Shape Analysis and Classification





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Shape Analysis and Classification





- Basic idea: extracting measures from shapes
- Useful standard measures:
 - mean (and other statistical moments, such as standard deviation, etc)
 - median, min, max
 - ratios such as max/min, etc.
- Acquisition information may play an important role (e.g. pixel dimensions)



- Perimeter:
 - number of boundary pixels (approx.)
 - for 8-connected chain-coded boundaries (N_e and N_o denote, respectively, the number of even and odd codes in the chain-coded contour representation):

$$P = N_e + N_o \sqrt{2}$$

- Perimeter:
 - If the contour is represented as a complexvalued signal u(n) = x(n) + j y(n):

$$P = \sum_{n=0}^{N-1} |u(n) - u(n-1)|$$



- Area:
 - May be approximated by the number of shape pixels, in case of region-based representations (e.g. by binary images)
 - The area of polygons may be calculated using triangle decomposition and vectorial products







Signed area compensates for concavities



<u>Algorithm:</u> Area-Based Object Sorting

1- Label each connected component in the image;
2- Calculate the histogram of the labeled image;
3- Sort the connected components as a function of the respective histogram heights, ignoring the background pixels;

- Centroid:
 - If the contour is represented as a complexvalued signal u(n) = x(n) + j y(n):

$$M = \frac{\sum_{n=0}^{N-1} u(n)}{N}$$

 Region based representations: average value of all pixel coordinates





- Centroid useful measures:
 - Maximum distance D_{max} between the centroid and the boundary points
 - Minimum distance D_{\min} between the centroid and the boundary points
 - Mean distance D_{mean} between the centroid and the boundary points
 - Histogram of the distances between the centroid and the boundary points



• Mean distance to the boundary:

$$\beta = \frac{1}{N} \sum d(r, boundary(g))$$

- May be calculated from the distance transform
- Derived complexity measure:





• Diameter







✓ Norm features ✓ 2n Euclidean norm \checkmark RMS size \checkmark Mean size ✓ Centroid size ✓ Normalized centroid size ✓ Baseline distance ✓ Landmark-based shape diameter

- The Karhunen-Loève Transform
- Let *X* be a random vector with covariance matrix *K*.
- Let v_i , (i = 1, 2, ..., N) be the eigenvectors of K, represented in terms of the following matrix:

$$OMEGA = \begin{bmatrix} \leftarrow \vec{v}_1 \rightarrow \\ \leftarrow \vec{v}_2 \rightarrow \\ \vdots \\ \leftarrow \vec{v}_N \rightarrow \end{bmatrix}$$





• The Karhunen-Loève Transform is defined as

 $\vec{X} = OMEGA \vec{X}$

• Useful for dimensionality reduction





• Major and minor axis of a shape

$$\{(x_1, y_1), (x_2, y_2), (x_3, y_3), \dots, (x_n, y_n)\}$$

• Regions, contours, etc.





✓ Shape measures from major/minor axes

- ✓ The lengths of the principal axes, which can be defined as the associated eigenvalues
- ✓ The *aspect ratio*, also known as *elongation*, defined by ratio the between the major and the minor axes' sizes
- \checkmark Rectangularity, defined as





Statistical moments

• As in the PCA case, the shape points are taken as samples from a given shape distribution:

$$\{(x_1, y_1), (x_2, y_2), (x_3, y_3), \dots, (x_n, y_n)\}$$

• Let g(p,q) be a binary image representing the shape.

Statistical moments

• The statistical moments of *g* are defined as:

$$m_{r,s} = \sum_{p=0}^{P-1} \sum_{q=0}^{Q-1} p^{r} q^{s} g(p,q)$$

Statistical moments

• Central moments are used for translation invariance

$$\mu_{r,s} = \sum_{p=0}^{P-1} \sum_{q=0}^{Q-1} (p - \overline{p})^r (q - \overline{q})^s g(p,q)$$

$$\overline{p} = \frac{m_{1,0}}{m_{0,0}}$$
 $\overline{q} = \frac{m_{0,1}}{m_{0,0}}$

Bilateral symmetry

- Simple method:
 - Reflection around major axis (passing through the centroid)
 - Sum
 - N: number of foreground pixels
 - N2: number of foreground pixels with graylevel=2
 - Symmetry measure: N2/N

