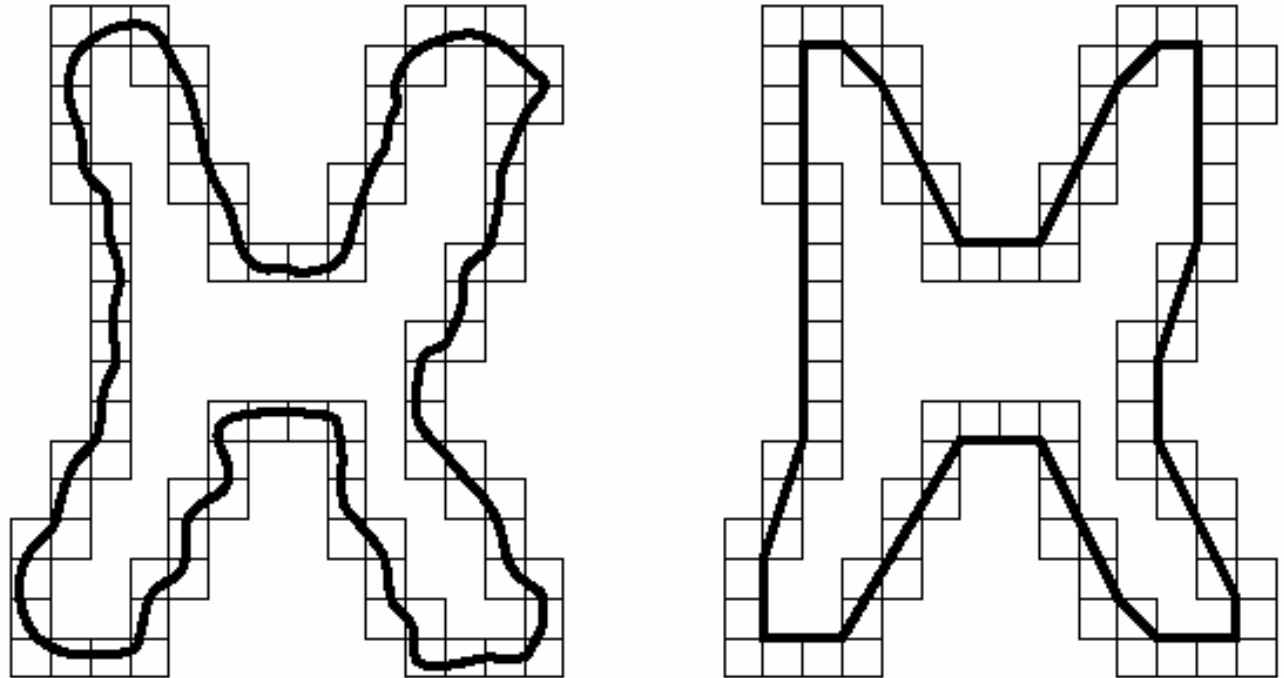


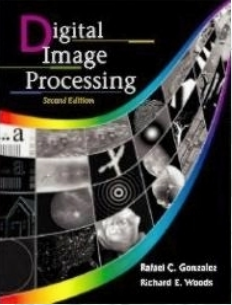
11.1 Representation - Polygon approximation

a b

FIGURE 11.3

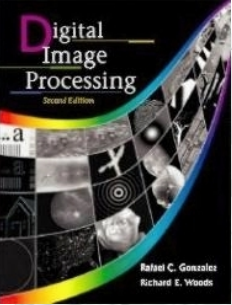
(a) Object boundary enclosed by cells.
(b) Minimum perimeter polygon.





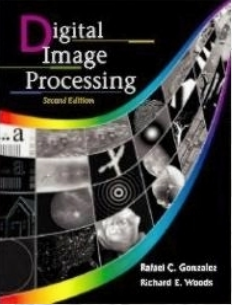
11.1 Representation - Polygon approximation

- **Merging technique**
 - Merge points along the boundary until the least square error line fit of the points merged so far exceeds a preset threshold.
 - Difficulties: the vertices do not always correspond to inflections (corners) in the original boundary.

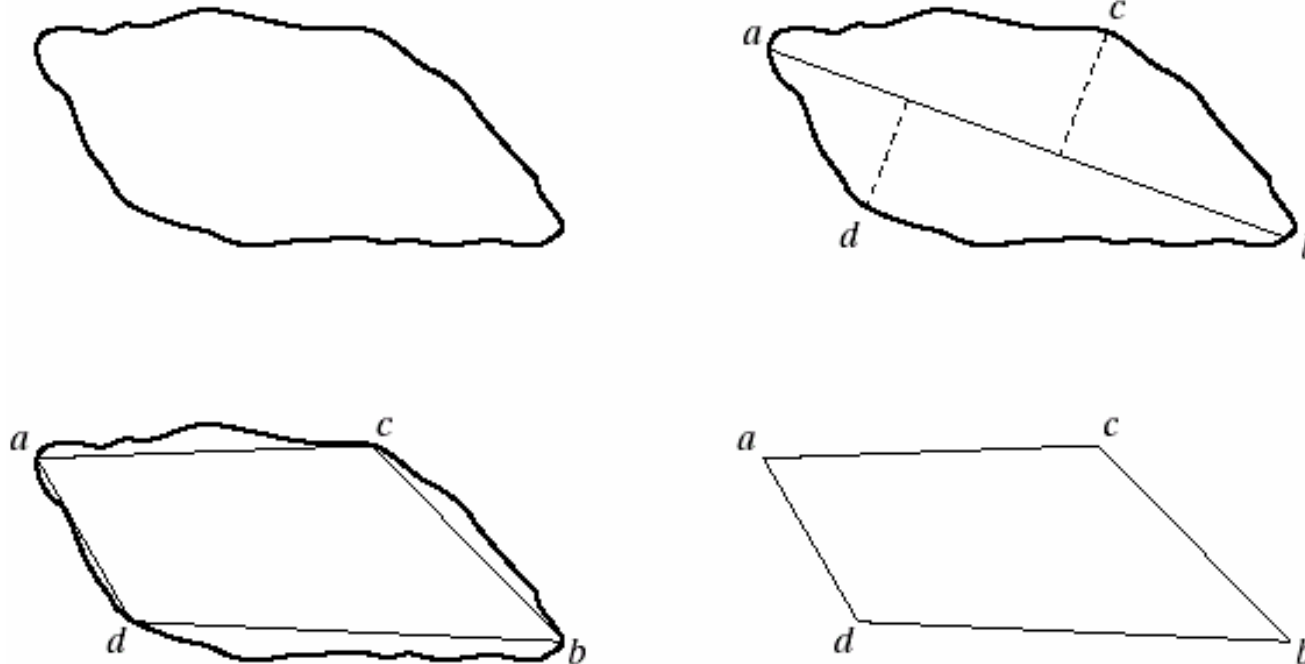


11.1 Representation Polygon approximation

- ***Splitting techniques:***
- Subdivide a segment successively into two parts until a specified criterion is satisfied.
- The maximum **perpendicular distance** from a boundary segment to the line joining its two end points not exceed a preset threshold.
- If it does, the farthest point from the line become a vertex, thus subdivide the segment into two sub-segments,
- This approach has the advantage in seeking prominent inflection points

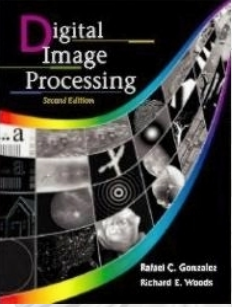


11.1 Representation - Polygon approximation



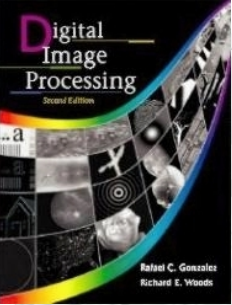
a	b
c	d

FIGURE 11.4
 (a) Original boundary.
 (b) Boundary divided into segments based on extreme points. (c) Joining of vertices. (d) Resulting polygon.



11.1 Representation - Polygon approximation

- **Signature**
- 1-D functional representation of a boundary.
 - 1) Plot the **distance** from the centroid to the boundary as a function of angles (Fig. 11.5), *i. e.*, $r(\theta)$.
 - Invariant to translation, but depend on the rotation and scaling.
 - Normalizing with respect to rotation.
 - Select the starting point as the point farthest to the centroid.
 - 2) Traverse the boundary and plot the **angle** between a line tangent to the boundary at that point and a reference line. Then use the **Slope density function**: (**histogram** of tangent-angle values) as signature.



11.1 Representation - Polygon approximation

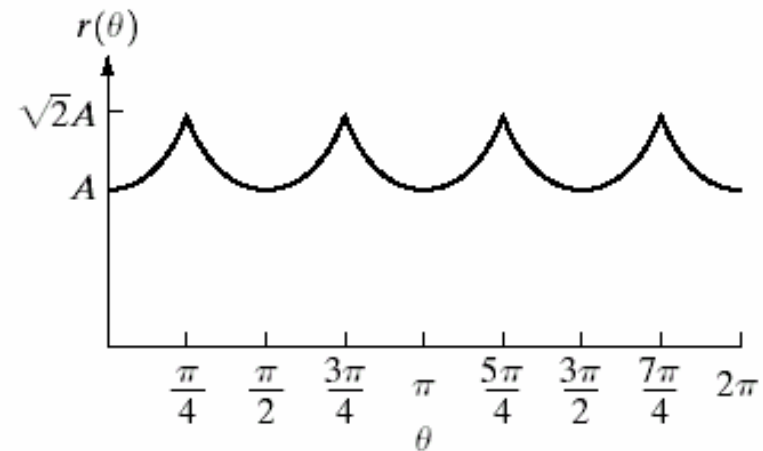
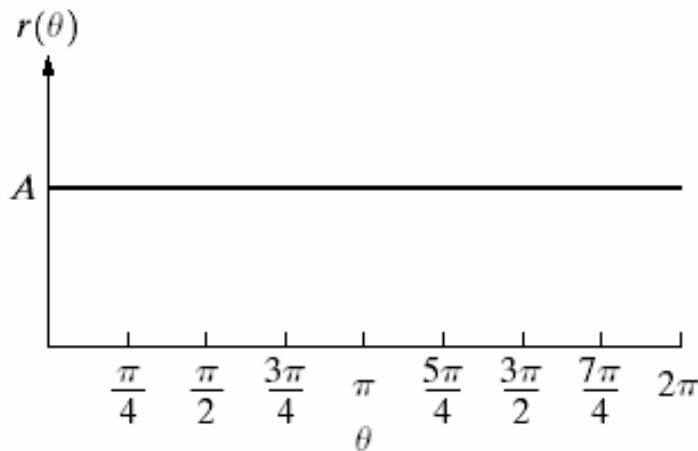
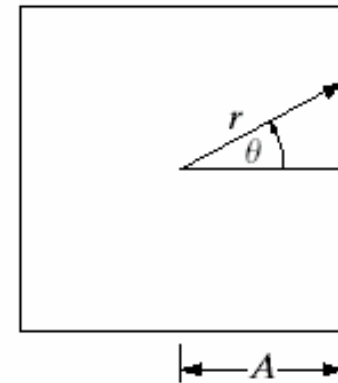
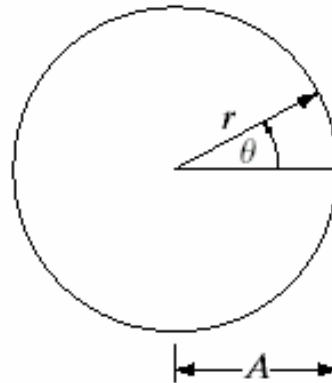
a b

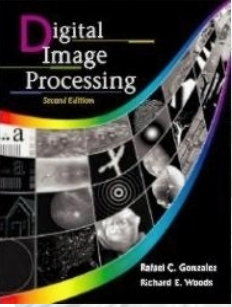
FIGURE 11.5

Distance-versus-angle signatures.

In (a) $r(\theta)$ is constant. In (b), the signature consists of repetitions of the pattern

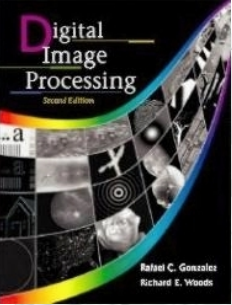
$r(\theta) = A \sec \theta$ for $0 \leq \theta \leq \pi/4$ and $r(\theta) = A \csc \theta$ for $\pi/4 < \theta \leq \pi/2$.



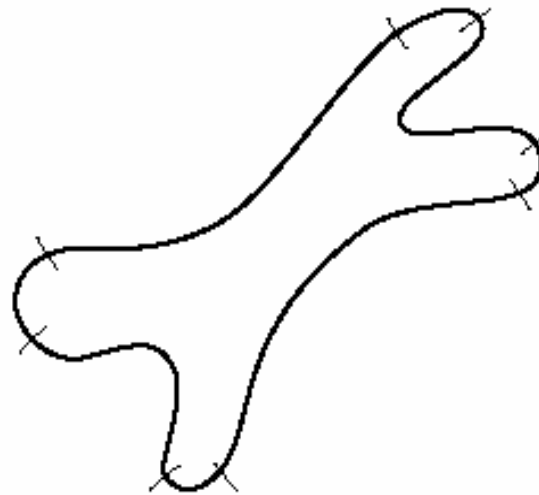
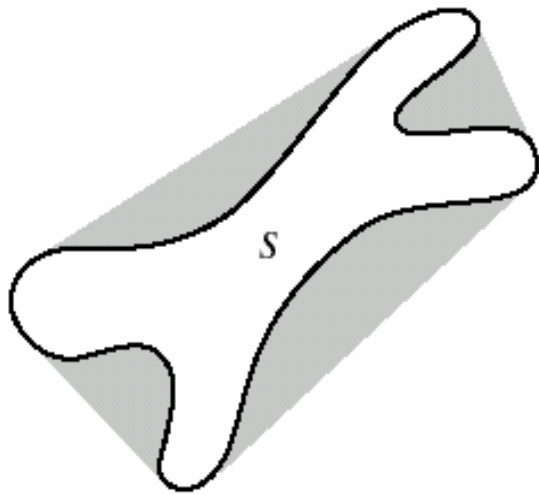


11.1 Representation-boundary segment

- Convex hull H of an arbitrary set S is the smallest convex set containing S .
- The difference $H - S$ is call *convex deficiency* D of the set S .
- The region boundary can be partitioned by following the contour of S and marking the points at which a transition is made into or out of a component of the *convex deficiency*.
- The concept of *convex hull* and its *deficiency* are equally useful for describing an *entire region*, as well as just its *boundary*.

