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Chain Codes

- Chain codes are used to represent a boundary by a connected sequence of straight-line segments of specified length and direction.
- The direction of each segment is coded by using a numbering scheme such as the ones shown in Fig11.1.



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Chain Codes

- The method generally is unacceptable for two principal reasons:
 - (1) The resulting chain of codes tends to be quite ling and,
 - (2) any small disturbances along the boundary due to noise or imperfect segmentation cause changes in the code that may not be related to the shape of the boundary.
- An approach frequently used to circumvent the problem just discussed is to resample the boundary by selecting a larger grid spacing, as illustrated in Fig 11.2(a).









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



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Chain Codes

- The chain code of a boundary depends on the starting point.
- We can normalize also for rotation by using the *first difference* of the chain code instead of the code itself.
- The first-difference of the 4-direction chain code 10103322 is 3133030.
- If we elect to treat the code as a circular.
- Here, the result is 33133030.



Polygonal Approximations

- A digital boundary can be approximated with arbitrary accuracy by a polygon.
- In practice, the goal of polygonal approximation is to capture the "essence" of the boundary shape with the fewest possible polygonal segments.

Minimum perimeter polygons

• Fig. 11.3(b), producing a polygon of minimum perimeter that fits the geometry established by the cell strip.



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a b

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





Splitting techniques

- One approach to boundary segment splitting is to subdivide a segment successively into two part until a specified criterion is satisfied.
- For a closed boundary, the best starting points usually are two farthest points in the boundary.
- Fig 11.4(c) shows the result of using the splitting procedure with a threshold equal to 0.25 times the length of line *ab*.









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.



Signatures

- A signature is a 1-D functional representation of a boundary and may be generated in various ways.
- One of the simplest is to plot the distance from the centroid to the boundary as a functoon of angle, as illustrated in Fig 11.5.



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Chapter 11 Representation & Description





Signatures

- Signatures generated by the approach just described are invariant to translation, but they do depend on rotation and scaling.
- Normalization with respect to rotation can be achieved by finding a way to select the same starting centroid.
- Another way us to select the point in the eigen axis.



Signatures

- One way to normalize for this result is to scale all functions so that they always span the same range of values, say, [0,1].
- Whatever the method used, keep in mind that the basic idea is to remove dependency on size while preserving the fundamental shape of the waveforms.



Boundary Segments

- Decomposing a boundary into segments often is useful.
- Decomposition reduces the boundary's complexity and thus simplifies the description process.
- In this case use of the convex hull of the region enclosed by the boundary is a powerful tool for robust decomposition of the boundary.

Boundary Segments

- *Convex hull* H of an arbitrary set *S* is the smallest convex set containing *S*.
- The set difference *H*-*S* is called the *convex deficiency D* of the set *S*.
- Fig 11.6(b) shows the result in this case.
- Note that in principle, this scheme is independent of region size and orentation.







a b

FIGURE 11.6

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



- An important approach to representing the structural shape of a plane region is to reduce it to a graph.
- This reduction may be accomplished by obtaining the *skeleton* of the region via a thinning (also called *skeletonizing*).



- The skeleton of a region may be defined via the medial axis transformation (MAT) proposed by Blum[1967].
- The MAT of a region has an intuitive definition based on the so-called "prairie fire concept."
- Consider an image region as a prairie of uniform, dry grass, and suppose that a fire is lit along its border.
- All fire fronts will advance into the region at the same speed.
- The MAT of the region is the set of points reached by more than one fire front at the same time.



- Numerous algorithms have been proposed for improving computational efficiency.
- Typically, these are thinning algorithm that iteratively delete edge points of a region subject to the constraints that deletion of these points:
 - -(1)does not remove end points
 - (2)does not break connectivity
 - (3)does not cause excessive erosion of the region.





