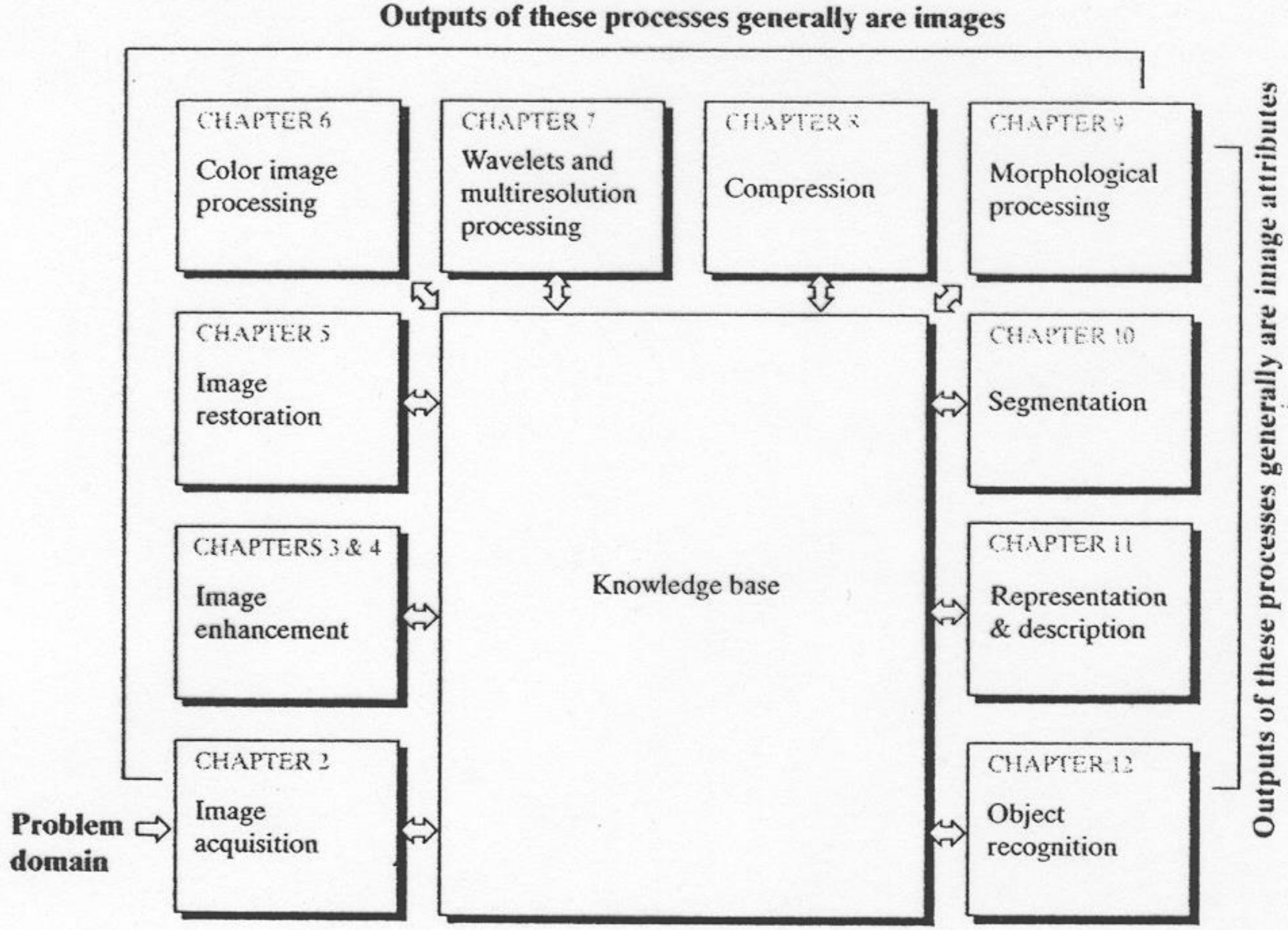
Object Representation/Coding for Recognition

Lecture-8

Spring 2019

FIGURE 1.23 Fundamental steps in digital image processing.



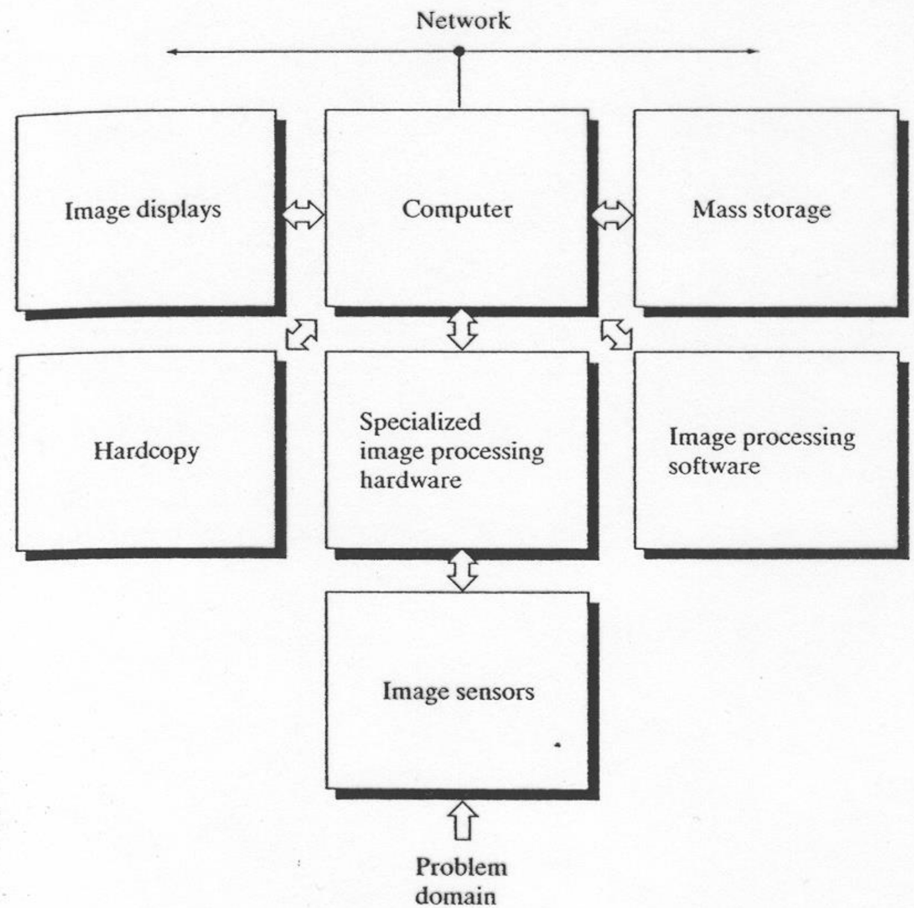
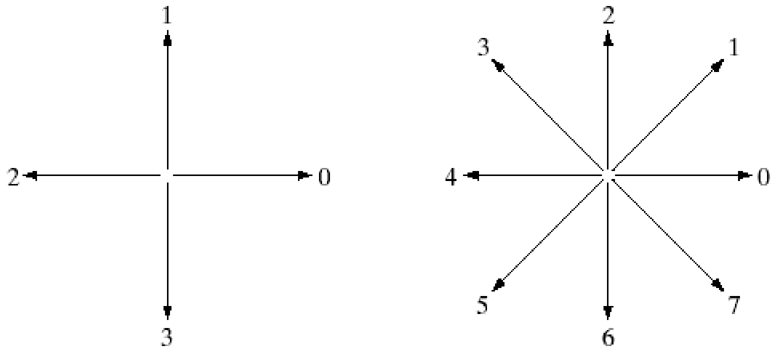


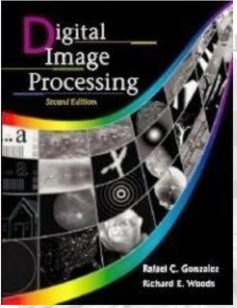
FIGURE 1.24 Components of a general-purpose image processing system.

Representation & Description

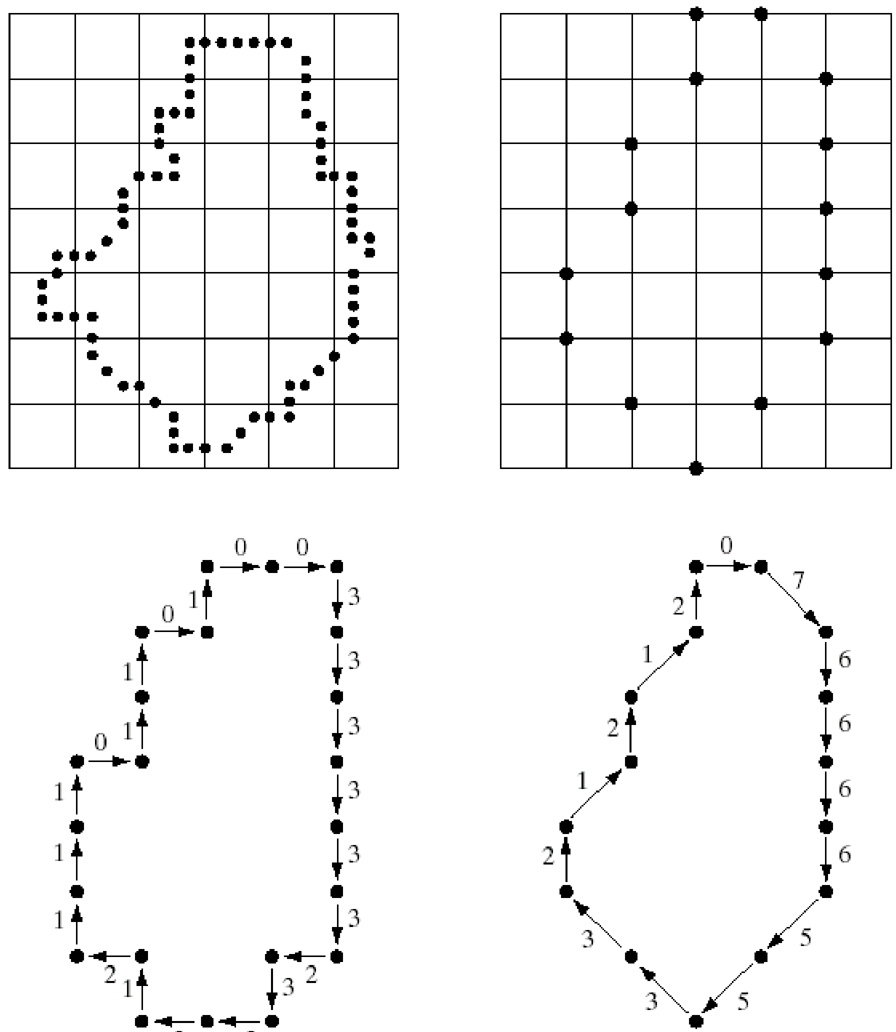


a b

FIGURE 11.1 Direction numbers for (a) 4-directional chain code, and (b) 8-directional chain code.