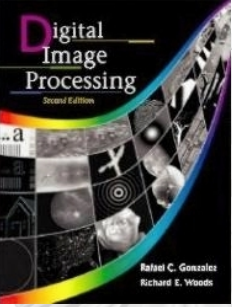


11.1 Representation-boundary segment



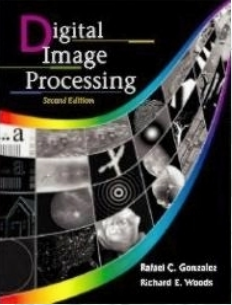
a b

FIGURE 11.6
(a) A region, S , and its convex deficiency (shaded).
(b) Partitioned boundary.

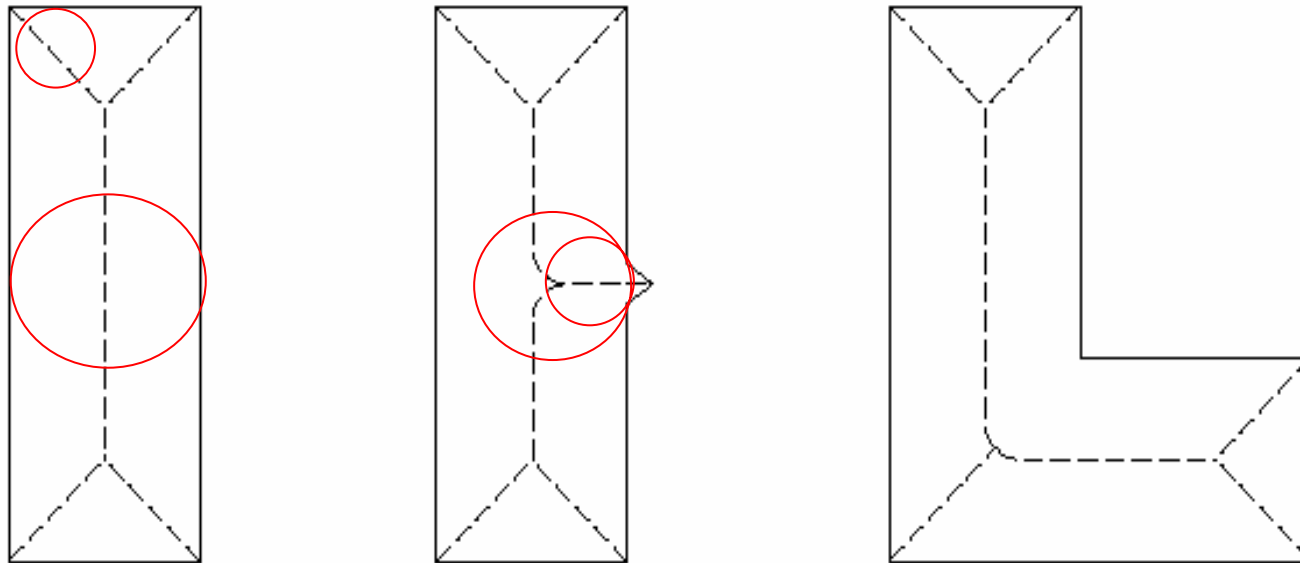


11.1 Representation - Polygon approximation

- ***Skeleton*** of a region can be obtained by ***thinning*** algorithm
- ***Medial axis transformation (MAT)***:
 - 1) For each point in region ***R***, we find its **closest neighbor** in border ***B***.
 - 2) If ***p*** has more than one such neighbor, it is said to belong to the medial axis (skeleton) of ***R***.
- ***Thinning algorithm***: iteratively delete the edge points of a region subject to
 - 1) Does not remove the end points
 - 2) Does not break connectivity
 - 3) Does not cause excessive erosion of the region.

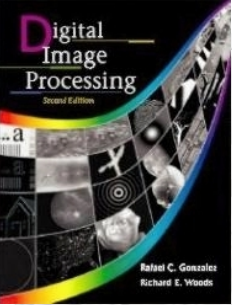


11.1 Representation - Polygon approximation



a b c

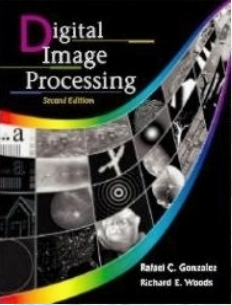
FIGURE 11.7
Medial axes
(dashed) of three
simple regions.



11.1 Representation - Polygon approximation

p_9	p_2	p_3
p_8	p_1	p_4
p_7	p_6	p_5

FIGURE 11.8
Neighborhood arrangement used by the thinning algorithm.



11.1 Representation - Polygon approximation

- **Thinning algorithm**

Step 1) flag a contour point p_1 for deletion if the following conditions are satisfied:

a) $2 \leq N(p_1) \leq 6$, where $N(p_1)$ is the number of neighbors of p_1 .

b) $T(p_1) = 1$, where $T(p_1)$ is number of 0-1 transitions in the ordered sequence $p_2, p_3, \dots, p_8, p_9, p_2$

c) $p_2 \bullet p_4 \bullet p_6 = 0$

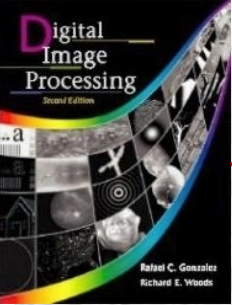
d) $p_4 \bullet p_6 \bullet p_8 = 0$

If all conditions are satisfied, the point is flagged for deletion.

Step 2) Conditions (c) and (d) changed to

c') $p_2 \bullet p_4 \bullet p_8 = 0$

d') $p_2 \bullet p_6 \bullet p_8 = 0$



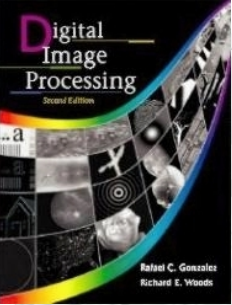
11.1 Representation - Polygon approximation

- **Thinning algorithm**

- 1) Apply step 1 to flag border points for deletion
- 2) Deleting the flagged point
- 3) Apply step 2 to flag the remaining border points for deletion.
- 4) Delete the flagged points

The basic procedure is applied iteratively until no further points are deleted.

- Condition (a) is violated when p_1 is the end point of a skeleton stroke.
- Condition (b) is violated when it is applied to points on stroke 1 pixel thick.

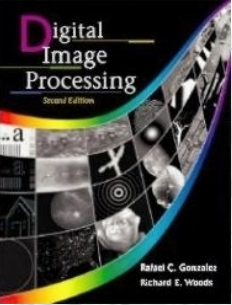


11.1 Representation - Polygon approximation

FIGURE 11.9

Illustration of conditions (a) and (b) in Eq. (11.1-1). In this case $N(p_1) = 4$ and $T(p_1) = 3$.

0	0	1
1	p_1	0
1	0	1



11.1 Representation - Polygon approximation

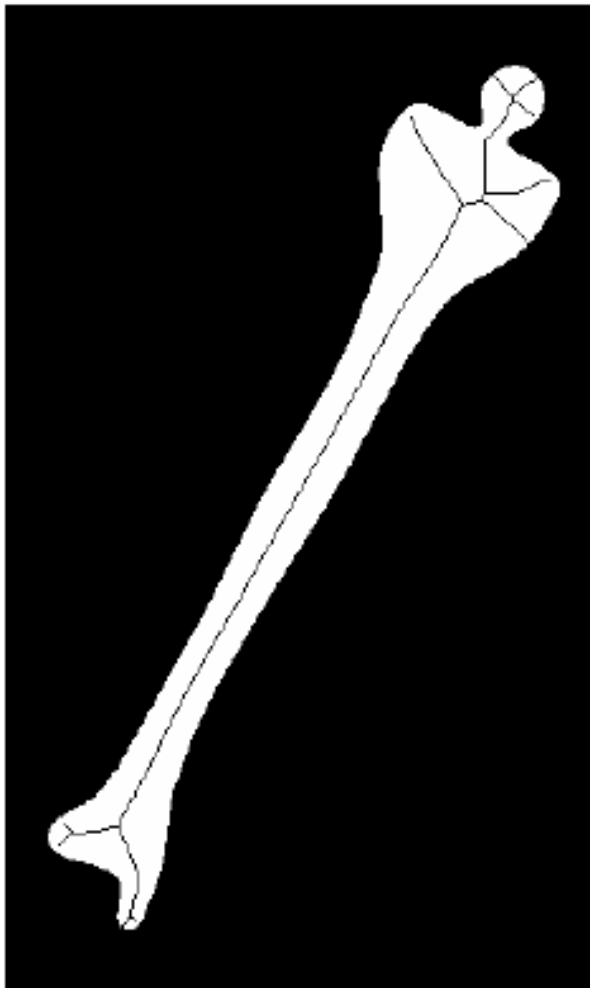
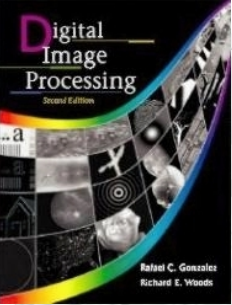


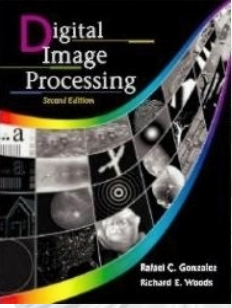
FIGURE 11.10
Human leg bone
and skeleton of
the region shown
superimposed.



11.2 Boundary descriptor

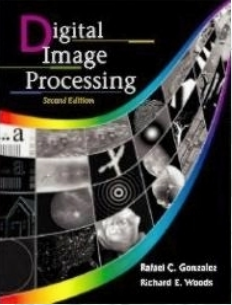
- Simple descriptors

- 1) Length
- 2) Diameter: $\text{Diam}(B) = \max[D(p_i, p_j)]$ where p_i and p_j are points on the boundary.
- 3) Major axis and minor axis
- 4) Basic rectangle
- 5) Eccentricity = major axis/minor axis
- 6) Curvature: changes of slope.
- 7) Point p belongs to a segment which is convex if the change of slope at p is nonnegative and concave otherwise.
- 8) P is a *corner* depends on the curvature.



11.2 Boundary Description - shape number

- The *first difference* of a chain-coded boundary depends on the starting point.
- The *shape number* of a chain coded boundary is defined as the first difference of smallest magnitude.
- The *difference* of a chain code is independent of its rotation, it depends on the orientation of the grid.
- The order n of a shape number is defined as the number of digits in its representation.



11.2 Boundary Description- shape number

Order 4

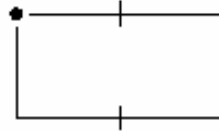


Chain code: 0 3 2 1

Difference: 3 3 3 3

Shape no.: 3 3 3 3

Order 6

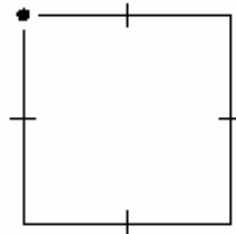


Chain code: 0 0 3 2 2 1

Difference: 3 0 3 3 0 3

Shape no.: 0 3 3 0 3 3

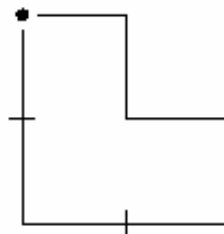
Order 8



Chain code: 0 0 3 3 2 2 1 1

Difference: 3 0 3 0 3 0 3 0

Shape no.: 0 3 0 3 0 3 0 3



Chain code: 0 3 0 3 2 2 1 1

Difference: 3 3 1 3 3 0 3 0

Shape no.: 0 3 0 3 3 1 3 3

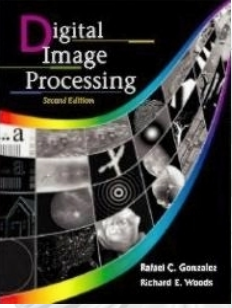


Chain code: 0 0 0 3 2 2 2 1

Difference: 3 0 0 3 3 0 0 3

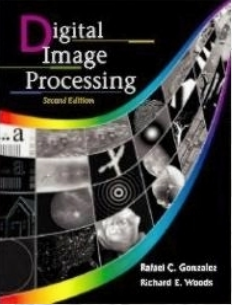
Shape no.: 0 0 3 3 0 0 3 3

FIGURE 11.11 All shapes of order 4, 6, and 8. The directions are from Fig. 11.1(a), and the dot indicates the starting point.



11.2 Boundary Description- shape number

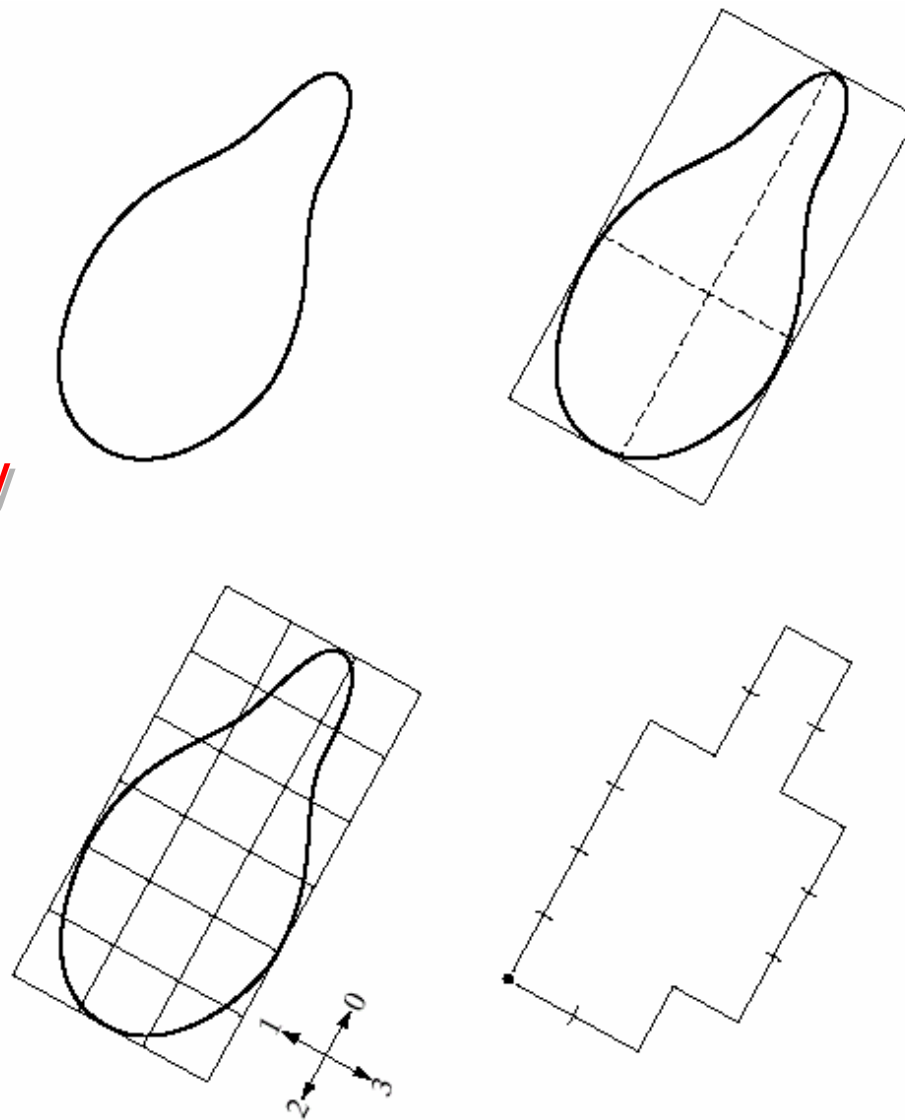
- Example (Fig. 11.12)
- 1. Find the basic rectangle for $n=18$ (boundary)
- 2. Find the major and minor axis
- 3. Find the closest rectangle of order 18 is 3×6
- 4. obtain chain code
- 5. find the difference
- 6. find the shape no.