• With reference to the 8-neighborhood notation shown in Fig 11.8, step 1 flags a contour point p_1 for deletion if the following conditions are satisfied:

(a)
$$2 \le N(p_1) \le 6$$

(b) $T(p_1) = 1$
(c) $p_2 \cdot p_4 \cdot p_6 = 0$
(d) $p_4 \cdot p_6 \cdot p_8 = 0$
where $N(p_1)$ is the number of nonzero neighbors of p_1 ; that is
 $N(p_1) = p_2 + p_3 + \dots + p_8 + p_9$



p_9	p_2	<i>p</i> ₃	
<i>p</i> ₈	p_1	p_4	
p_7	p_6	p_5	

FIGURE 11.8

Neighborhood arrangement used by the thinning algorithm.



- T(*p*₁) is the number of 0-1 transitions in the ordered sequence *p*₂,*p*₃,...,*p*₈,*p*₉,*p*₂.
- For example, $N(p_1)=4$ and $T(p_1)=3$ in Fig 11.9.
- In step 2, conditions (a) and (b) remain the same, but conditions (c) and (d) are changed to

(c')
$$p_2 \cdot p_4 \cdot p_8 = 0$$

(d') $p_2 \cdot p_6 \cdot p_8 = 0$



- Step 1 is applied to every border pixel in the binary region under consideration.
- If all conditions are satisfied the point is flagged for deletion.
- However, the point is not deleted until all border points have been processed.
- After step 1 has been applied to all border points, those that were flagged are deleted (changed to 0).
- Then step 2 is applied to the resulting data in exactly the same manner as step 1.
- The basic procedure is applied iteratively until no further points are deleted.



FIGURE 11.9	0	0	1
Illustration of			
conditions (a)			
and (b) in	1	p_1	0
Eq. (11.1-1). In			
this case			
$N(p_1) = 4$ and	1	0	1
$T(p_1) = 3.$			





FIGURE 11.10

Human leg bone and skeleton of the region shown superimposed.



Some Simple Descriptors

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- The *length* of a boundary is one of its simplest descriptors.
- The *diameter* of a boundary *B* us defined as $Diam(B) = \max_{i,j} [D(p_i, p_j)]$, this line is so-called the *major axis* of the boundary.
- The minor axis of a boundary is defined as the line perpendicular to the major axis.



Shape Numbers

- As explained in Section 11.1.1, the first difference of a chain-coded boundary depends on the starting point.
- The *shape number* of such a boundary, bssed on the 4-directional code of Fig 11.1(a), is defined as the first difference of smallest magnitude.
- The *order n* of a shape number is defined as the number of digits in its representation..
- Moreover, *n* is even for a closed boundary.









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 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



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Digital Image Processing, 2nd ed. Fourier Descriptors





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.



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Chapter 11 Representation & Description

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



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Digital Image Processing, 2nd ed. Statistical Moments







Some simple Descriptors

Digital Image Processing, 2nd ed.

- The area of a region is defined as the number of pixels in the region.
- The perimeter of a region is the length of its boundary.
- Compactness of a region, defined as (perimeter)^2/area, and is minimal for a disk-shape region.
- Other simple measures used as region descriptors include the mean and median of the gray levels, the minimum and maximum gray-level values, and the number of pixels with above and below the mean.



Topological Descriptors

- If a topological descriptors is defined by the number of holes in the region, this property obviously will not be affected by a stretching or rotation transformation.
- Another topological property useful for region description is the number of connected components.
- The number of holes *H* and connected components *C* in a figure can be used to define the *Euler Number E*: *E*=*C*-*H*



Digital Image Processing, 2nd ed. Topological Descriptors

- The Euler number is also a topological property.
- The regions shown in Fig 11.19, for example, have Euler numbers equal to 0 and -1.
- Denoting the number of vertices by *V*, the number of edges by *Q*, and the number of faces by *F* gives the following relationship, called the *Euler Formula*:

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

$$=E.$$



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





FIGURE 11.17 A region with two holes.