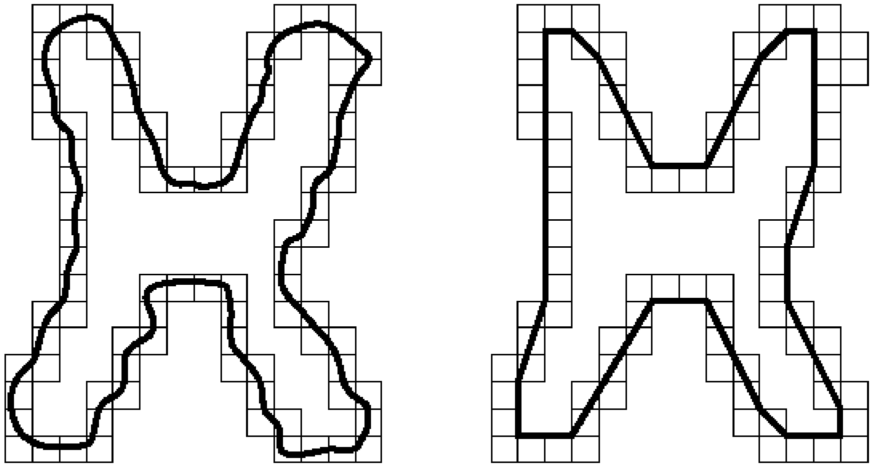
Representation & Description



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.

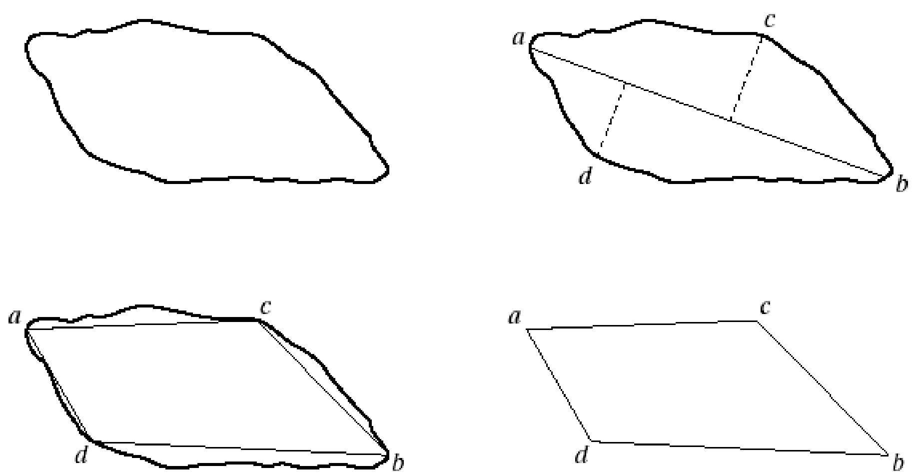
Representation & Description



a b

FIGURE 11.3 (a) Object boundary enclosed by cells. (b) Minimum perimeter polygon.

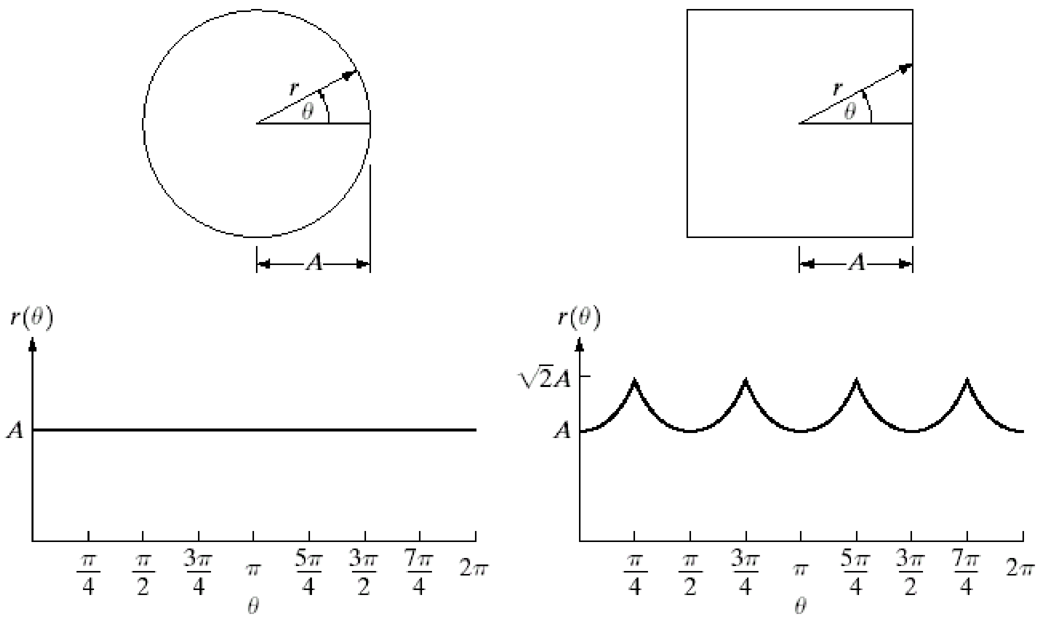
Representation & Description



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.

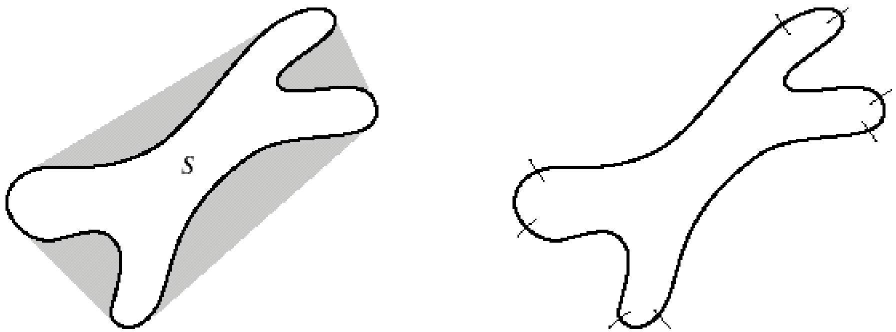
Representation & Description



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 $\pi/4 < \theta \leq \pi/2$.

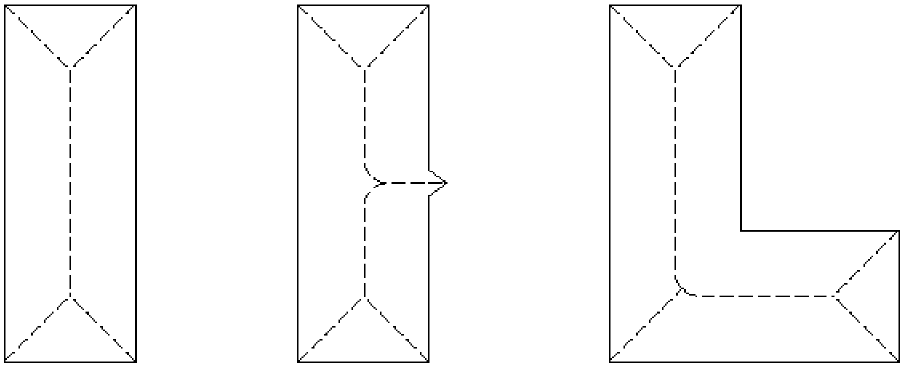
Representation & Description



a b

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

Representation & Description



a b c

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

Representation & Description

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.

Representation & Description

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

Representation & Description

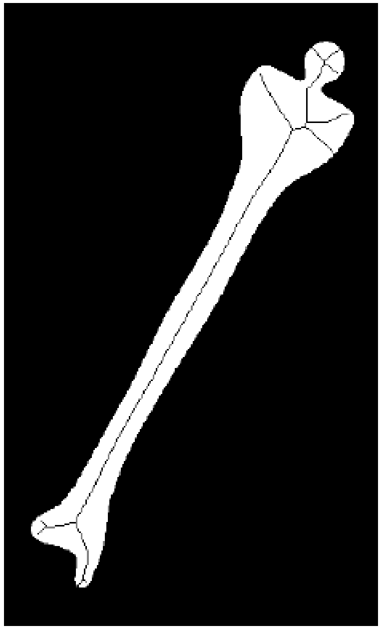
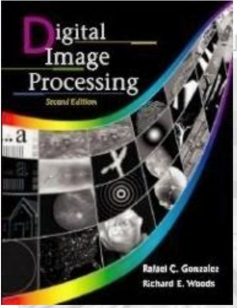
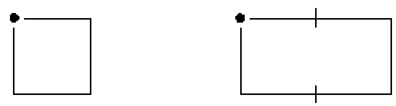


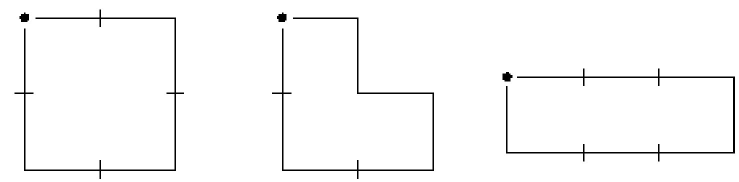
FIGURE 11.10 Human leg bone and skeleton of the region shown superimposed.