11.2 Boundary Description

a b
c d

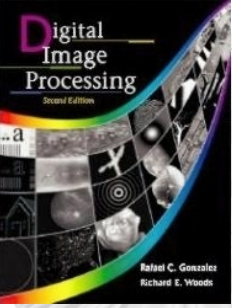
FIGURE 11.12
Steps in the generation of a shape number.



Chain code: 0 0 0 0 3 0 0 3 2 2 3 2 2 2 1 2 1 1

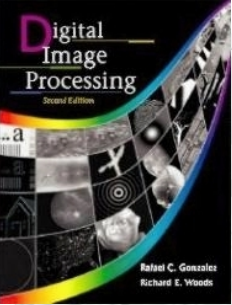
Difference: 3 0 0 0 3 1 0 3 3 0 1 3 0 0 3 1 3 0

Shape no.: 0 0 0 3 1 0 3 3 0 1 3 0 0 3 1 3 0 3



11.2 Boundary Description–Fourier Descriptor

- For a K -point digital boundary, starting at an arbitrary point (x_0, y_0) , K coordinate pairs (x_0, y_0) , (x_{01}, y_{01}) , $\dots, (x_{K-1}, y_{K-1})$ are encountered in counterclockwise direction.
- Let $s(k) = [x(k), y(k)]$ for $k=0, 1, \dots, K-1$,
or $s(k) = x(k) + jy(k)$
- The 1-D DFT of $s(k)$ is $a(u) = \frac{1}{K} \sum_{k=0}^{K-1} s(k) e^{-j2\pi uk/K}$
- The inverse DFT of $a(u)$ is $s(k) = \frac{1}{K} \sum_{k=0}^{K-1} a(u) e^{j2\pi uk/K}$



11.2 Boundary Description- Fourier Descriptor

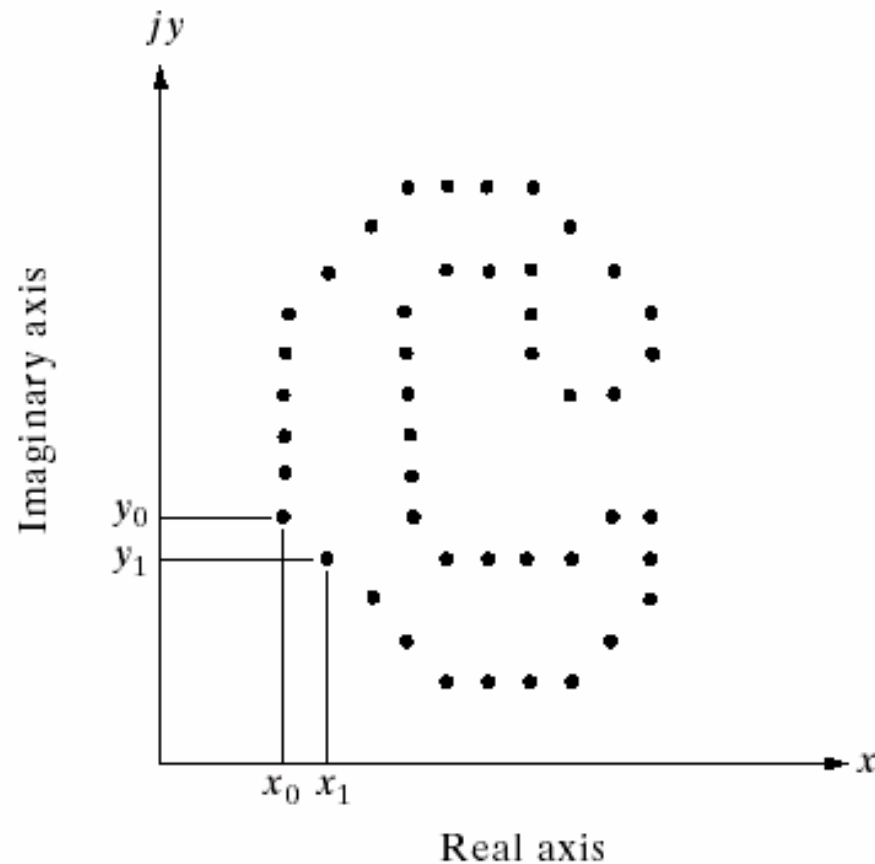
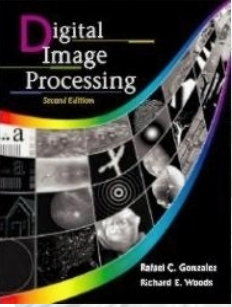


FIGURE 11.13 A digital boundary and its representation as a complex sequence. The points (x_0, y_0) and (x_1, y_1) shown are (arbitrarily) the first two points in the sequence.



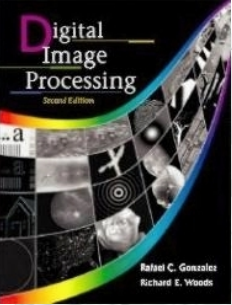
11.2 Boundary Description - Fourier Descriptor

- If only the first P coefficients ($P < K$) are used then

$$\hat{s}(k) = \sum_{u=0}^{P-1} a(u) e^{j2\pi uk / K}$$

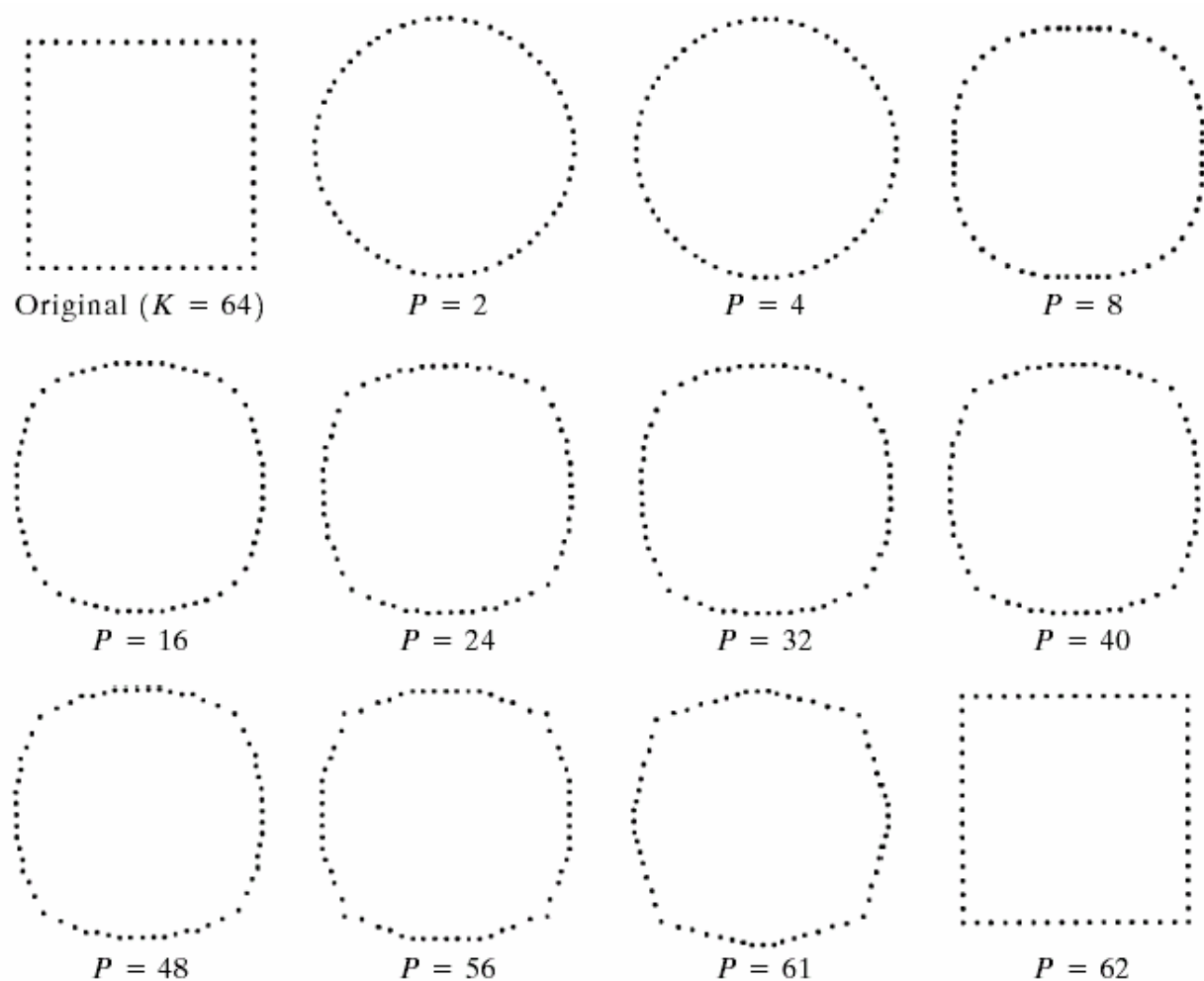
- The coefficients $\{a(u)\}$ carry shape information which are insensitive to translation, rotation, and scale change of the shape.
- The descriptors are insensitive to the change of starting point.
- Rotation of a point by an angle θ about the origin of the complex plane is accomplished by multiplying the point by $e^{j\theta}$.
- The rotated sequence $s(k)e^{j\theta}$ whose Fourier descriptors are

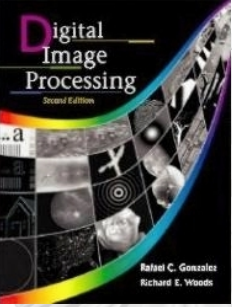
$$a_r(u) = \frac{1}{K} \sum_{k=0}^{K-1} s(k) e^{j\theta} e^{-j2\pi uk / K} = a(u) e^{j\theta}$$



11.2 Boundary Description - Fourier-Descriptor

FIGURE 11.14
Examples of reconstruction from Fourier descriptors. P is the number of Fourier coefficients used in the reconstruction of the boundary.





11.2 Boundary Description -Fourier-Descriptor

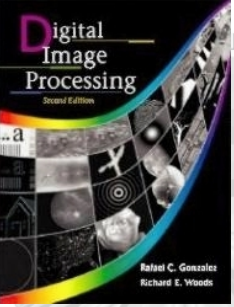
Transformation	Boundary	Fourier Descriptor
Identity	$s(k)$	$a(u)$
Rotation	$s_r(k) = s(k)e^{j\theta}$	$a_r(u) = a(u)e^{j\theta}$
Translation	$s_t(k) = s(k) + \Delta_{xy}$	$a_t(u) = a(u) + \Delta_{xy}\delta(u)$
Scaling	$s_s(k) = \alpha s(k)$	$a_s(u) = \alpha a(u)$
Starting point	$s_p(k) = s(k - k_0)$	$a_p(u) = a(u)e^{-j2\pi k_0 u / K}$

TABLE 11.1
Some basic properties of Fourier descriptors.

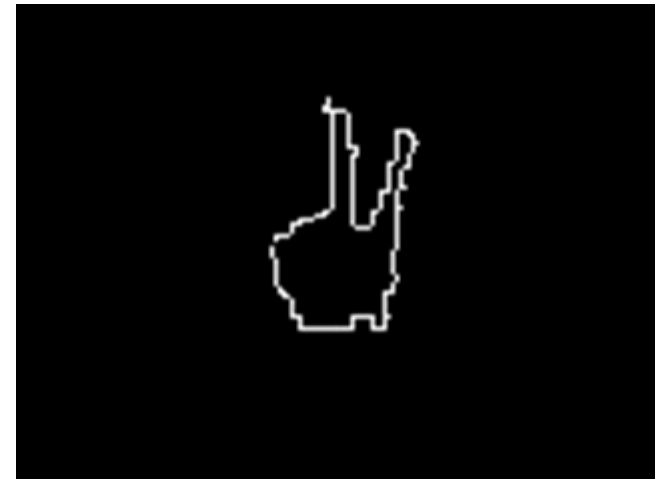
1) Translation: $s_t(k) = s(k) + \Delta_{xy} = [x(k) + \Delta x] + j[y(k) + \Delta y]$

2) Change the starting point of the sequence to $k = k_0$ from $k = 0$ as

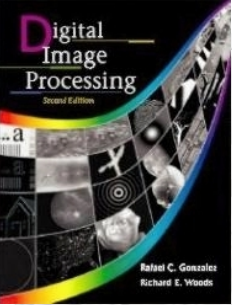
$$s_p(k) = s(k - k_0) = x(k - k_0) + j y(k - k_0)$$



11.2 Boundary Description – Fourier Descriptor



The contour of hand silhouette.