Bilateral symmetry







0.93

symmetry = 0.97688





0.97



Shape signatures



1D signals that represent the shape

Shape signatures

- x, y, x + jy or by some function of each such complex values, such as magnitude or phase.
- Chain-code and shape number
- Curvature
- Distance to the centroid.
- Number of intersections: this signature is possible only for the above described angle-based parameterization, being defined by the number of times that the current line intersects the shape boundary.
- Angle with an axis: the angle-based parameterization can be inverted in order to produce an interesting signature.
- Affine signatures: affine curvature and affine parameterization
- Sholl diagrams

Topological descriptors

- The number of holes NH
- The number of connected components NC. It is important to note that this feature applies to composed shapes (e.g. Arabic character recognition)
- The Euler number, which is defined as E = NC NH

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Polygonal descriptors

- Number of corners or vertices
- Angle and sides statistics, such as mean, median, variance and moments, to name but a few
- Major and minor sides lengths
- Major and minor sides ratio
- Major and minor angles ratio
- Ratio between the major angle and the sum of all angles
- Ratio between the standard deviations of sides and angles
- Mean absolute difference of adjacent angles





Simple

Complex



• Circularity

• Thinness ratio

• Area to perimeter ratio

• Rectangularity







- Fractal dimension: box-counting approach
- The *topological dimension:* number of degrees of freedom (points = 0, curves=1, planes=2, etc.)
- *Hausdorff-Besicovitch* dimension
- Benoit Mandelbrot: fractal set $d \ge d_T$

• Let S be a set of R^2 , and $M(\varepsilon)$ the number of open balls of radius ε that are necessary to cover S.

• An open ball of radius ε and centered at (x_0, y_0) , in R^2 , can be defined as the set $\{(x, y) \in R^2 \mid ((x - x_0)^2 + (y - y_0)^2)^{1/2} < \varepsilon \}.$



- The box-counting fractal dimension d is defined as $M(\varepsilon) \sim \varepsilon^{-d}$
- Example 1: for a point, d = 0
- Example 2: for a straight line, d = 1
- Example 3: for plane, d = 2







Koch's triadic curve





3	ME)	Measured Curve Length
$\frac{1}{2} = (1/2) (1) = (1/2) (1/3)$	1 = 40	1
1/6 = (1/2) (1/3) = (1/2) (1/3)	$4 = 4^{1}$	1.33
1/18 = (1/2) (1/9) = (1/2) (1/3)	16 = 4	1.78
		•••

 $4 \sim (1/3)^{-d}$

 $d = \log(4) / \log(3) \cong 1.26$

Estimating the box-counting dimension











The Minkowsky Sausage or Dilation Method









d = 2 - slope









Table 6. 1:

Summary of some important curvature properties

Curvature	Geometrical Aspect
	(assuming counterclockwise
	parameterization)
Curvature local absolute value	Generic corner
maximum	
Curvature local positive maximum	Convex corner
Curvature local negative minimum	Concave corner
Constant zero curvature	Straight line segment
Constant non-zero curvature	Circle segment
Zero crossing	Inflection point
Average high curvature in absolute	Shape complexity, related to the
or squared values	bending energy (Chapter 7)

$$k(t) = \frac{\dot{x}(t) \ddot{y}(t) - \ddot{x}(t) \dot{y}(t)}{\left(\dot{x}(t)^2 + \dot{y}(t)^2\right)^{3/2}}$$

Problem to be solved: numerical differentiation

• Definition of alternative curvature measures based on angles between vectors defined in terms of the discrete contour elements

• Interpolation of and and differentiation of the interpolated curves

Curvature $c(n_0)$ $c(n_0)$ $c(n_0)$ (b) (a) (c)

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$$r_{i}(n) = \frac{v_{i}(n)w_{i}(n)}{\|v_{i}(n)\|\|w_{i}(n)\|}$$









Multiscale approach obtained by varying the neighborhood size

- Curvature features:
 - Sampled curvature
 - Curvature statistics
 - Maxima, minima, inflection points
 - Bending energy

$$B = \frac{1}{P} \int k(t)^2 dt$$



Fourier descriptors

- Basic idea: Fourier transform of the shape
- Contours and regions
- Many variations (for invariance, etc)
- Many interesting properties have been explored in the literature

Fourier descriptors







Fourier descriptors



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Fourier descriptors