Representation & Description



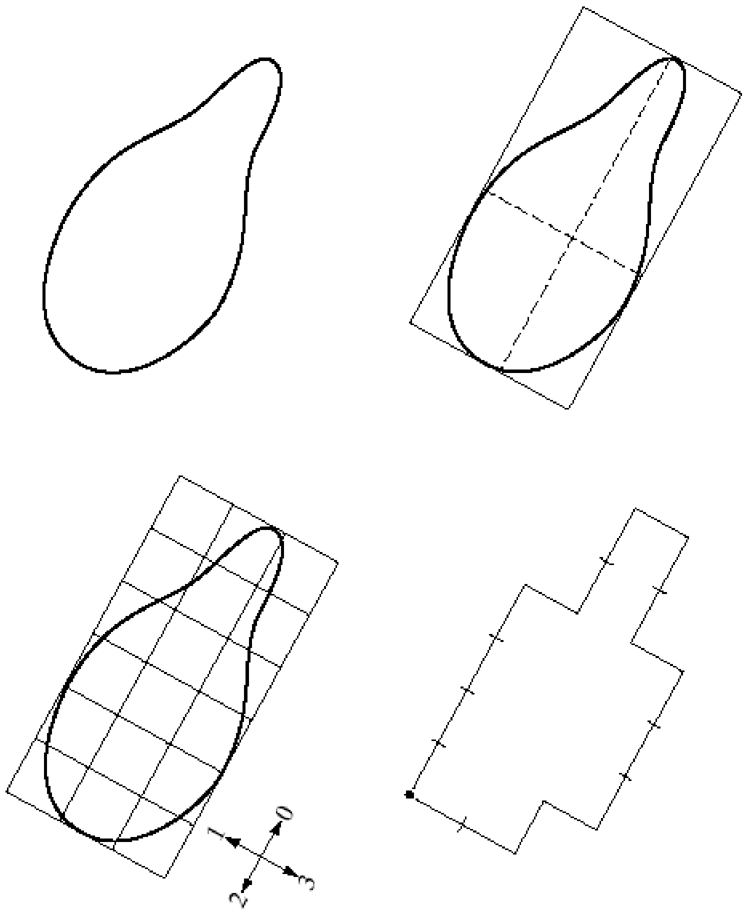
	Order 4	Order 6
Chain code:	0 3 2 1	0 0 3 2 2 1
Difference:	3 3 3 3	3 0 3 3 0 3
Shape no.:	3 3 3 3	0 3 3 0 3 3



Chain code:	0 0 3 3 2 2 1 1	0 3 0 3 2 2 1 1	0 0 0 3 2 2 2 1
Difference:	3 0 3 0 3 0 3 0	3 3 1 3 3 0 3 0	3 0 0 3 3 0 0 3
Shape no.:	0 3 0 3 0 3 0 3	0 3 0 3 3 1 3 3	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.

Representation & Description



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

a b
c d

FIGURE 11.12 Steps in the generation of a shape number.

Representation & Description

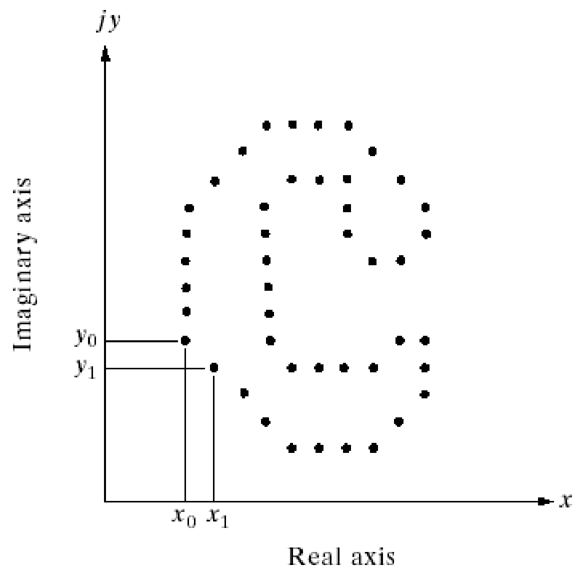


FIGURE 11.13 A digital boundary and its representation as a complex sequence. The points (x_0, y_0) and (x_1, y_1) shown are (arbitrarily) the first two points in the sequence.

Representation & Description

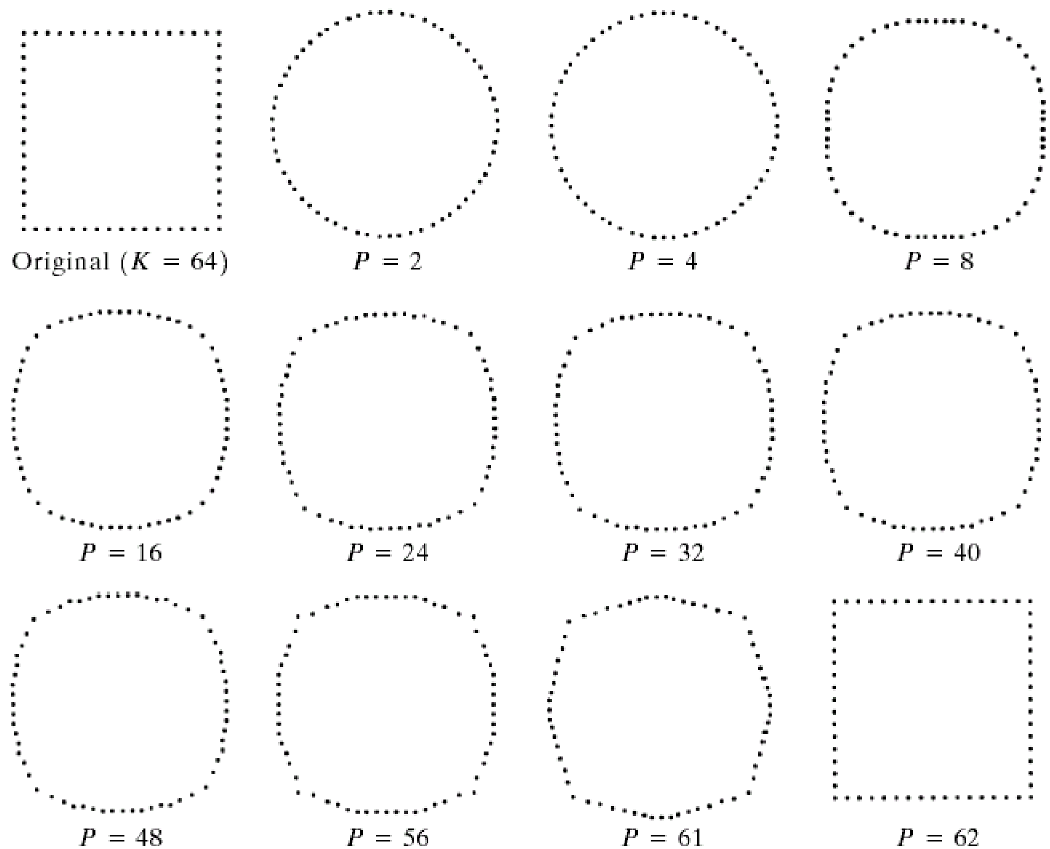


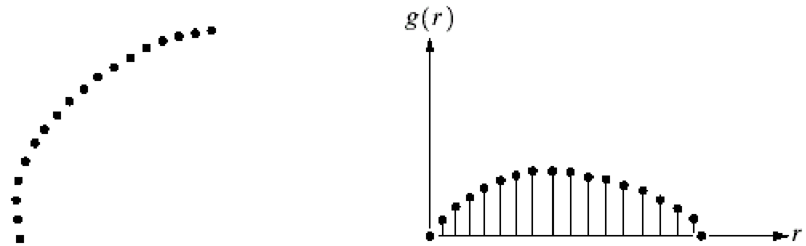
FIGURE 11.14 Examples of reconstruction from Fourier descriptors. P is the number of Fourier coefficients used in the reconstruction of the boundary.

Representation & Description

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.

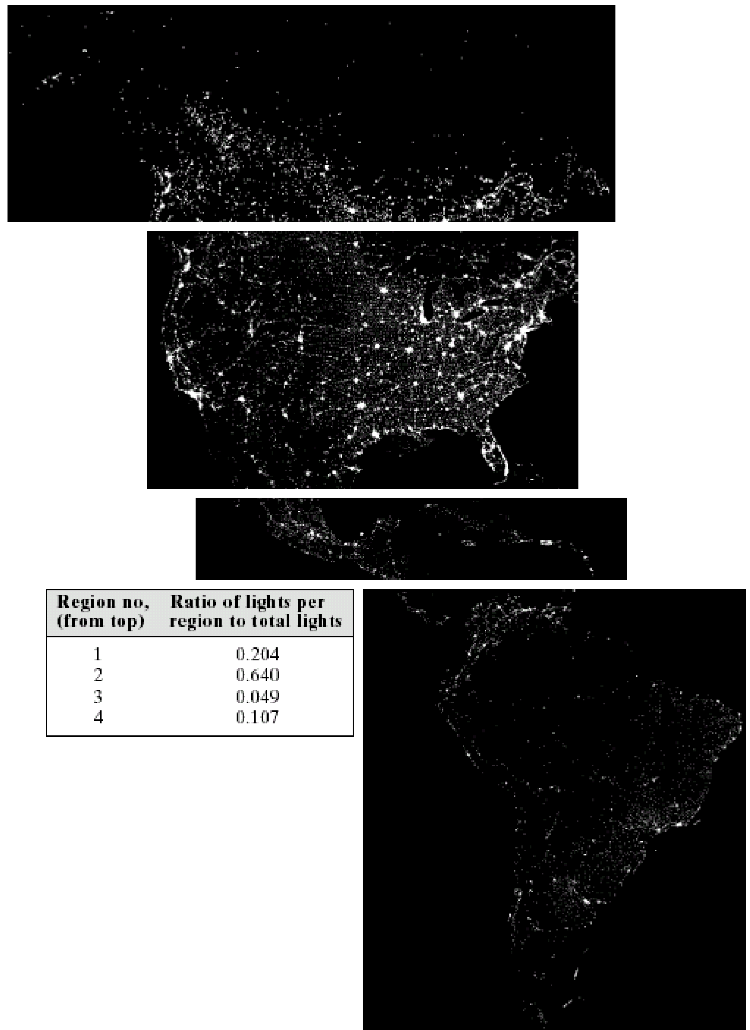
Representation & Description



a b

FIGURE 11.15
(a) Boundary segment.
(b) Representation as a 1-D function.

Representation & Description



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.)

Representation & Description

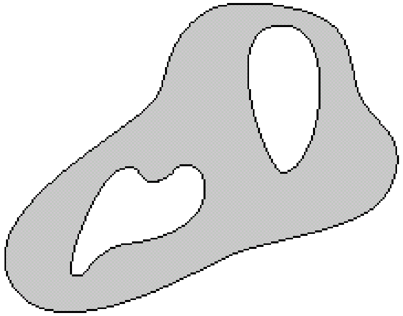


FIGURE 11.17 A region with two holes.

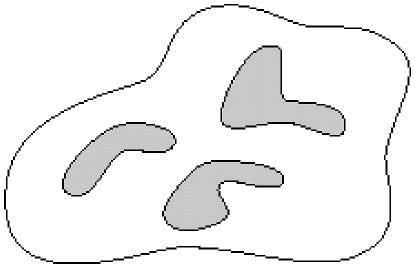
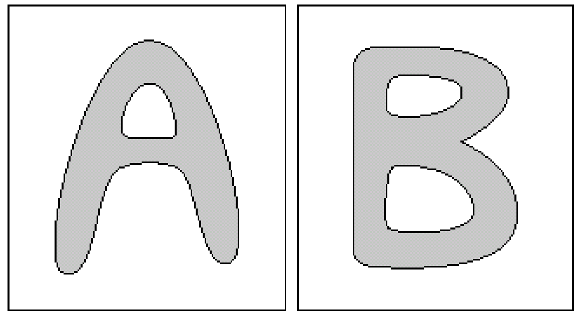


FIGURE 11.18 A region with three connected components.