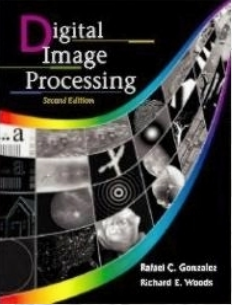
11.2 Fourier Descriptor

- Fourier series of a sequence of points $\{x(m), y(m)\}$ can be defined as

$$x(m) = \sum a(n)e^{j2\pi nm/N} \quad y(m) = \sum b(n)e^{j2\pi nm/N}$$

where $a(n)$ and $b(n)$ are the Fourier coefficient

$$a(n) = \sum_{m=1}^N x(m)e^{-j2\pi nm/N} \quad b(n) = \sum_{m=1}^N y(m)e^{-j2\pi nm/N}$$

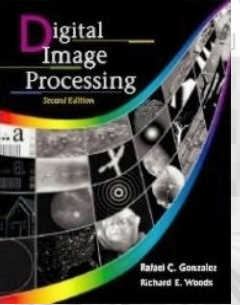


11.2 Fourier Descriptor

- Assuming local variation of hand shape is smooth so that the higher order terms of the Fourier descriptor are not necessary.
- To normalize the size of hand gesture we let $S(n)=r(n)/r(1)$ (normalization), and we have

$$r(n) = \sqrt{|a(n)|^2 + |b(n)|^2} \quad n=1,2,\dots,22$$

- Using 22 harmonics of the FD's coefficient, $S(n)$, is enough to describe the macroscopic information of the hand shape.
- FD is translation, rotation, and scaling invariance.



11.2 Fourier Descriptor

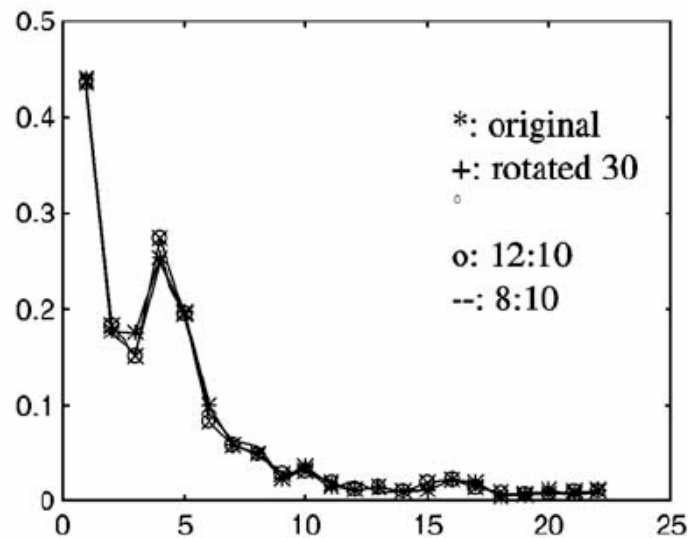


(a) Original image

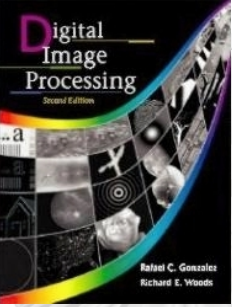
(b) Rotation 90°

(c) Zoom in 12:10

(d) Zoom out 8:10

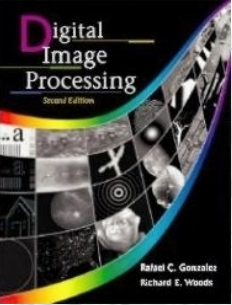


(e) Fourier descriptor vectors of the four different shapes without the first term.



11.2 Boundary Description -Statistical moment

- The shape of boundary segments can be described quantitatively by using simple statistical moments such as *mean*, *variance*, and *higher-order moments*.
- Figure 11.5 represented as 1-D function $g(r)$.
- Treat the amplitude of g as a discrete random variable v and form an amplitude histogram $p(v_i)$, $i=0, 1, \dots, A-1$, where A is the number of discrete amplitude increments in which we divide the amplitude scale.



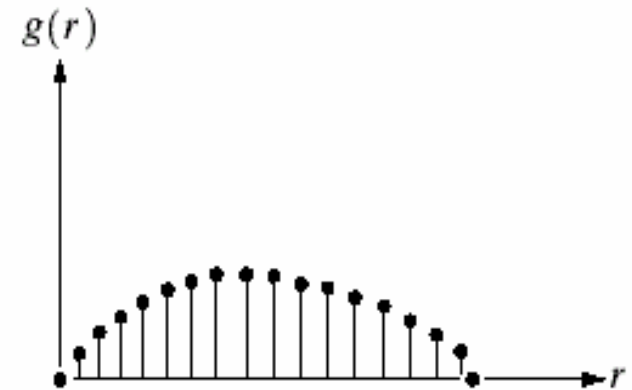
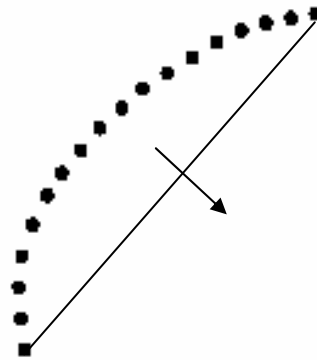
11.2 Boundary Description -Statistical moment

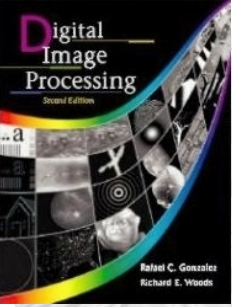
a b

FIGURE 11.15

(a) Boundary segment.

(b) Representation as a 1-D function.





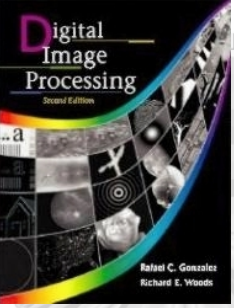
11.2 Boundary Description -Statistical moment

- The n th moment of v about its mean m is

$$\mu_n(v) = \sum_{i=0}^{A-1} (v_i - m)^n p(v_i)$$

where the mean is $m = \sum_{i=0}^{A-1} v_i p(v_i)$

- The m is the mean and μ_2 is the variance.



11.2 Boundary Description -Statistical moment

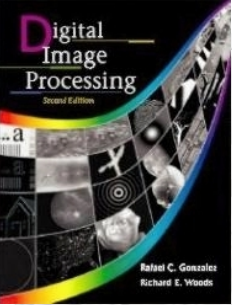
- An alternative approach is normalize $g(r)$ to unit area and treat it as histogram.
- $g(r_i)$ is treated as the probability of value r_i occurring.
- The moments are
$$\mu_n(r) = \sum_{i=0}^{K-1} (r_i - m)^n g(r_i)$$

where
$$m = \sum_{i=0}^{K-1} r_i g(r_i)$$

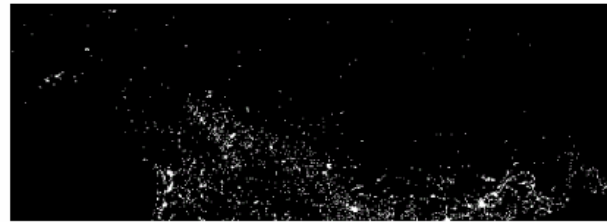


11.3 Regional Descriptors -Simple Descriptor

- Area is the number of pixels in the regions
- Perimeter is the length of the boundary.
- Compactness= $(\text{perimeter})^2/\text{area}$.



11.3 Regional Descriptors



Region no. (from top)	Ratio of lights per region to total lights
1	0.204
2	0.640
3	0.049
4	0.107

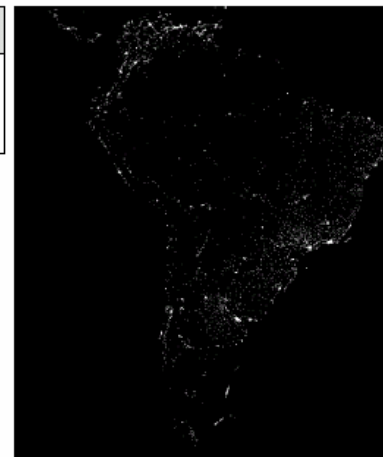
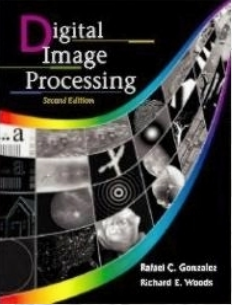
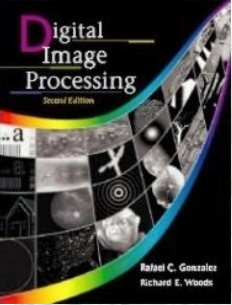


FIGURE 11.16 Infrared images of the Americas at night. (Courtesy of NOAA.)



11.3 Regional Descriptors -Topological Descriptor

- Topology is the study of properties of a figure that are unaffected by any deformation (rubber-sheet distortion).
- The number of *holes*: H
- The number of *connected components*: C
- *Euler number* E : $E=C-H$.



11.3 Regional Descriptors -Topological Descriptor

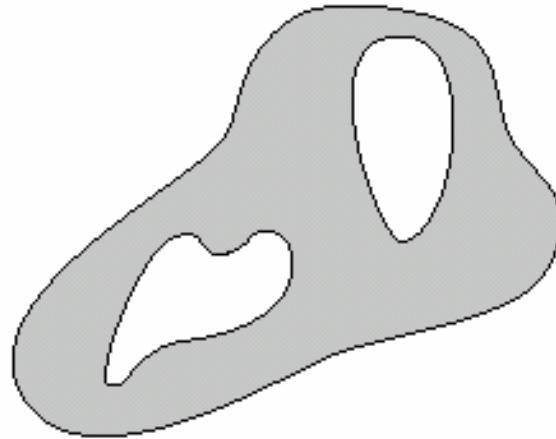


FIGURE 11.17 A region with two holes.

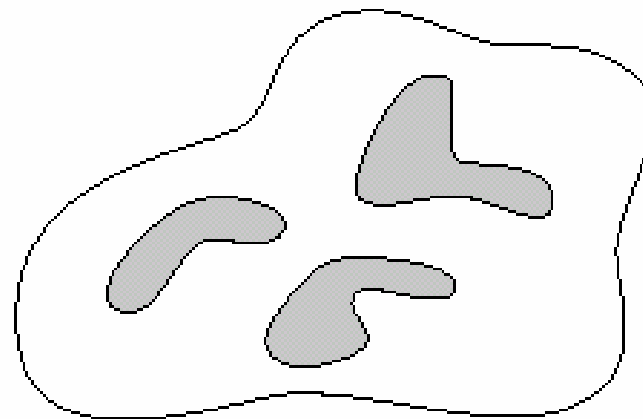
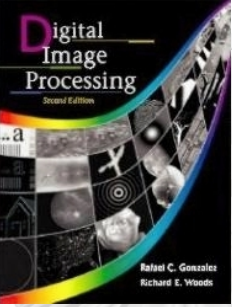


FIGURE 11.18 A region with three connected components.



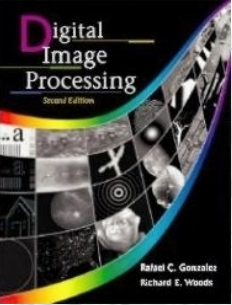
11.3 Regional Descriptors -Topological Descriptor

- Regions represented by straight-line segments (polygonal networks), such as Fig. 11.20, has the following relationship in topology as

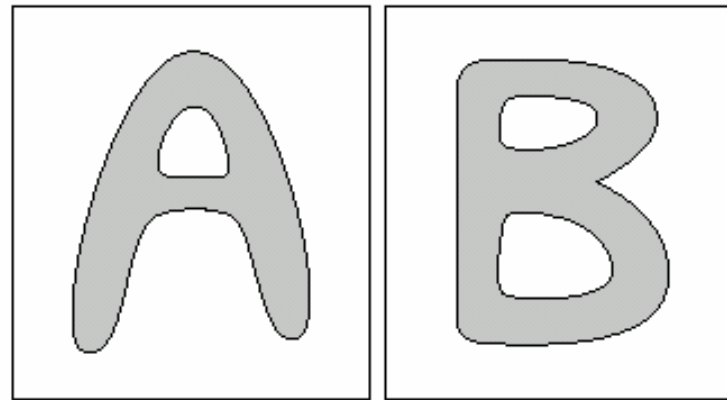
$$E = V - Q + F = C - H$$

where V is the number of vertices and Q is the number of edges.

- Segmentation is based on the thresholding.
- How the connected components can be used to “finish” the segmentation.
- Figure 11.21(b) has 1591 connected components, $C=1591$, and its Euler number $E=1552$, and $H=39$. Figure 11.21(c) shows the connected component with 8479 elements



11.3 Regional Descriptors -Topological Descriptor



a b

FIGURE 11.19 Regions with Euler number equal to 0 and -1 , respectively.