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



FIGURE 11.20 A region containing a polygonal network.







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Texture

An important approach to region description is to quantify its *texture* content.



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abc

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.)



Statistical approaches

• The *n*th moment of *z* about the mean is

$$\mu_{n}(z) = \sum_{i=0}^{L-1} (z_{i} - m)^{n} p(z_{i}) \qquad m = \sum_{i=0}^{L-1} z_{i} p(z_{i})$$

- The second moment is of particular importance in texture description.
- It is a measure of gray-level contrast that can be used to establish descriptors of relative smoothness.
- For example, the measure is 0 for areas of contrast intensity (the variance is 0 here) and approaches 1 for large value of $\sigma^2(z)$. $R = 1 - \frac{1}{1 + \sigma^2(z)}$

Statistical approaches

- The third moment $\mu_3(z) = \sum_{i=0}^{L-1} (z_i m)^3 p(z_i)$ is a measure of the skewness of the histogram while the fourth moment is a measure of its relatives flatness.
- Some useful additional texture measures bases on histograms include a measure of "uniformity", given by $U = \sum_{i=0}^{L-1} p^2(z_i)$ average entropy measure $e = -\sum_{i=0}^{L-1} p(z_i) \log_2 p(z_i)$



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



Statistical approaches

• C is called the gray-level co-occurrence matrix

- 1. Maximum probability $\max_{i,j} (c_{ij})$
- 2.Element difference moment of order k

$$\sum_{i} \sum_{j} \left(i - j \right)^k c_{ij}$$

– 3.Inverse element difference moment of order k

$$\sum_{i} \sum_{j} c_{ij} / (i - j)^{k} \qquad i \neq$$

$$- 4. \text{Uniformity} \qquad \sum_{i} \sum_{j} c_{ij}^{2}$$

$$- 5. \text{Entropy} - \sum_{i} \sum_{j} c_{ij} \log_{2} c_{ij}$$



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Chapter 11 Representation & Description



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- **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 $S(\theta)$. a b
- c d
- (Courtesy of Dr. Dragana Brzakovic, University of Tennessee.) e f





Digital Image Processing, 2nd ed. Use of Principal Components for Description

$$m_{\rm x} = \mathrm{E}\{\mathrm{x}\}$$

covariance matrix of the vector population is defined as $C_{x} = E \left\{ (x - m_{x})(x - m_{x})^{T} \right\}$ $m_{x} = \frac{1}{K} \sum_{k=1}^{K} x_{k}$ $C_{x} = \frac{1}{K} \sum_{k=1}^{K} x_{k} x_{k}^{T} - m_{x} m_{x}^{T}$



Digital Image Processing, 2nd ed. Use of Principal Components for Description

$$y = A(x - m_x)$$

$$m_y = E\{y\} = 0$$

$$C_y = AC_x A^T$$

$$C_y = \begin{bmatrix} \lambda_1 & 0 \\ \lambda_2 & 0 \\ & \ddots & 0 \\ 0 & & \lambda_n \end{bmatrix}$$

$$x = A^{T} y + m_{x}$$

$$\hat{x} = A_{k}^{T} y + m_{x}$$

$$e_{ms} = \sum_{j=1}^{n} \lambda_{j} - \sum_{j=1}^{k} \lambda_{j}$$

$$= \sum_{j=k+1}^{n} \lambda_{j}$$





a bc de

FIGURE 11.25 Images used to demonstrate properties of moment

invariants (see Table 11.3).

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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



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





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





 x_2 x_3 x_4

x =

λ ₁	λ_2	λ_3	λ_4	λ_5	λ_6
3210	931.4	118.5	83.88	64.00	13.40

Spectral band 4

Spectral band 3

Spectral band 2

Spectral band 1

TABLE 11.5Eigenvalues ofthe covariancematrix obtainedfrom the imagesin Fig. 11.26.



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Chapter 11 **Representation & Description**





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.)

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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.

























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