Representation & Description



a b

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

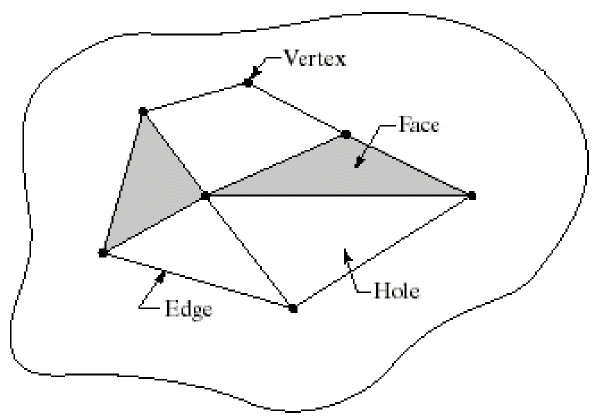
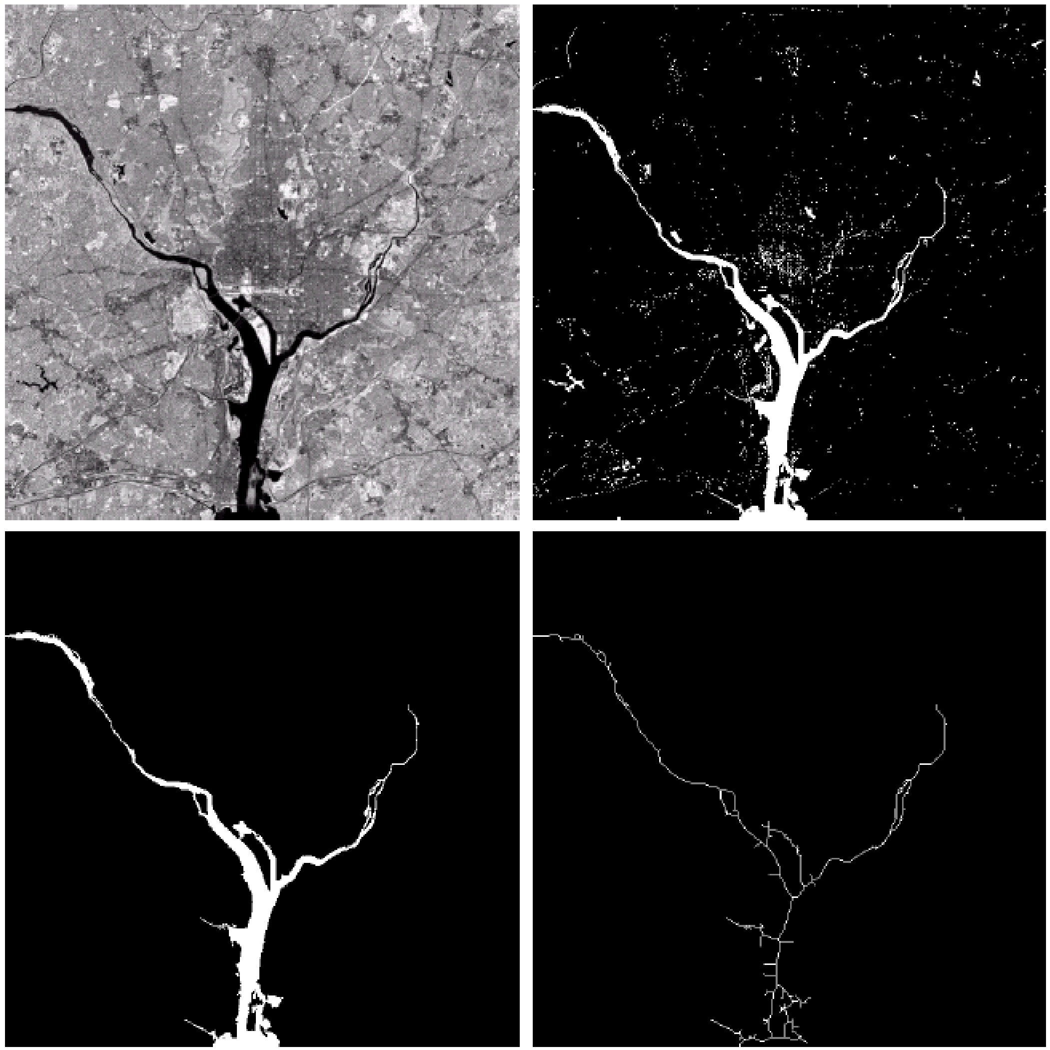


FIGURE 11.20 A region containing a polygonal network.

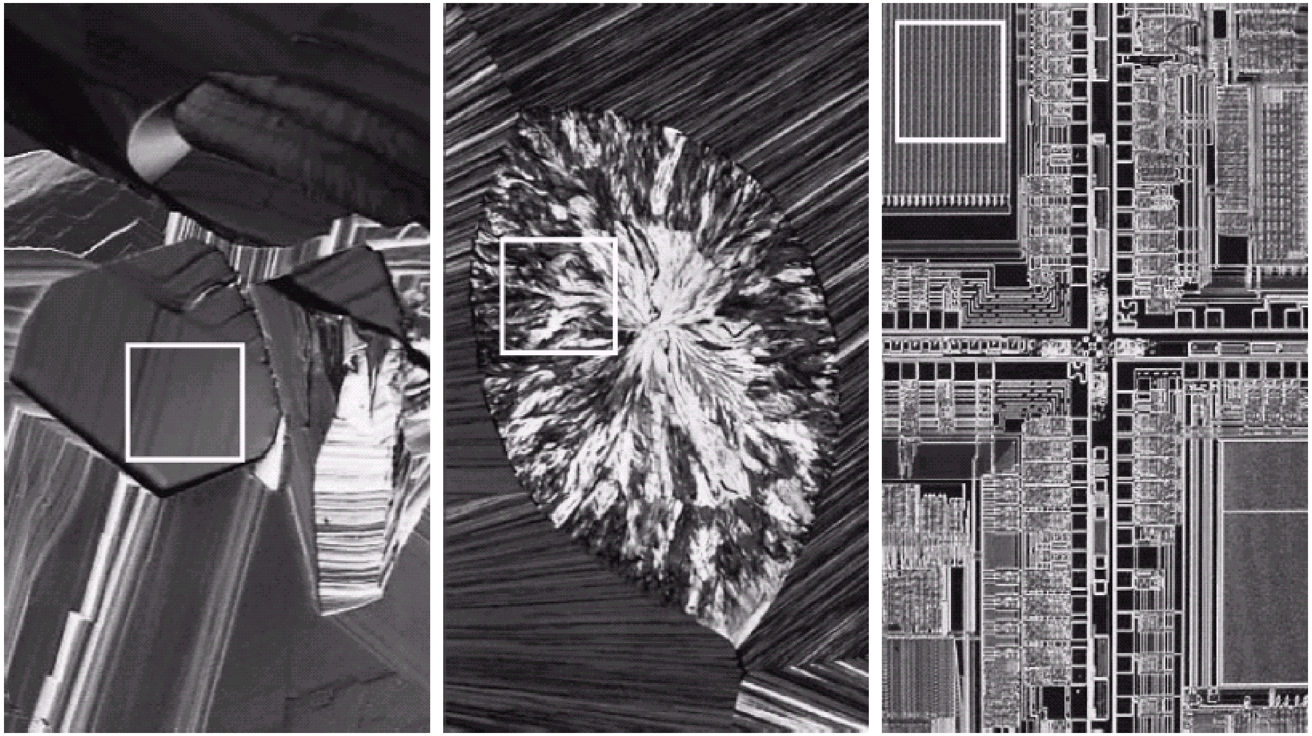
Representation & Description



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).

Representation & Description



a b c

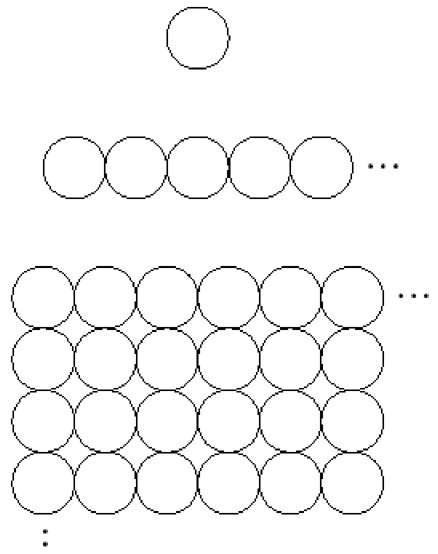
FIGURE 11.22 The white squares mark, from left to right, smooth, coarse, and regular textures. These are optical microscope images of a superconductor, human cholesterol, and a microprocessor. (Courtesy of Dr. Michael W. Davidson, Florida State University.)