$$V - Q + F = C - H = E$$

$$7 - 11 + 2 = 1 - 3 = -2$$

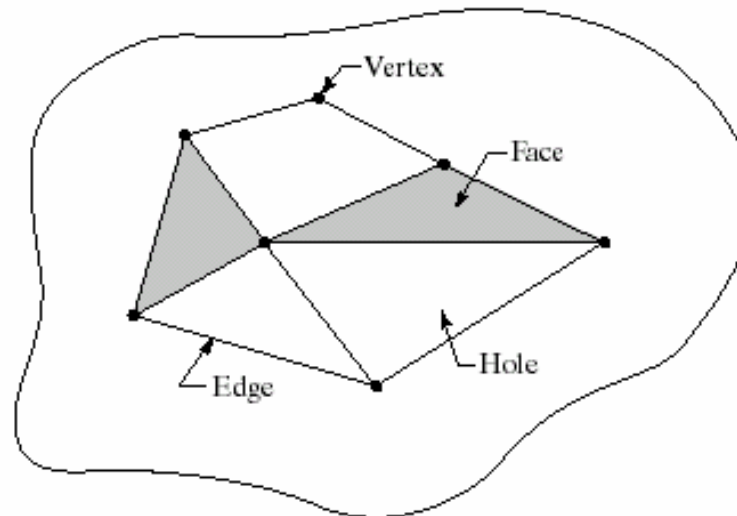
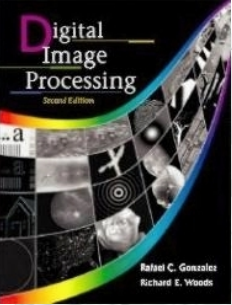
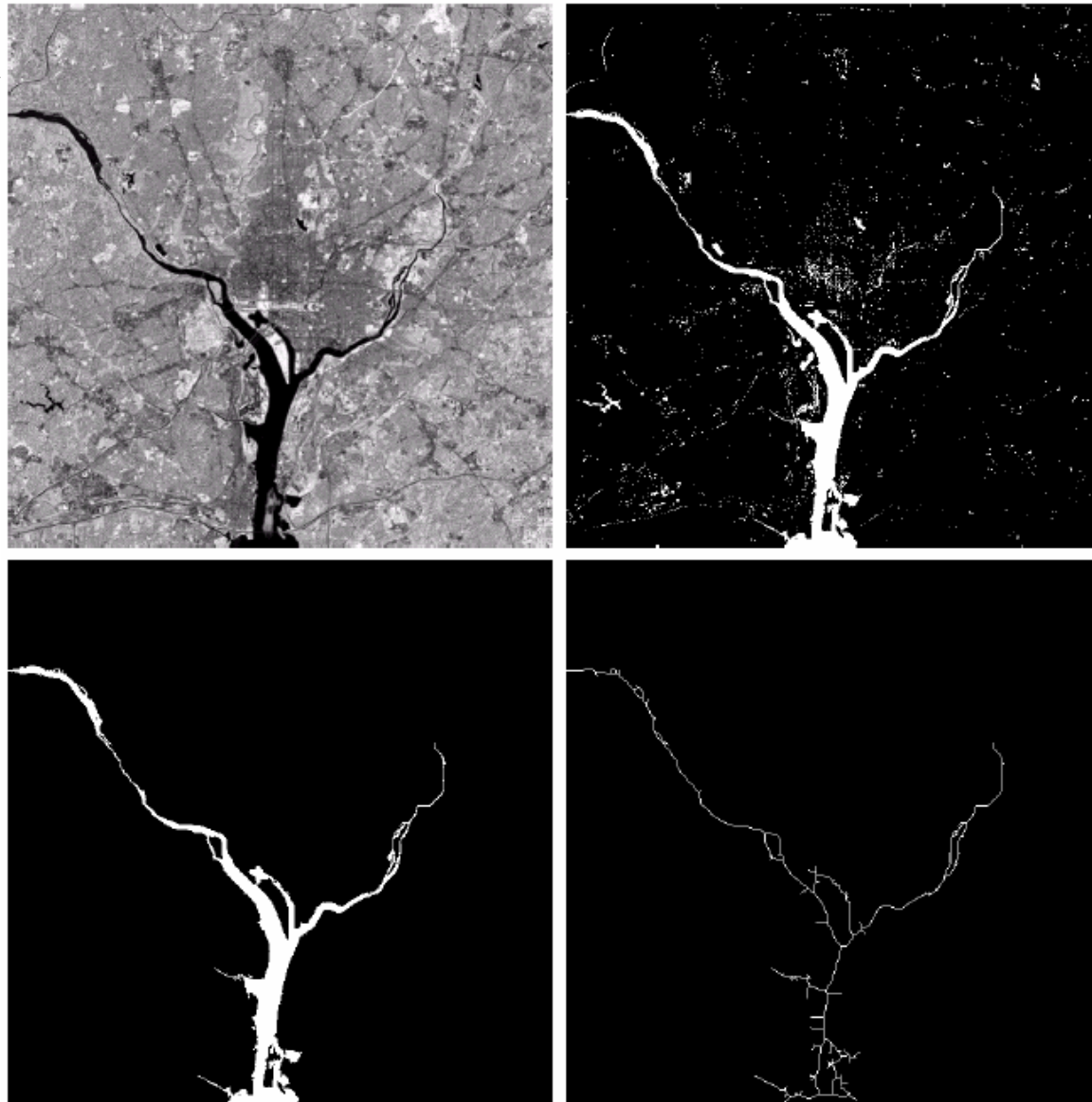


FIGURE 11.20 A region containing a polygonal network.

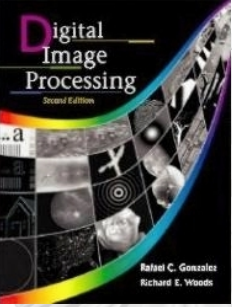


11.3 Regional Descriptors - Topological Descriptor



a	b
c	d

FIGURE 11.21
 (a) Infrared image of the Washington, D.C. area.
 (b) Thresholded image. (c) The largest connected component of (b).
 Skeleton of (c).



11.3 Regional Descriptors -Texture

- The texture measurement provides the properties such as *smoothness, coarseness, and regularity*.
- Three principal approaches: *statistical, structure, and spectral*.
- ***Statistical approaches:***

Let z be a random variable and $p(z_i)$, $i=0,1,\dots,L-1$ is the corresponding **histogram**, L is the number of gray-levels.

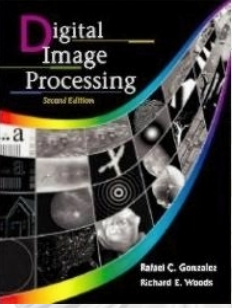
The n th moment of z about the mean (m) is

$$\mu_n(z) = \sum_{i=0}^{L-1} (z_i - m)^n g(z_i)$$

The second moment μ_2 (=variance σ^2) can be used to define the measure R as

$$R = 1 - \frac{1}{1 + \sigma^2(z)}$$

$R=0$ (for constant density, $\sigma=0$), $R \rightarrow 1$ (for large σ)



11.3 Regional Descriptors -Texture

- *Statistical approach*

The 2nd moment μ_2 (=variance σ^2) is used to measure the **contrast**.

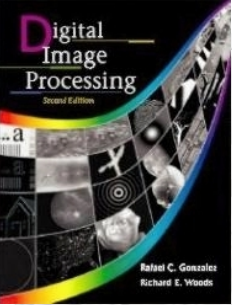
The 3rd moment μ_3 is used to measure the **skewness** of the histogram.

The 4th moment μ_4 is used to measure the **relative flatness** of the histogram.

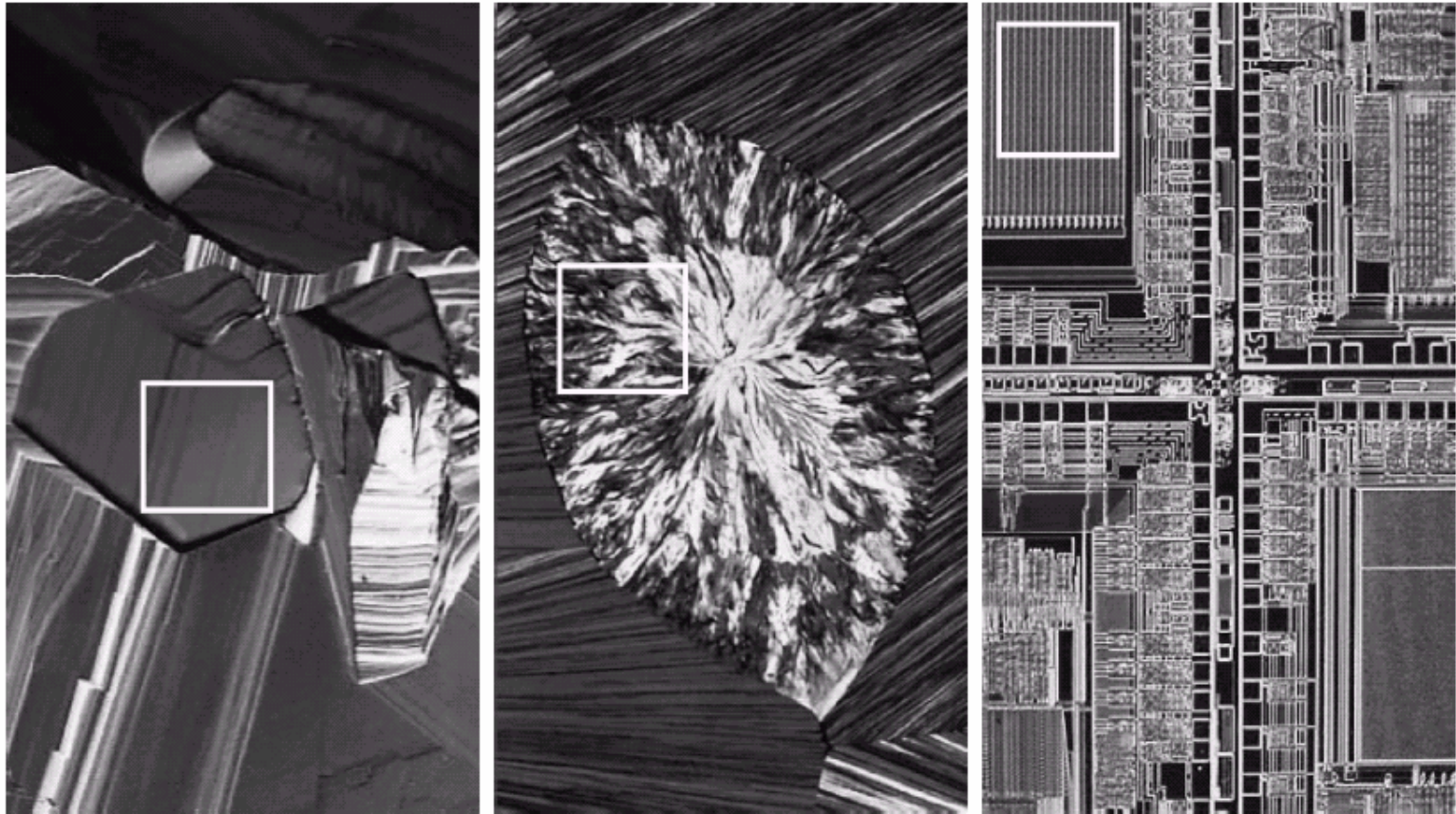
The measure of “uniformity” of the histogram as
$$U = \sum_{i=0}^{L-1} p^2(z_i)$$

The average entropy measure as
$$e = -\sum_{i=0}^{L-1} p(z_i) \log_2 p(z_i)$$

This approach measure no information regarding to the relative position of pixels with respect to each other.



11.3 Regional Descriptors - Texture



a b c

FIGURE 11.22 The white squares mark, from left to right, smooth, coarse, and regular textures. These are optical microscope images of a superconductor, human cholesterol, and a microprocessor. (Courtesy of Dr. Michael W. Davidson, Florida State University.)

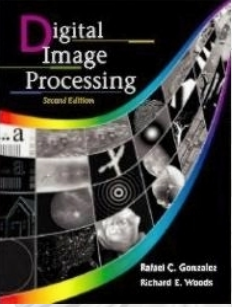


11.3 Regional Descriptors -Texture

TABLE 11.2

Texture measures for the subimages shown in Fig. 11.22.

Texture	Mean	Standard deviation	R (normalized)	Third moment	Uniformity	Entropy
Smooth	82.64	11.79	0.002	-0.105	0.026	5.434
Coarse	143.56	74.63	0.079	-0.151	0.005	7.783
Regular	99.72	33.73	0.017	0.750	0.013	6.674

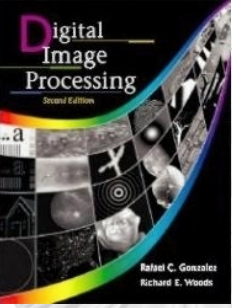


11.3 Regional Descriptors -Texture

- Let P be a **position operator**, A be a $k \times k$ matrix whose element a_{ij} is the number of times that points with gray level z_i occur (in position specified by P) relative to points with gray level z_j , with $1 \leq i, j \leq k$.
- For example, an image with $z_1=0$, $z_2=1$, $z_3=2$ as
- Define the position operator P as “**one pixel below and one-pixel to the right**” yields a 3×3 matrix A as
- a_{11} is the number of times that a point with level $z_1=0$ appears related with another point **of the same level**
- a_{13} is the number of times that a point with level $z_1=0$ appears related with another point with gray-level $z_3=2$

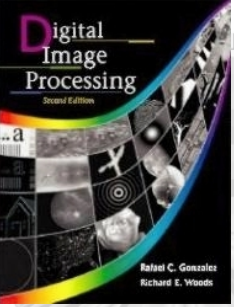
0	0	0	1	2
1	1	0	1	1
2	2	1	0	0
1	1	0	2	0
0	0	1	0	1

$$A = \begin{bmatrix} \textcircled{4} & 2 & \textcircled{1} \\ 2 & 3 & 2 \\ 0 & 2 & 0 \end{bmatrix}$$



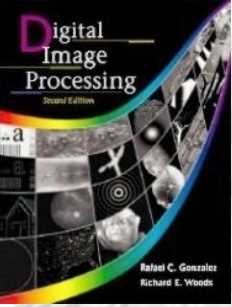
11.3 Regional Descriptors -Texture

- Let n be the number of point pairs in the image that satisfy P ($n=16$).
- If $C=A/n$ then c_{ij} is the estimate of the joint probability that a pair of points satisfying P will have values (z_i, z_j)
- The matrix C is called ***gray-level co-occurrence matrix***.
- C depends on P .
- To analyze a given C to categorize the texture of region over which C was computed.



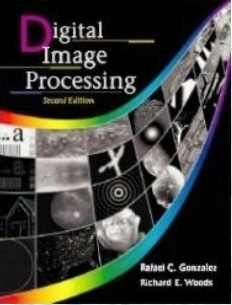
11.3 Regional Descriptors -Texture

- A set of descriptors based on C are
 - 1) Maximum probability
 - 2) Element difference moment of order k
 - 3) Inverse element difference moment of order k
 - 4) Uniformity
 - 5) Entropy



11.3 Regional Descriptors -Texture

- **Structural approach:** a simple “texture” primitive can be used to form more complex texture pattern.
 - 1) Define a rule of the form : $S \rightarrow aS$, which indicates that the symbol S may be written as aS .
 - 2) Let a represents a circle, and the meaning of “**circles to the right**” is assign a string of the form $aaa\dots$, and the rule $S \rightarrow aS$ generates *Fig11.23(b)*.
 - 3) Define new rules: $S \rightarrow bA$, $A \rightarrow cA$, $A \rightarrow c$, $A \rightarrow bS$, $S \rightarrow a$, where b represents “**circle down**” and c means “**circle to the left**”
 - 4) Generate a string of the form $aaabccbaa$ that corresponding to a 3×3 matrix of circles.