Representation & Description

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

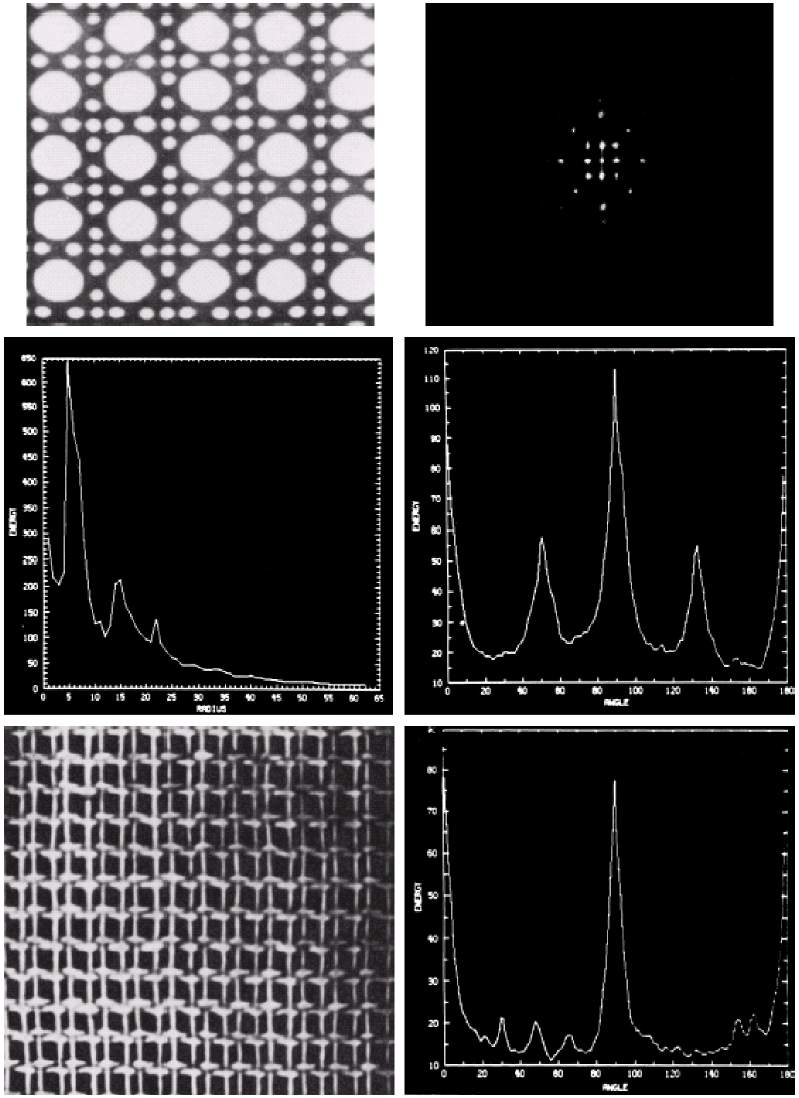
Representation & Description



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.

Representation & Description



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.)

Representation & Description

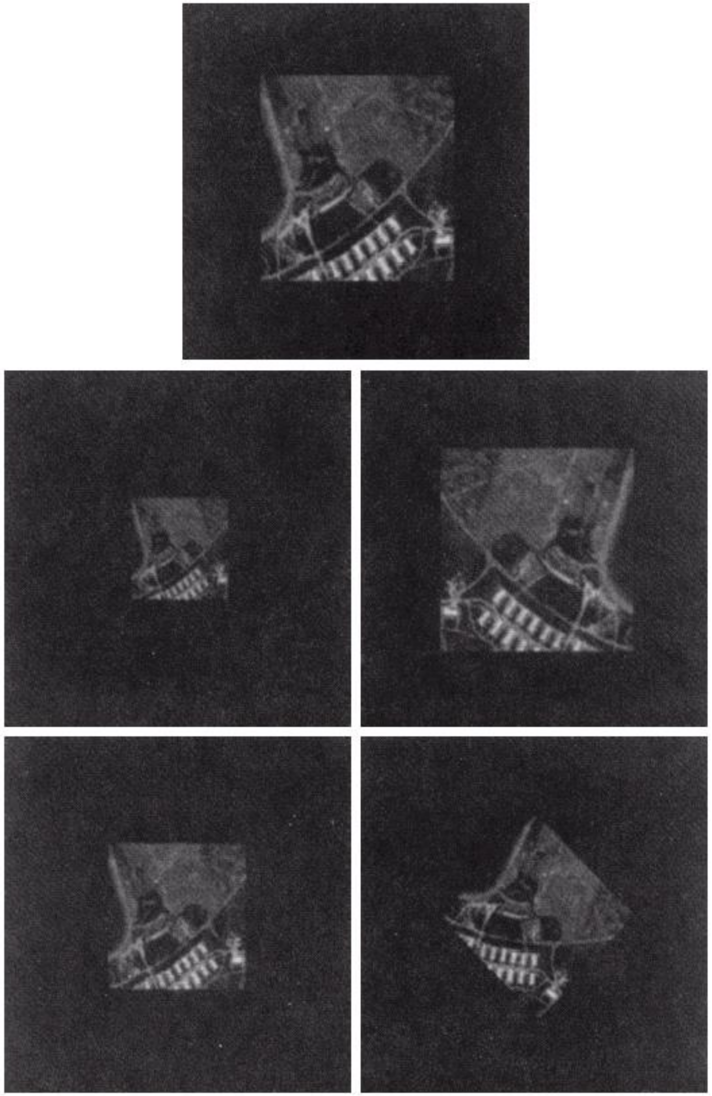


FIGURE 11.25 Images used to demonstrate properties of moment invariants (see Table 11.3).

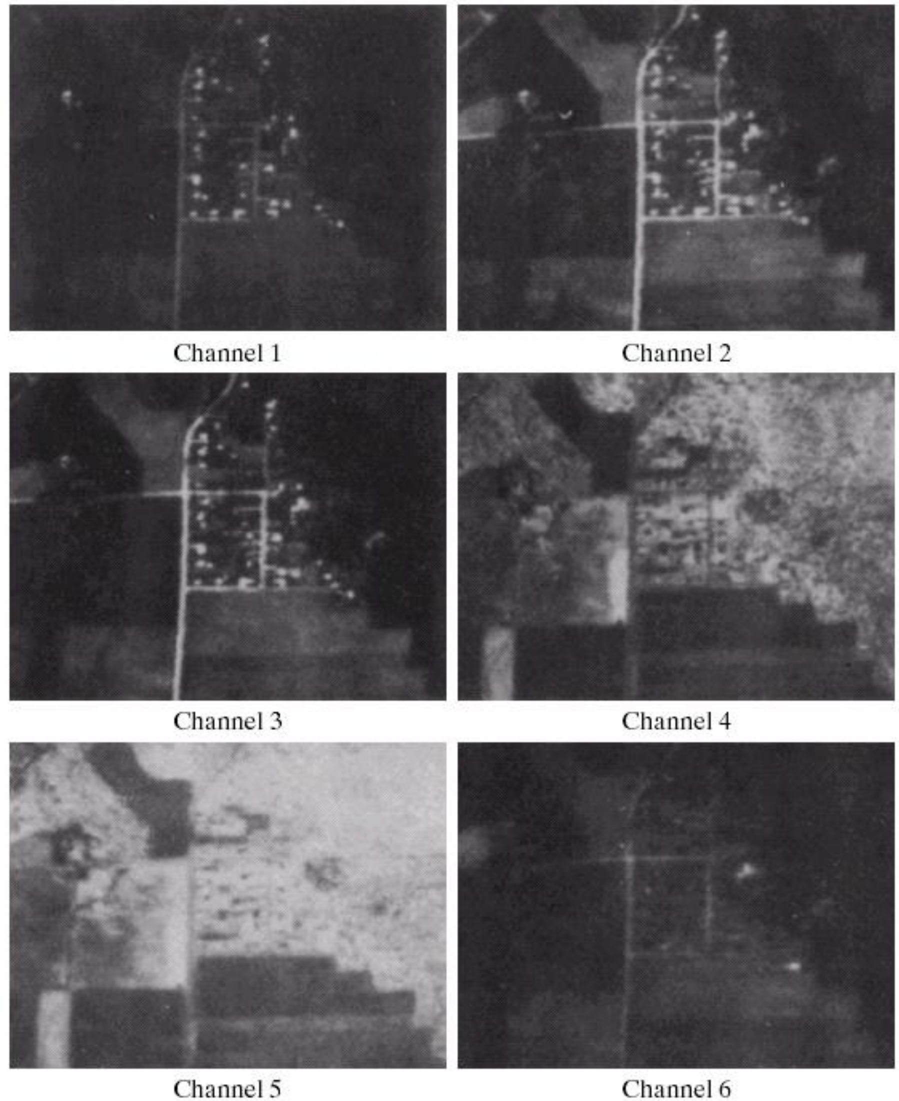
Representation & Description

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).

Representation & Description

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



Representation & 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

Representation & Description

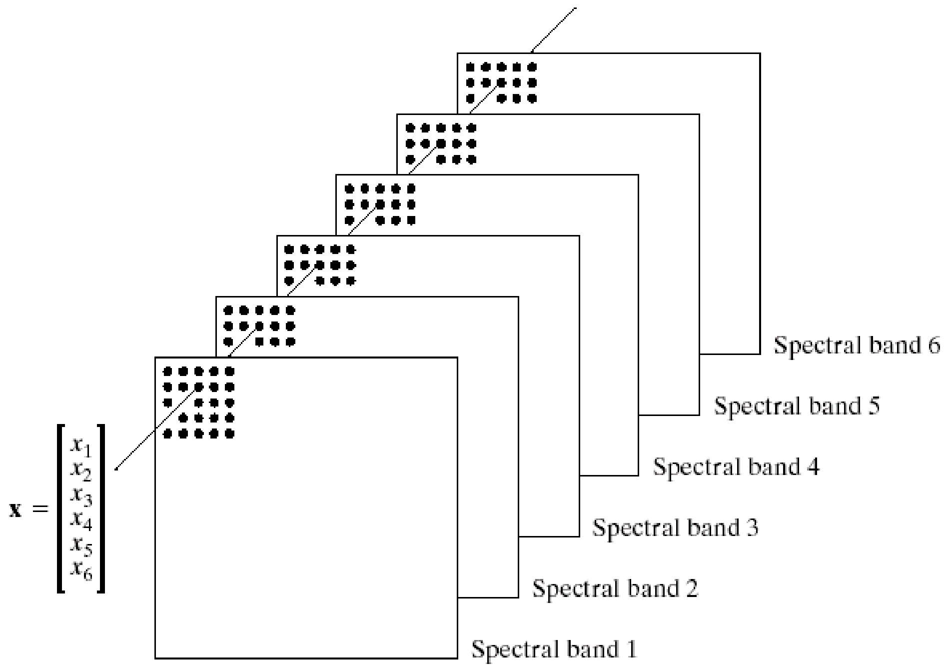


FIGURE 11.27 Formation of a vector from corresponding pixels in six images.

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.