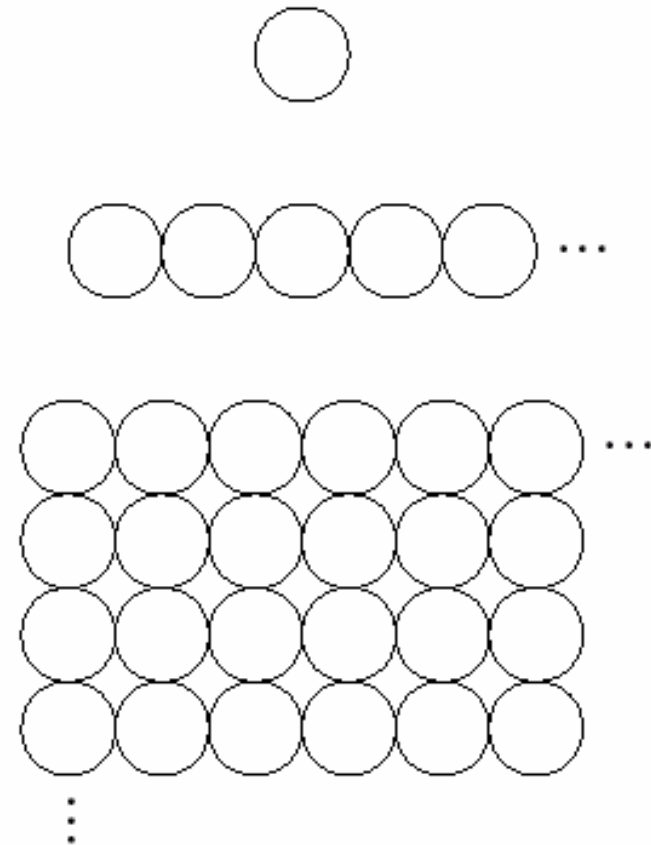


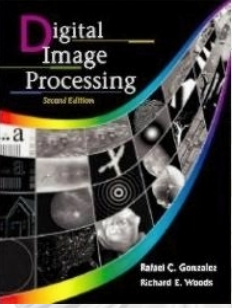
11.3 Regional Descriptors -Texture

a
b
c

FIGURE 11.23

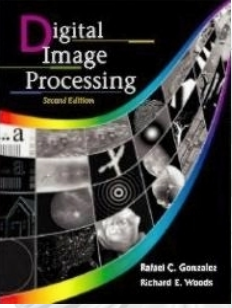
(a) Texture primitive.
 (b) Pattern generated by the rule $S \rightarrow aS$.
 (c) 2-D texture pattern generated by this and other rules.





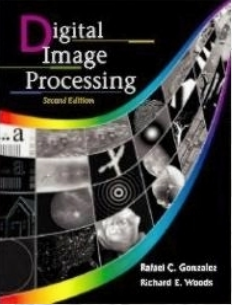
11.3 Regional Descriptors -Texture

- *Spectral approach*
- **Fourier spectrum** is suitable for describing the directionality of periodic in 2-D image.
- Three features in Fourier spectrum:
 - 1) **Prominent peaks** give the principal **direction** of the texture patterns.
 - 2) The **location of the peaks** give the fundamental spatial period of the patterns.
 - 3) By filtering the periodic component, the other **non-periodic pattern** can be described by statistical technique.



11.3 Regional Descriptors -Texture

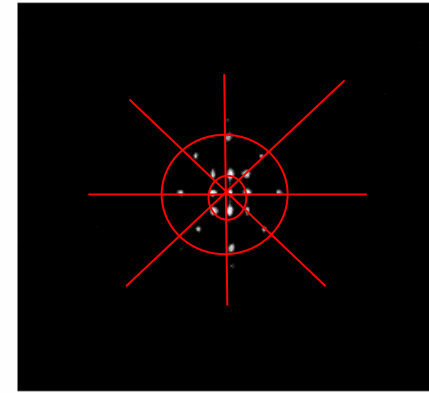
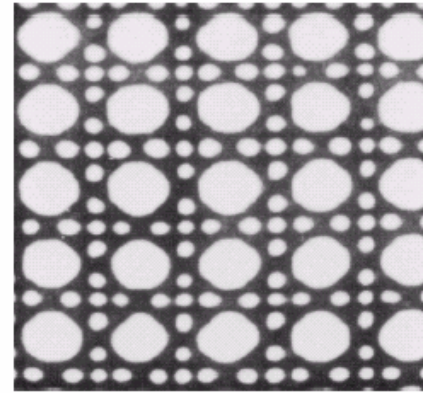
- *Spectral approach*
- Express the spectral in polar coordinates as $S(r, \theta)$.
- For each direction θ , we have a 1-D expression of the spectrum as $S_{\theta}(r)$.
- Global description as $S(r) = \sum_{\theta} S_{\theta}(r)$.
- For each frequency r , we have a 1-D expression of the spectrum as $S_r(\theta)$.
- Global description as $S(\theta) = \sum_r S_r(\theta)$.
- Constitute $[S(r), S(\theta)]$ for each pair of (r, θ)



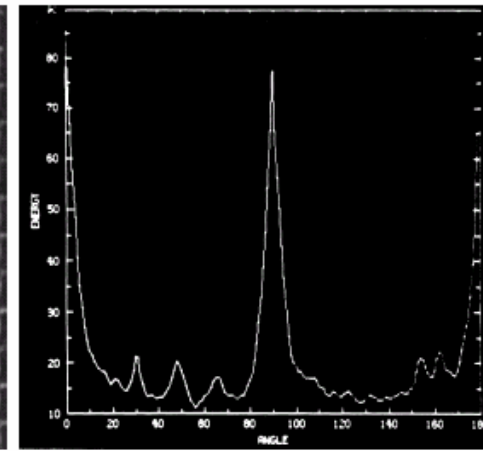
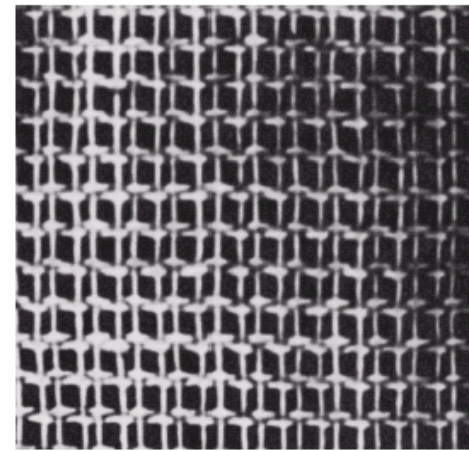
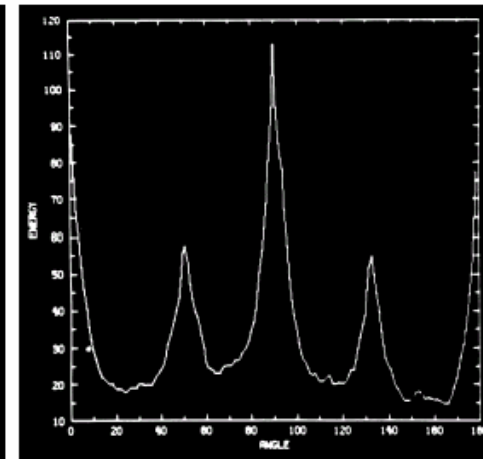
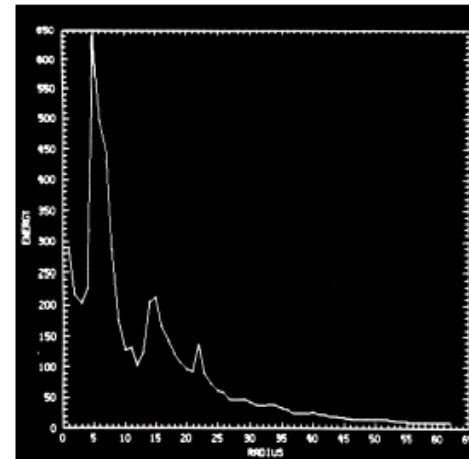
11.3 Regional Descriptors - Texture

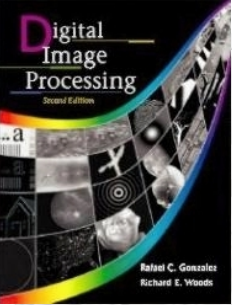
a
b
c
d
e
f

FIGURE 11.24 (a) Image showing periodic texture. (b) Spectrum. (c) Plot of $S(r)$. (d) Plot of $S(\theta)$. (e) Another image with a different type of periodic texture. (f) Plot of $S(\theta)$. (Courtesy of Dr. Dragana Brzakovic, University of Tennessee.)



$S(r)$





11.3 Regional Descriptors -Texture

- ***Moment of two dimensional functions***

- For 2-D continuous function $f(x, y)$, the moment of order $(p+q)$ is defined as

$$m_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x, y) dx dy = \sum_x \sum_y x^p y^q f(x, y)$$

- The central moments are

$$\mu_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x})^p (y - \bar{y})^q f(x, y) dx dy$$

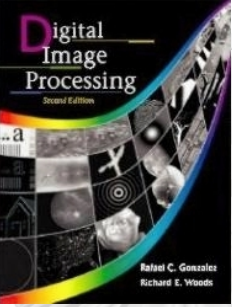
• or

$$\mu_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q f(x, y)$$

where $\bar{x} = m_{10}/m_{00}$ and $\bar{y} = m_{01}/m_{00}$

The central moments are $\mu_{00}(=m_{00})$, $\mu_{10}(=0)$, $\mu_{01}(=0)$, μ_{11} ,

μ_{20} , μ_{02} , μ_{21} , μ_{12} ,



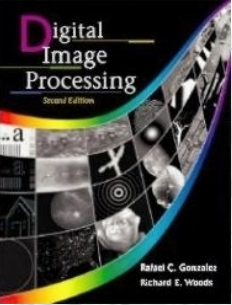
11.3 Regional Descriptors -Texture

- The ***normalized central moment*** is defined as

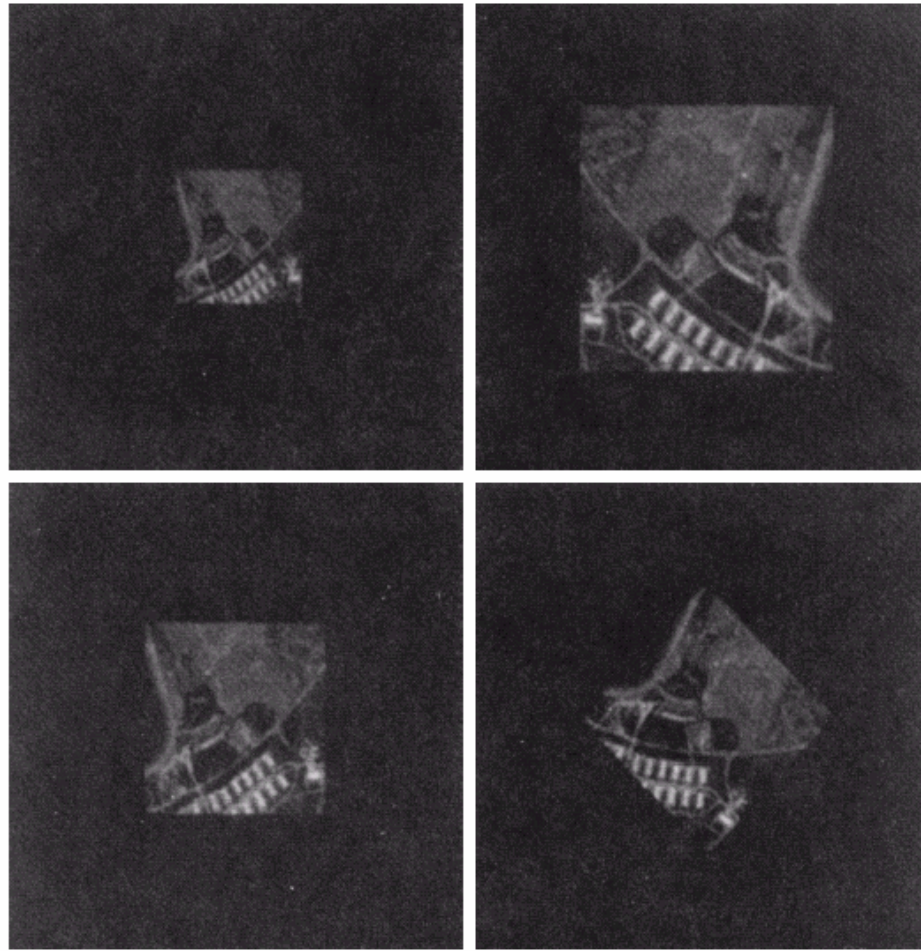
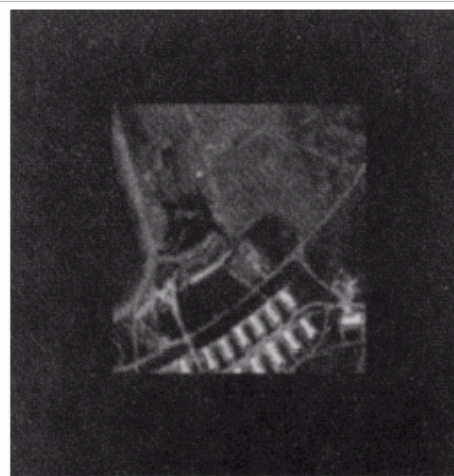
$$\eta_{pq} = \mu_{pq} / \mu_{00}^{\gamma}$$

where $\gamma = (p+q)/2 + 1$, for $p+q=2, 3, \dots$

- Seven invariant moments Φ_1, \dots, Φ_7 are shown in textbook
- Examples of the invariant moments are shown in Figure 11.25.

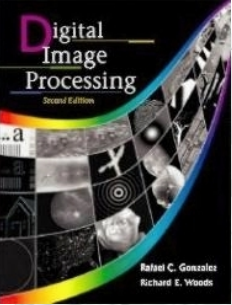


11.3 Regional Descriptors - Texture



a
b c
d e

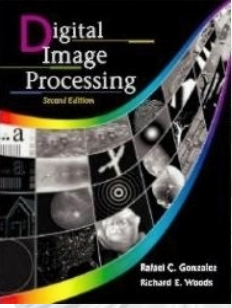
FIGURE 11.25
Images used to demonstrate properties of moment invariants (see Table 11.3).



11.3 Regional Descriptors -Texture

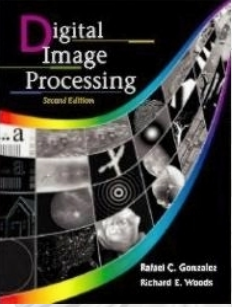
Invariant (Log)	Original	Half Size	Mirrored	Rotated 2°	Rotated 45°
ϕ_1	6.249	6.226	6.919	6.253	6.318
ϕ_2	17.180	16.954	19.955	17.270	16.803
ϕ_3	22.655	23.531	26.689	22.836	19.724
ϕ_4	22.919	24.236	26.901	23.130	20.437
ϕ_5	45.749	48.349	53.724	46.136	40.525
ϕ_6	31.830	32.916	37.134	32.068	29.315
ϕ_7	45.589	48.343	53.590	46.017	40.470

TABLE 11.3
Moment invariants for the images in Figs. 11.25(a)-(e).



11.4 Use of Principal Component Description

- Treat the vectors \mathbf{x} as a random quantity.
- The **mean vector** is $\mathbf{m}_x = E\{\mathbf{x}\}$
- The **covariance** matrix: $\mathbf{C}_x = E\{(\mathbf{x} - \mathbf{m}_x)(\mathbf{x} - \mathbf{m}_x)^T\}$
which is real and symmetric.
- c_{ii} is variance of x_i , and c_{ij} is the covariance between elements x_i and x_j .
- If element x_i and x_j are uncorrelated then $c_{ij} = c_{ji} = 0$.



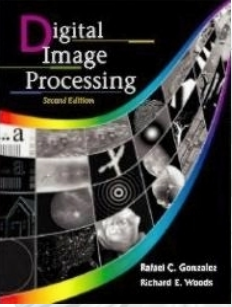
11.4 Use of Principal Component Description

- For K vector samples from random population, the mean vector is

$$\mathbf{m}_x = \frac{1}{K} \sum_{k=1}^K \mathbf{x}_k$$

- By expanding the product $(\mathbf{x} - \mathbf{m}_x)(\mathbf{x} - \mathbf{m}_x)^T$, the covariance matrix can be approximated as

$$\mathbf{C}_x = \frac{1}{K} \sum_{k=1}^K \mathbf{x}_k \mathbf{x}_k^T - \mathbf{m}_x \mathbf{m}_x^T$$

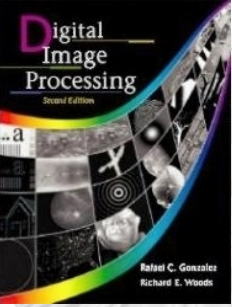


11.4 Use of Principal Component Description

- Example 11.9. $\mathbf{x}_1=[0, 0, 0]^T$, $\mathbf{x}_2=[1, 0, 0]^T$, $\mathbf{x}_3=[1, 1, 0]^T$, $\mathbf{x}_4=[1, 0, 1]^T$.
- We may compute \mathbf{m}_x and \mathbf{C}_x as

$$\mathbf{m}_x = 1/4[3, 1, 1]^T \quad \mathbf{C}_x = \frac{1}{16} \begin{bmatrix} 3 & 1 & 1 \\ 1 & 3 & -1 \\ 1 & -1 & 3 \end{bmatrix}$$

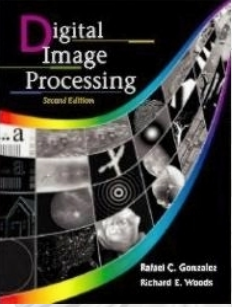
- The diagonal terms indicate that the three components of the vectors have the same variance.
- x_1 and x_2 , x_1 and x_3 are positive related.
- x_2 and x_3 are negative related.



11.4 Use of Principal Component Description

- Because \mathbf{C}_x is real and symmetric, we may find a set of n orthonormal **eigenvectors**.
- Let \mathbf{e}_i and λ_i , $i=1, 2, \dots, n$ be the eigenvectors and eigenvalues of \mathbf{C}_x , with $\lambda_i \geq \lambda_{i+1}$.
- Let \mathbf{A} be the matrix whose rows are formed from the eigenvectors of \mathbf{C}_x ordered so that the first row of \mathbf{A} is eigenvector corresponding to the largest eigenvalue, and the last row is the eigenvector corresponding to the smallest eigenvalue.
- Suppose \mathbf{A} is used as a transformation matrix to map the \mathbf{x} 's into vector denoted by \mathbf{y} 's as follows:

$$\mathbf{y} = \mathbf{A}(\mathbf{x} - \mathbf{m}_x)$$



11.4 Use of Principal Component Description

- The above expression is called *Hotelling transform* or *Principal component transform*.

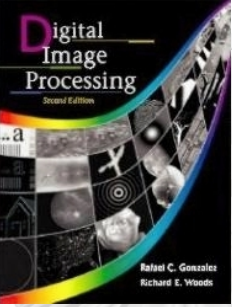
- $\mathbf{m}_y = E\{\mathbf{y}\} = 0$

- \mathbf{C}_y is $\mathbf{A}\mathbf{C}_x\mathbf{A}^T$.

- \mathbf{C}_y is a diagonal matrix.

$$\mathbf{C}_y = \begin{bmatrix} \lambda_1 & & & 0 \\ & \lambda_2 & & \\ & & \cdot & \\ & & & \cdot \\ 0 & & & & \lambda_n \end{bmatrix}$$

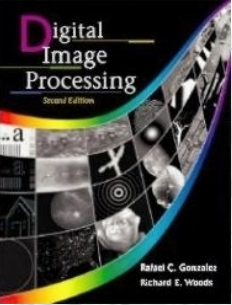
- The reconstruction of \mathbf{x} is $\mathbf{x} = \mathbf{A}^T\mathbf{y} + \mathbf{m}_x$



11.4 Use of Principal Component Description

- Instead of using all eigenvectors of \mathbf{C}_x , we form matrix \mathbf{A}_k from k eigenvector corresponding to k largest eigenvalues.
- \mathbf{A}_k is a transformation matrix of order $k \times n$.
- The \mathbf{y} vector would be k dimension.
- The reconstructed vector is no longer exact as

$$\hat{\mathbf{x}} = \mathbf{A}_k^T \mathbf{y} + \mathbf{m}_x$$



11.4 Use of Principal Component Description

FIGURE 11.26 Six spectral images from an airborne scanner. (Courtesy of the Laboratory for Applications of Remote Sensing, Purdue University.)



Channel 1



Channel 2



Channel 3



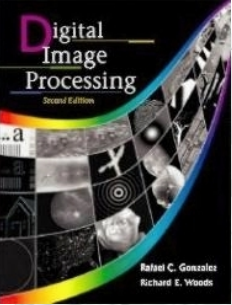
Channel 4



Channel 5



Channel 6



11.4 Use of Principal Component Description

TABLE 11.4

Channel numbers
and wavelengths.

Channel	Wavelength band (microns)
1	0.40–0.44
2	0.62–0.66
3	0.66–0.72
4	0.80–1.00
5	1.00–1.40
6	2.00–2.60

11.4 Use of Principal Component Description

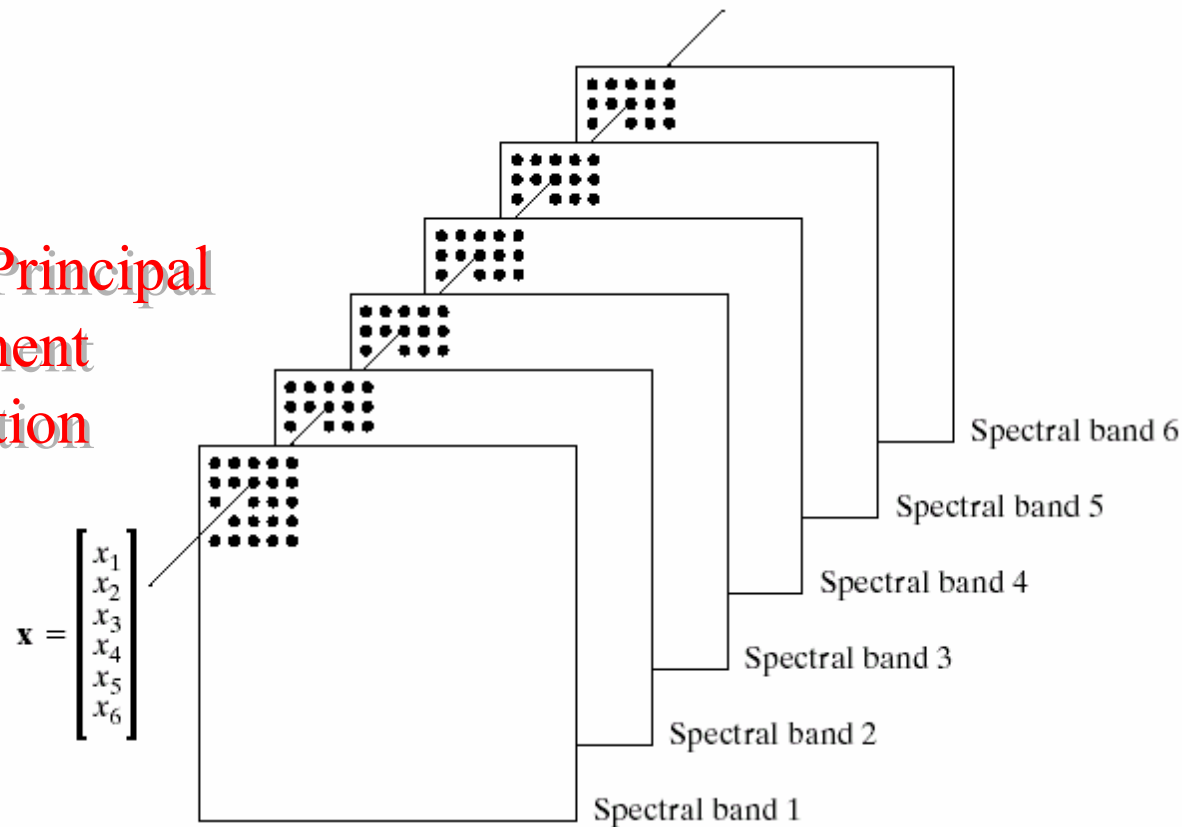
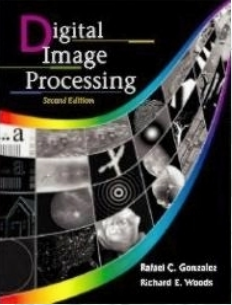


FIGURE 11.27 Formation of a vector from corresponding pixels in six images.

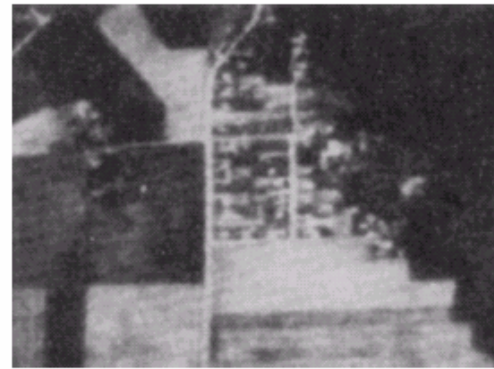
λ_1	λ_2	λ_3	λ_4	λ_5	λ_6
3210	931.4	118.5	83.88	64.00	13.40

TABLE 11.5

Eigenvalues of the covariance matrix obtained from the images in Fig. 11.26.



11.4 Use of Principal Component Description



Component 1



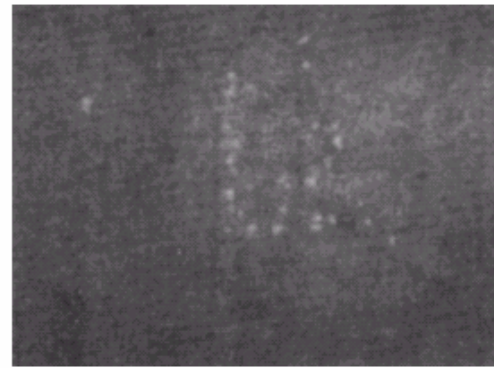
Component 2



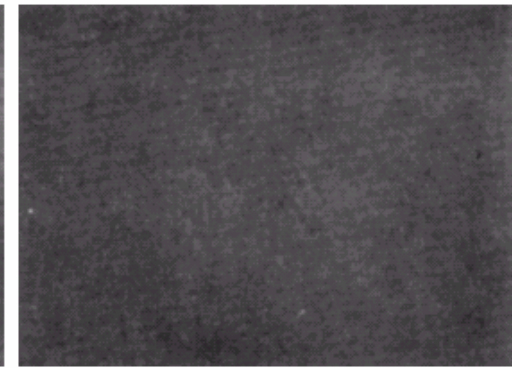
Component 3



Component 4



Component 5

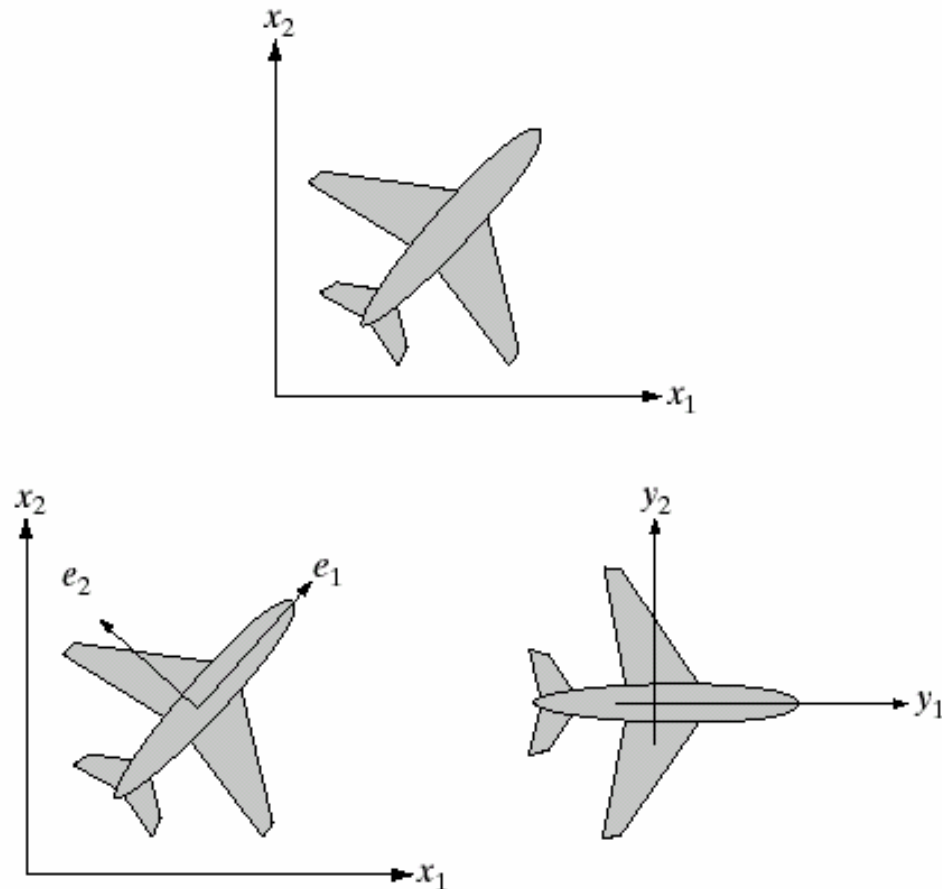


Component 6

FIGURE 11.28 Six principal-component images computed from the data in Fig. 11.26. (Courtesy of the Laboratory for Applications of Remote Sensing, Purdue University.)