Representation & Description

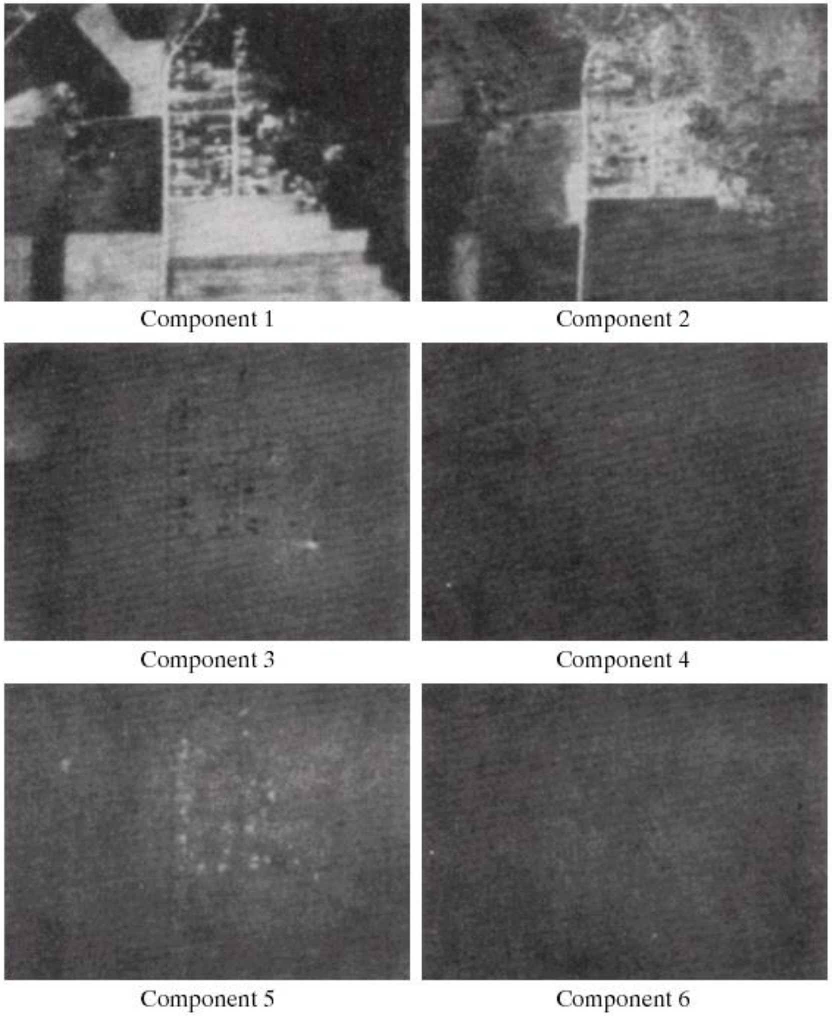


FIGURE 11.28 Six principal-component images computed from the data in Fig. 11.26. (Courtesy of the Laboratory for Applications of Remote Sensing, Purdue University.)

Representation & Description

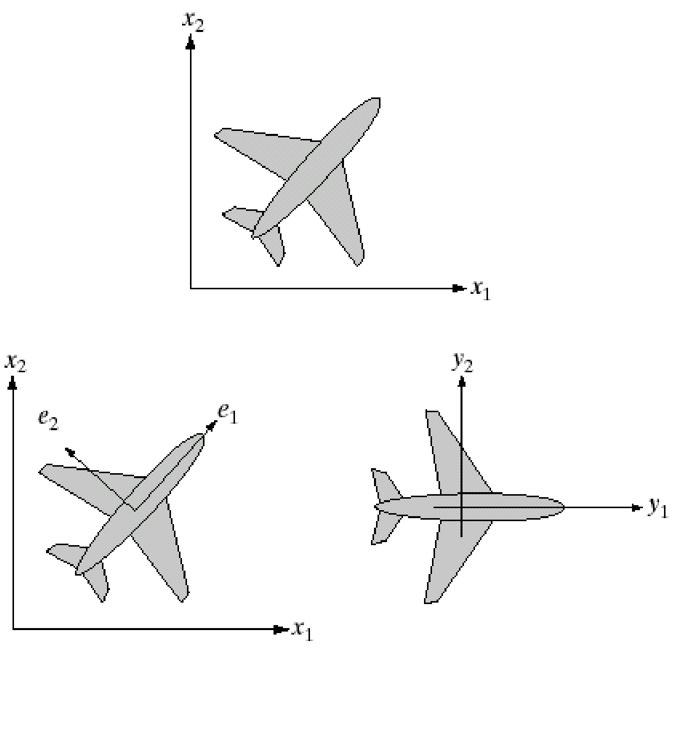
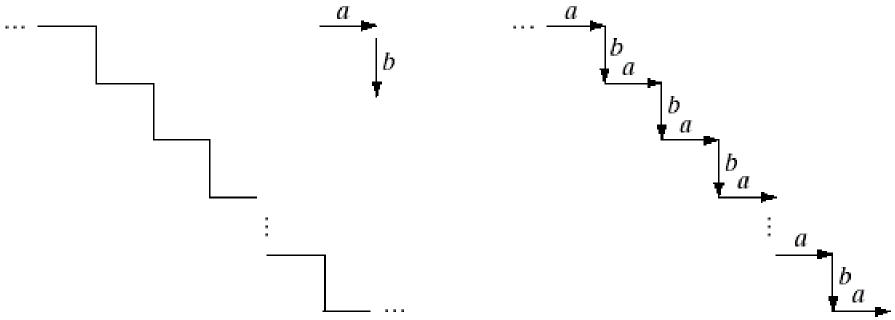


FIGURE 11.29 (a) An object. (b) Eigenvectors. (c) Object rotated by using Eq. (11.4-6). The net effect is to align the object along its eigen axes.

Representation & Description



a b

FIGURE 11.30 (a) A simple staircase structure. (b) Coded structure.

Representation & Description

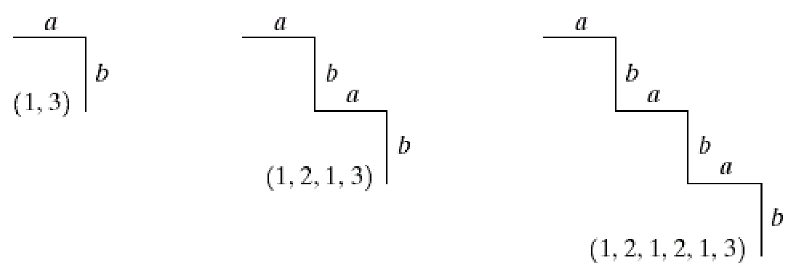


FIGURE 11.31 Sample derivations for the rules $S \rightarrow aA$, $A \rightarrow bS$, and $A \rightarrow b$.

Representation & Description

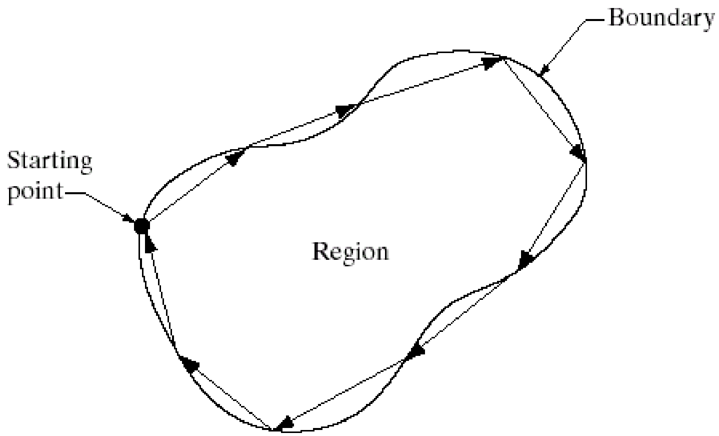
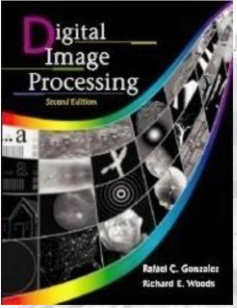
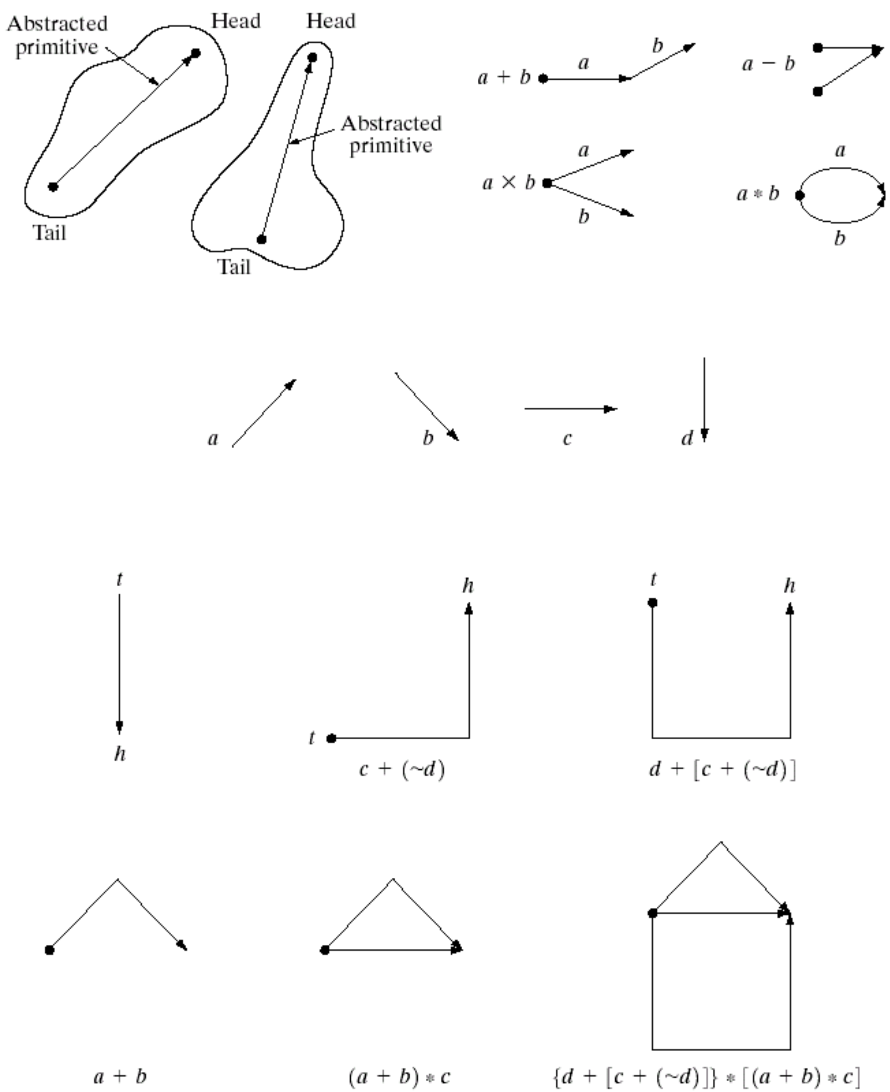


FIGURE 11.32 Coding a region boundary with directed line segments.



Representation & 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.

Representation & Description

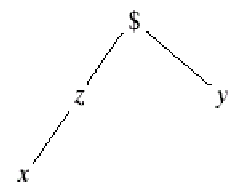
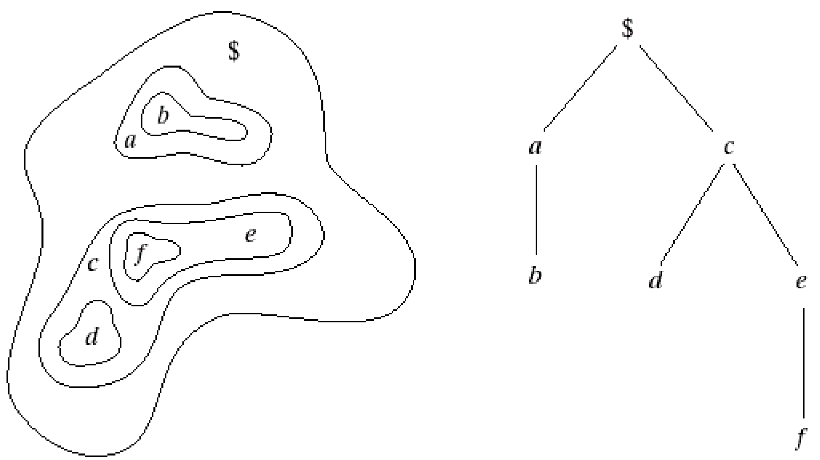


FIGURE 11.34 A simple tree with root \$ and frontier *xy*.



a b

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

from Gonzalez & Woods

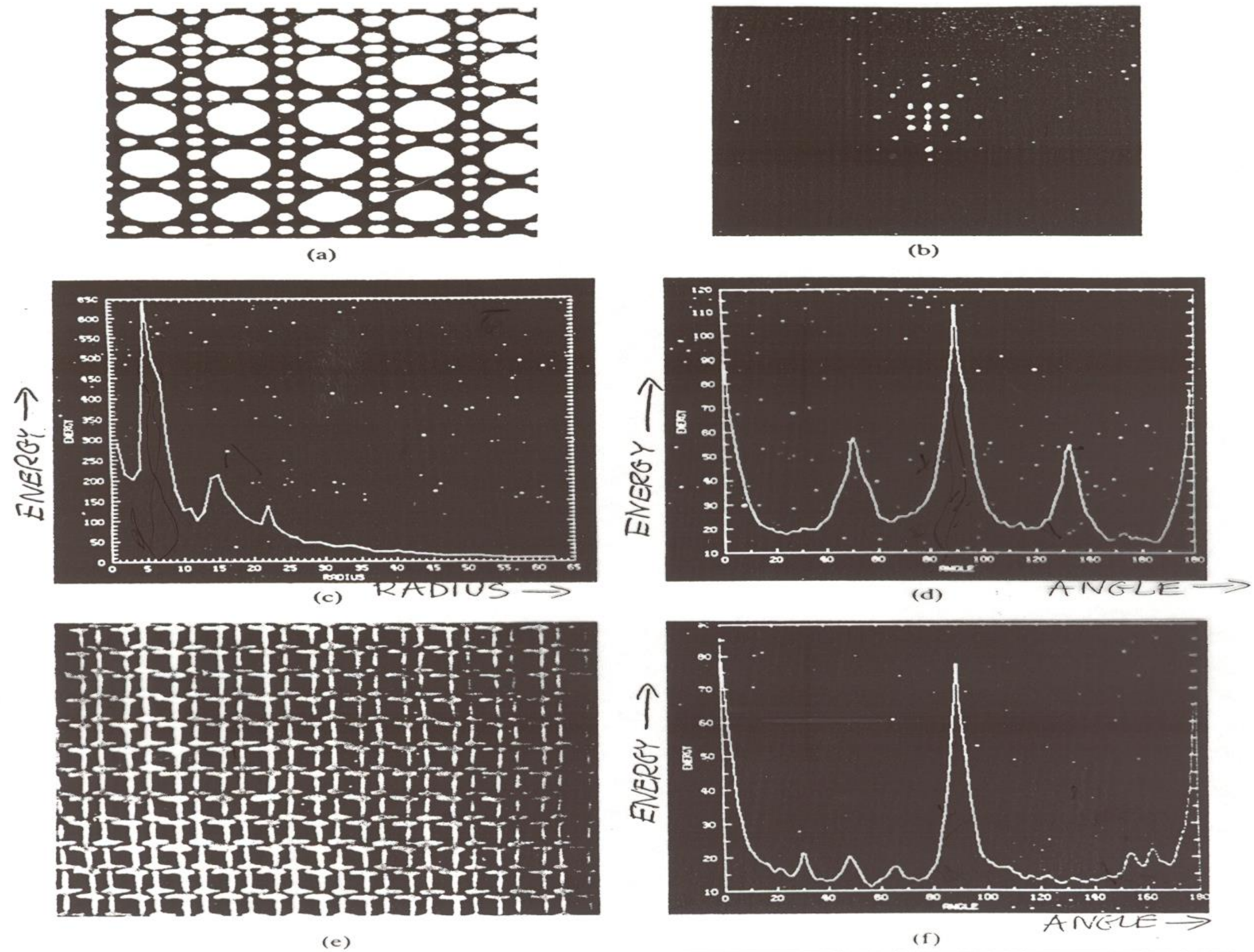


Figure 8.23 (a) Image showing periodic texture; (b) spectrum; (c) plot of $S(r)$; (d) plot of $S(\theta)$; (e) another image with a different type of periodic texture; (f) plot of $S(\theta)$. (Courtesy of D. Brzakovic, University of Tennessee.)

9

SPECTRAL ANALYSIS

- Fourier spectrum is ideally suited for describing the directionality of periodic or almost periodic 2-D patterns in an image
- features of the Fourier spectrum used for texture description:
  - (a) prominent peaks in the spectrum give the direction of texture patterns
  - (b) location of the peaks in the frequency domain gives the fundamental spatial period of the patterns
  - (c) eliminating any periodic components via filtering leaves nonperiodic image elements, which can then be described by statistical techniques.

From Gonzalez & Woods "Digital Image Processing"

Detection and interpretation of the spectrum features just mentioned often are simplified by expressing the spectrum in polar coordinates to yield a function $S(r, \theta)$, where S is the spectrum function and r and θ are the variables in this coordinate system. For each direction θ, $S(r, \theta)$ may be considered a 1-D function $S_\theta(r)$. Similarly, for each frequency r, $S_r(\theta)$ is a 1-D function. Analyzing $S_\theta(r)$ for a fixed value of θ yields the behavior of the spectrum (such as the presence of peaks) along a radial direction from the origin, whereas analyzing $S_r(\theta)$ for a fixed value of r yields the behavior along a circle centered on the origin.

A more global description is obtained by integrating (summing for discrete variables) these functions:

$$S(r) = \sum_{\theta=0}^{\pi} S_\theta(r) \tag{8.3-7}$$

and

$$S(\theta) = \sum_{r=1}^{R} S_r(\theta) \tag{8.3-8}$$

where R is the radius of a circle centered at the origin. For an $N \times N$ spectrum, R typically is chosen as $N/2$.

.com

The results of Eqs. (8.3-7) and (8.3-8) constitute a pair of values $[S(r), S(\theta)]$ for each pair of coordinates (r, θ). By varying these coordinates, we can generate two 1-D functions, $S(r)$ and $S(\theta)$, that constitute a spectral-energy description of texture for an entire image or region under consideration. Furthermore, descriptors of these functions themselves can be computed in order to characterize their behavior quantitatively. Descriptors typically used for this purpose are the location of the highest value, the mean and variance of both the amplitude and axial variations (see Section 8.2.4), and the distance between the mean and the highest value of the function.

Example: Figure 8.23 illustrates the use of Eqs. (8.3-7) and (8.3-8) for global texture description. Figure 8.23(a) shows an image with periodic texture, and Fig. 8.23(b) shows its spectrum. Figures 8.23(c) and (d) show plots of $S(r)$ and $S(\theta)$, respectively. The plot of $S(r)$ is a typical structure, having high energy content near the origin and progressively lower values for higher frequencies. The plot of $S(\theta)$ shows prominent peaks at intervals of 45°, which clearly correspond to the periodicity in the texture content of the image.

As an illustration of how a plot of $S(\theta)$ could be used to differentiate between two texture patterns, Fig. 8.23(e) shows another image whose texture pattern is predominantly in the horizontal and vertical directions. Figure 8.23(f) shows the plot of $S(\theta)$ for the spectrum of this image. As expected, this plot shows high peaks at 90° intervals. Discriminating between the two texture patterns by analyzing their corresponding $S(\theta)$ waveforms would be straight forward. ☐

"From V. Nalwa - Guided tour of computer vision"

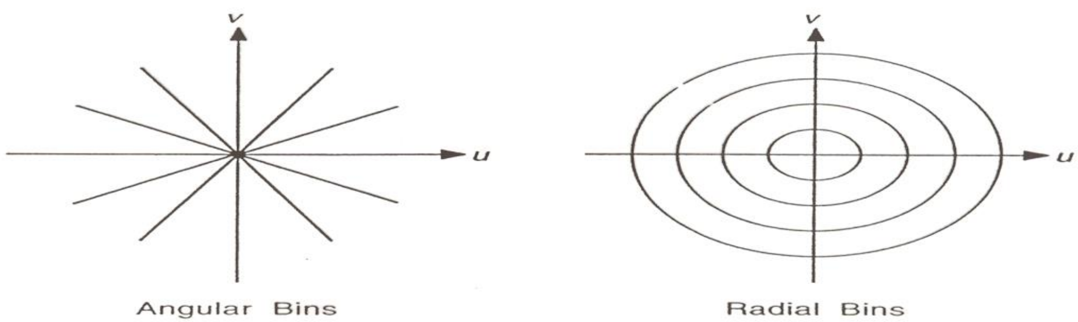


Figure 6.3 Angular and radial bins in the Fourier domain. Angular and radial bins in the Fourier domain capture the directionality and the rapidity of fluctuation of an image texture, respectively. Any image pattern can be mapped uniquely onto the Fourier domain by the Fourier transform. Loosely speaking, the *Fourier transform* decomposes a signal into sinusoidal waves, the frequency of each sinusoid (given by $\sqrt{u^2 + v^2}$ in the figure) indexing the rapidity of change, and the orientation of each sinusoid (given by $\tan^{-1}(v/u)$ in the figure) indexing the direction of change. (After [Lendaris and Stanley 1970].)

8

STRUCTURAL ANALYSIS OF ORDERED TEXTURE

- When the size of the texture primitive is large, it becomes necessary to first determine the shape and properties of the basic primitive and then determine the rules which govern the placement of these primitives, forming macrotextures.