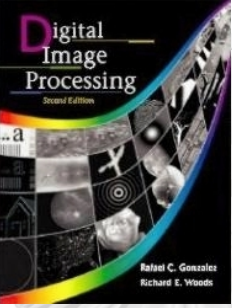


11.4 Use of Principal Component Description



a
b c

FIGURE 11.29 (a) An object. (b) Eigenvectors. (c) Object rotated by using Eq. (11.4-6). The net effect is to align the object along its eigen axes.



11.5 Relational Description

- Rules for describing the context of relation.
- Apply equally to boundaries and regions.
- Define two primitives a and b as shown in Fig. 11.30.
- We define rewriting rules as

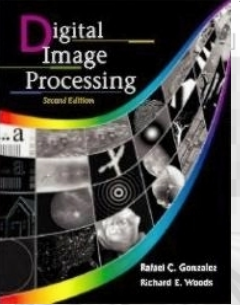
$$(a) S \rightarrow aA$$

$$(b) A \rightarrow bS$$

$$(c) A \rightarrow b.$$

where A and S are variables, and the elements a and b are constant corresponding to the primitives.

Rule 1 indicates the starting symbols S can be replaced by aA .

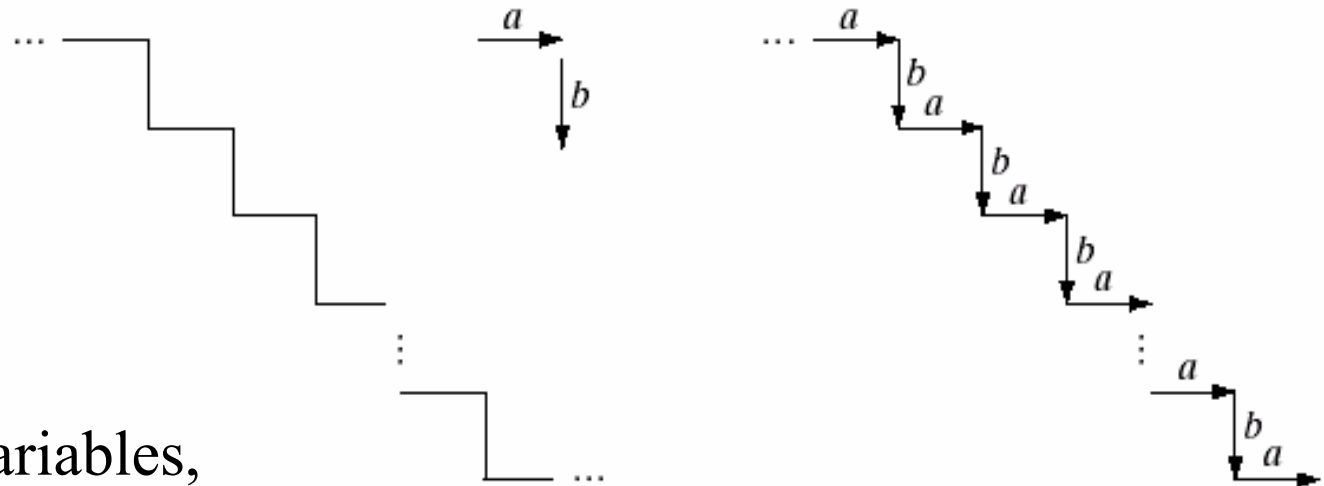


11.5 Relational Description

a b

FIGURE 11.30

- (a) A simple staircase structure.
- (b) Coded structure.



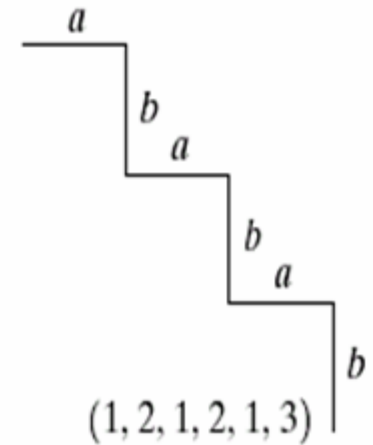
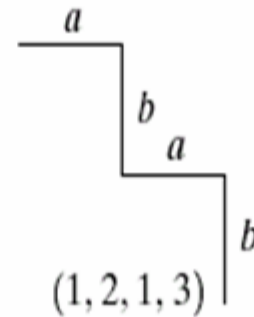
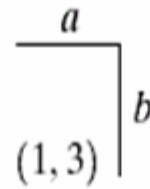
Let A and S are variables,
define rewriting rules as

- (a) $S \rightarrow aA$
- (b) $A \rightarrow bS$
- (c) $A \rightarrow b.$



11.5 Relational Description

FIGURE 11.31
Sample derivations for the rules $S \rightarrow aA$, $A \rightarrow bS$, and $A \rightarrow b$.



11.5 Relational Description

- For 2-D object description, we follow the contour of an object and code the result with segments of specific direction and/or length as shown in Figure 11.32.

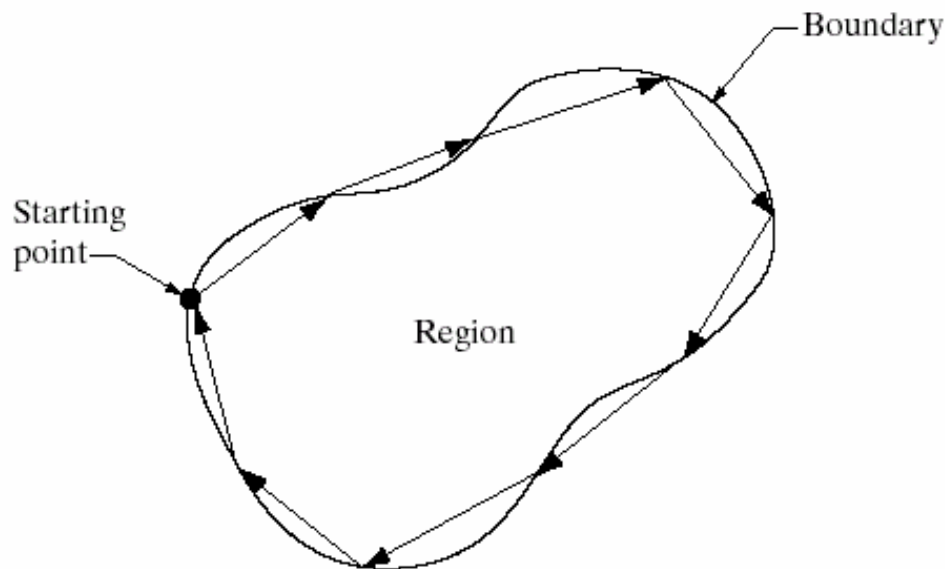
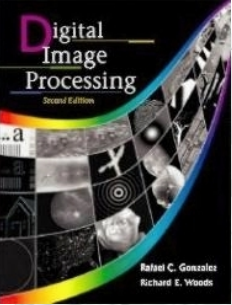
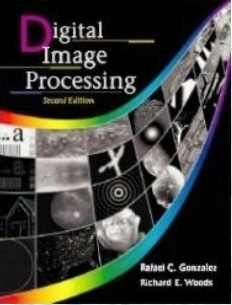


FIGURE 11.32
Coding a region boundary with directed line segments.

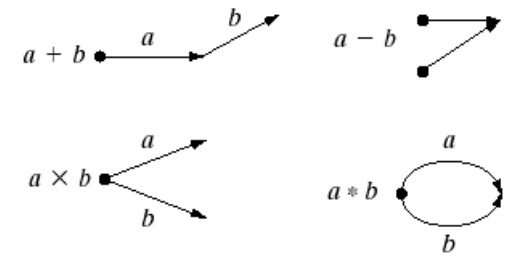
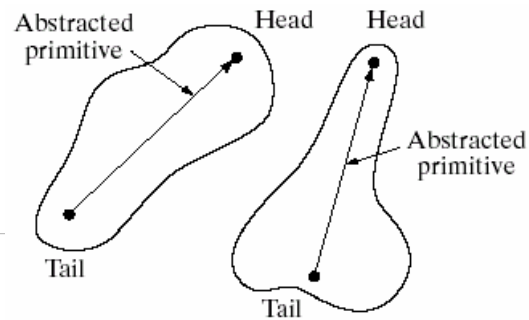


11.5 Relational Description

- Another description is to describe the sections of an image (small homogeneous region) by **direct line segments**, which can be joined in other ways besides head-to-tail connections as shown in Figure 11.33.
- Sting descriptions are best suited for applications in which connectivity of primitives can be expressed in a head-to-tail or other connected manner.



11.5 Relational Description



a b
c
d

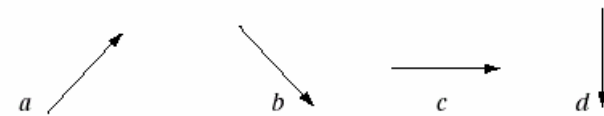
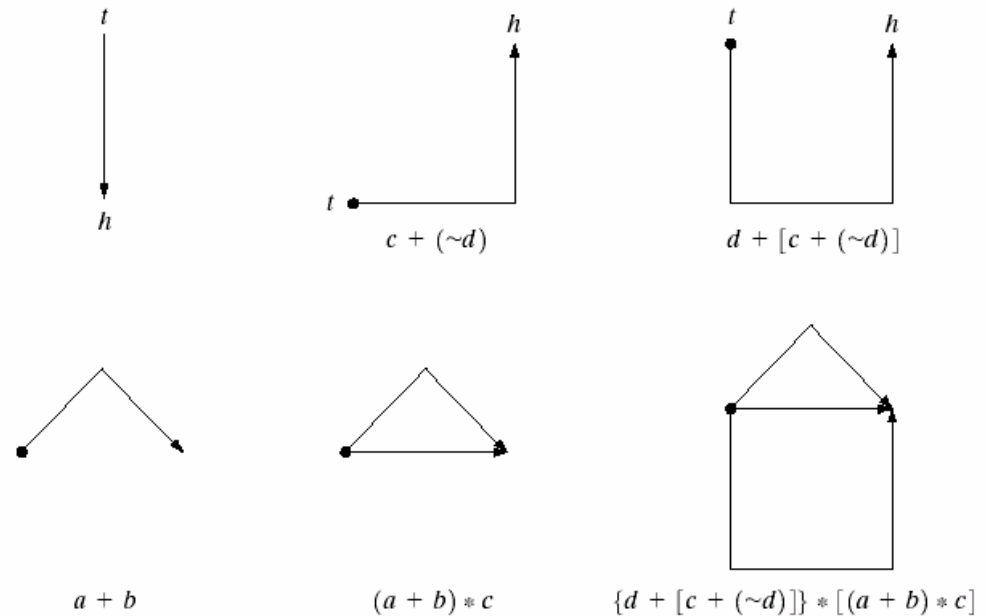
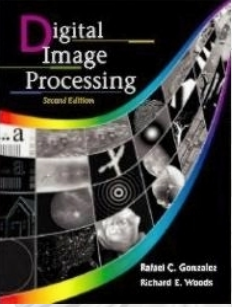


FIGURE 11.33 (a) Abstracted primitives. (b) Operations among primitives. (c) A set of specific primitives. (d) Steps in building a structure.





11.5 Relational Description

- Sometimes regions may not be contiguous, and we use Tree to describe such regions.
- A tree T is a finite set of one or more nodes for which
 - a) there is a unique node $\$$ designated the **root**
 - b) the remaining nodes are partitioned into m disjoint sets T_1, \dots, T_m , each of which in turn is a tree called a subtree of T .

The tree **frontier** is a set of nodes at the bottom of the tree (the leaves), taken in order from left to right, (see Figure 11.34).

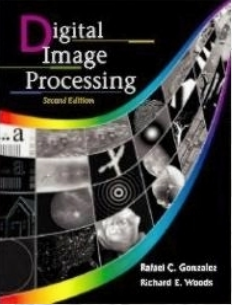


11.5 Relational Description

Two types of information in a tree

- a) information about a node
- b) information relating a node to its neighbors

For image description, the 1st type of information identifies an image **structure**, whereas the 2nd type of information defines the **physical relationship** of that substructure to other substructure.



11.5 Relational Description

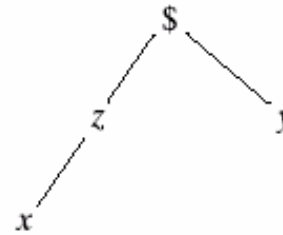
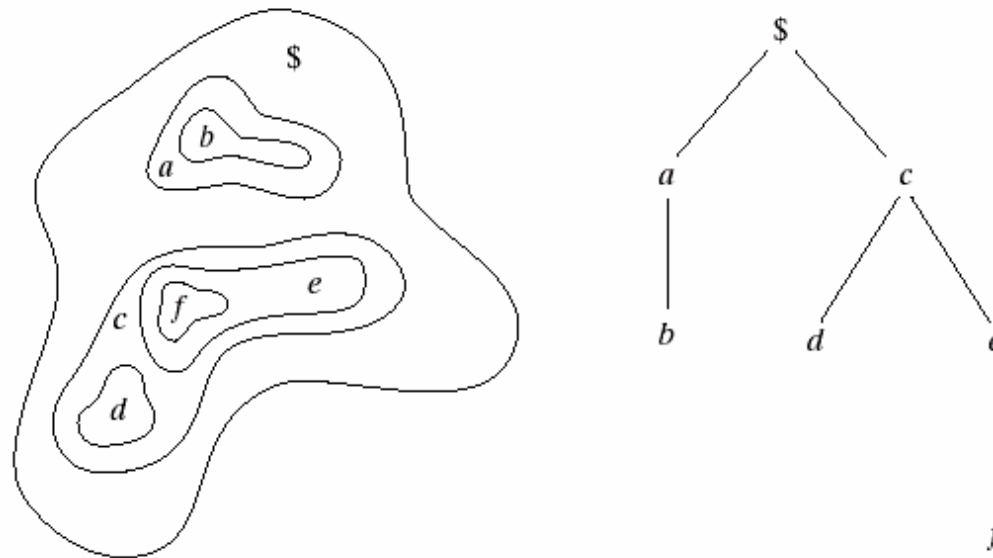


FIGURE 11.34 A simple tree with root \$ and frontier xy .



a b

FIGURE 11.35 (a) A simple composite region. (b) Tree representation obtained by using the relationship “inside of.”