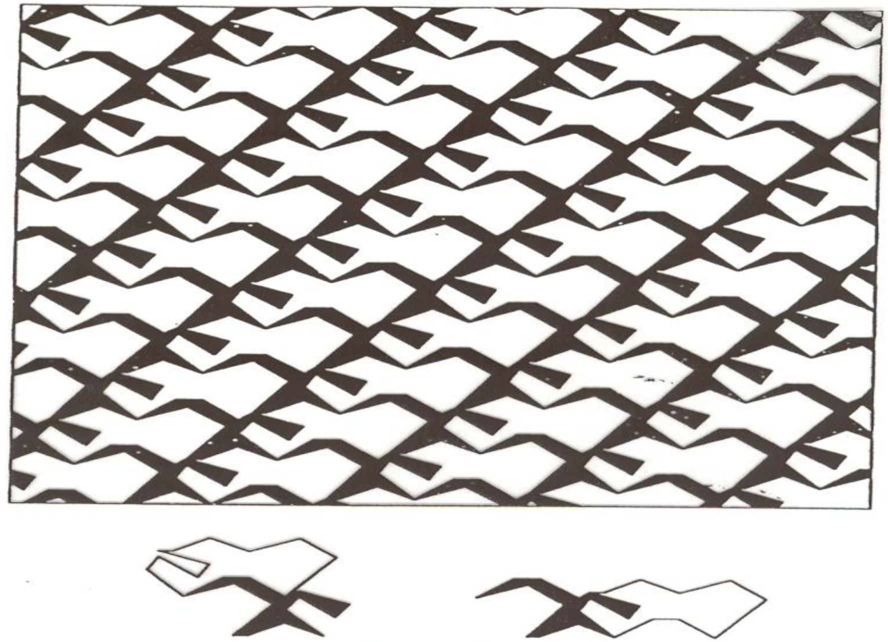
TEXEL

For example:

(1) segment the disks using a simple method such as connected component labeling
(2) calculate centroids of all the components
(3) analyze the structure formed by the centroids of the components

- General strategy:
  (1) segmentation of objects (primitives) – use any segmentation technique, edge-based or region-based
  (2) calculate some properties of the primitives (for example; size, elongation, orientation, etc.)
  (3) calculate co-occurrence matrix of these properties
  (4) use measures based on co-occurance matrix to characterize the texture

from V. Nalwa



Candidate Texels

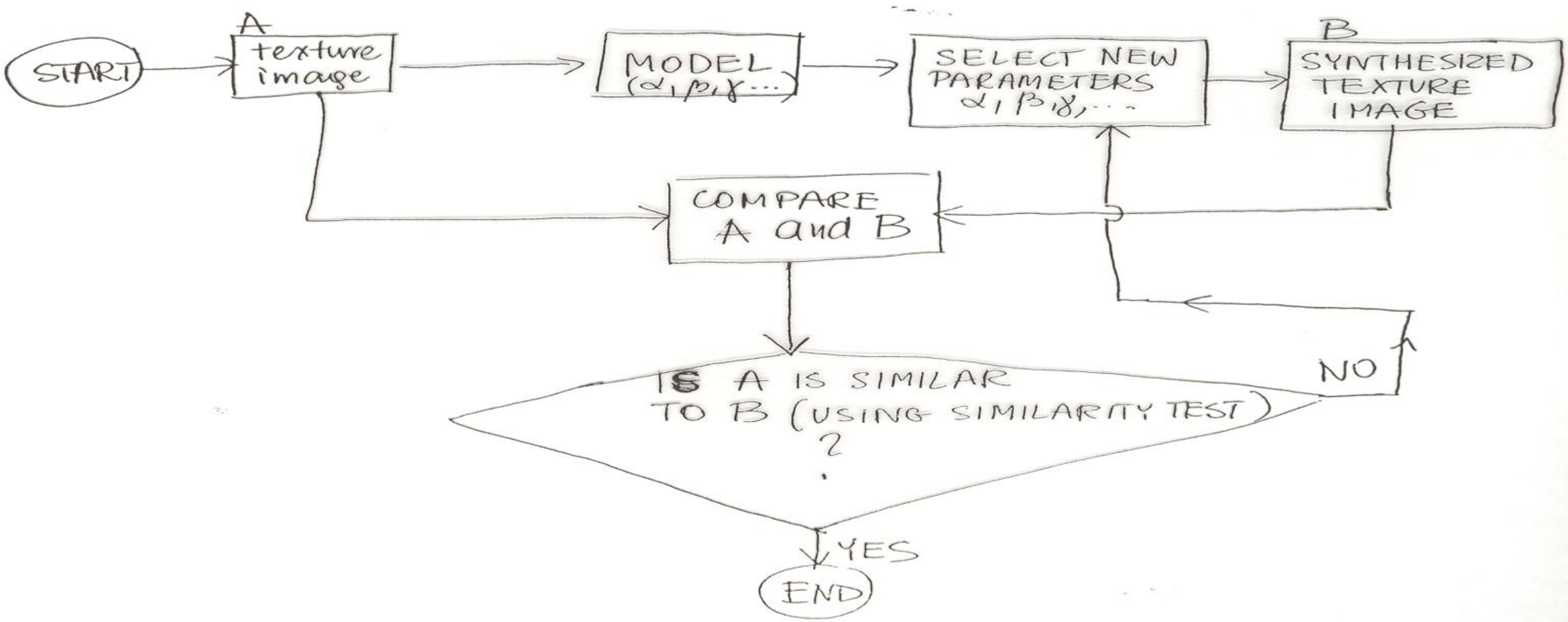
Figure 6.5 An Escher-inspired pattern with two of several possible candidate *texels* (an abbreviation for *texture elements*). On repetition, each of the two candidate texels shown can be made to cover the illustrated pattern completely. An alternative to the choices of texels shown is a texel that is either completely black or completely white—such a choice assumes that the pattern comprises a foreground residing on a background of the opposite color. (Escher was a famous graphic artist whose work has received considerable attention in both art and psychology—we saw an example of his work, *Belvedere*, in Figure 1.6.)

MODEL-BASED METHODS FOR TEXTURE ANALYSIS

- sometimes it is possible to characterize texture using an analytical model ; models have parameters

values of parameters determine the texture properties

the challenge is to estimate these parameters, so the synthesized texture is visually very similar to the texture being analyzed.



- Examples : Markov random fields , fractal-based models, etc.

SHAPE FROM TEXTURE

- Variations in the size, shape, and intensity of texture primitives provide clues for estimation of surface shape and orientation

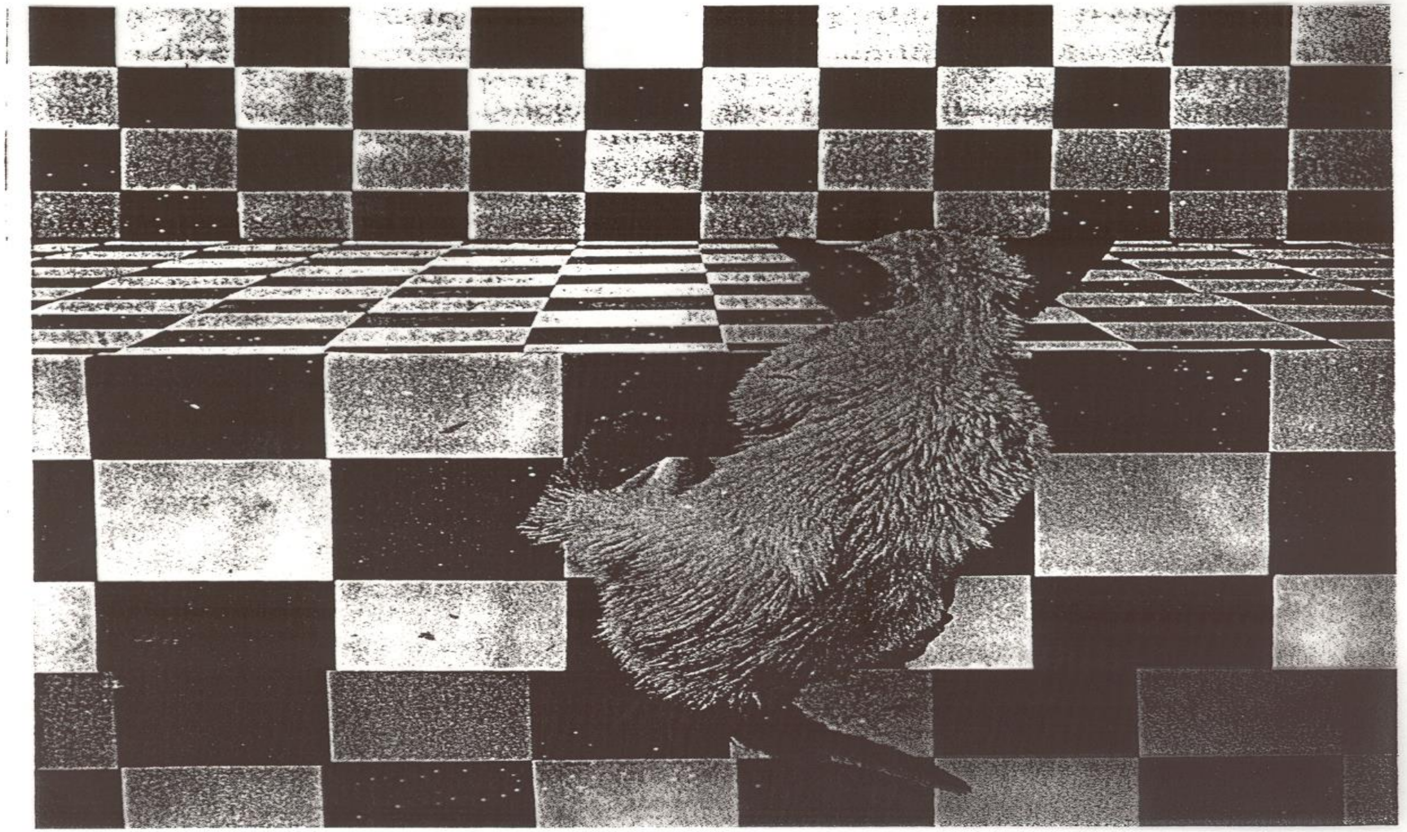


Figure 6.1 *The Visual Cliff,* by William Vandivert, 1960. This photograph of a Siamese kitten peering over a checkered cliff demonstrates how variation in the image characteristics of a spatial texture may affect our perception of the depth and layout of the texture in space. The kitten in the photograph is on a ledge, with its tail protruding over a shallow drop. (A similar photograph by the same photographer first appeared on the cover of *Scientific American,* April 1960.)