

# **Object description**

# What is an object descriptor?

- An **object** is a collection of pixels in an image
- A **descriptor** is a representation for some property of the group of pixels
  - generally a scalar

*Need for a descriptor:* quantification, recognition

# Desired properties of a descriptor

1. **Completeness** – Two objects can have identical descriptors iff the objects are identical in shape
2. **Congruence** – Similar objects must have similar descriptors
3. **Invariance** – Descriptor must be invariant to scale, rotation, orientation, etc.
4. **Compactness** – Descriptor must be an efficient representation for the object.  
i.e capture the uniqueness with minimal information

# Classes of object descriptors

- Shape boundary-based
  - Chain codes
  - Fourier descriptor
- Region-based
  - Basic (area, perimeter, compactness, dispersion)
  - Moments (First order, Centralised, Zernike)

# Boundary descriptor 1

## {Boundary, region}

- Boundary – A pixel which belongs to the object and has at least one background pixel as a neighbour
  - The entire set is found by contour following
- Region – A pixel in the interior of the object
  - Pixel which belongs to the object but not on the boundary

The above will change depending on connectivity rules

# Boundary descriptor 2

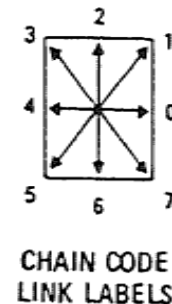
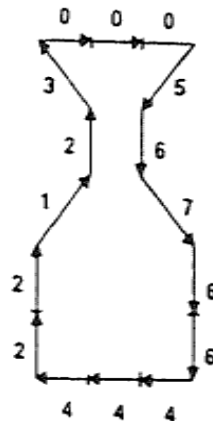
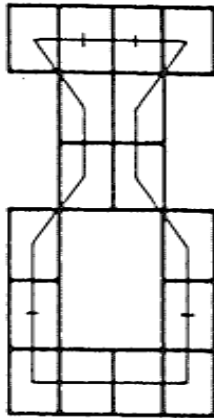
## Chain Codes

- A representation for shape of an object

Version1: Store coordinates of boundary pixels

version 2: Store only their relative positions

Unlike version1 version2 preserves order and is more compact



# Fourier descriptor

- Fourier theory applied to shapes
  - descriptor encodes the shape in terms of frequency

## Approach:

- Treat the locus (trace) of the boundary points as a periodic function ➔ Expand using Fourier series

# 1-D Fourier transform- review

- N-length sequence  $f[n] \Leftrightarrow$  DFT  $F[k]$

$$F[k] = \frac{1}{N} \sum_{n=0}^{N-1} f[n] e^{-j \frac{2\pi k n}{N}} ; \quad k = 0, 1, \dots, N-1$$

$$f[n] = \sum_{k=0}^{N-1} F[k] e^{j \frac{2\pi k n}{N}} \quad n = 0, 1, \dots, N-1$$

- $f$  can be real or complex
- $F$  is generally complex



# Fourier descriptor – for shapes

Given a set of  $N$  boundary points for the shape, with coordinates  $(x,y)$

1. define  $b[l] = x[l] + j y[l]$
2. Find the DFT of  $b[l]$  as

$$B[k] = \frac{1}{N} \sum_l b(l) e^{-j \frac{2\pi k l}{N}} = \frac{1}{N} \sum_l x(l) e^{-j \frac{2\pi k l}{N}} + j \frac{1}{N} \sum_l y(l) e^{-j \frac{2\pi k l}{N}}$$
$$k, l = 0, 1 \dots N-1$$

$B[k]$  is the **Fourier descriptor** of the shape (*Elliptic form*)

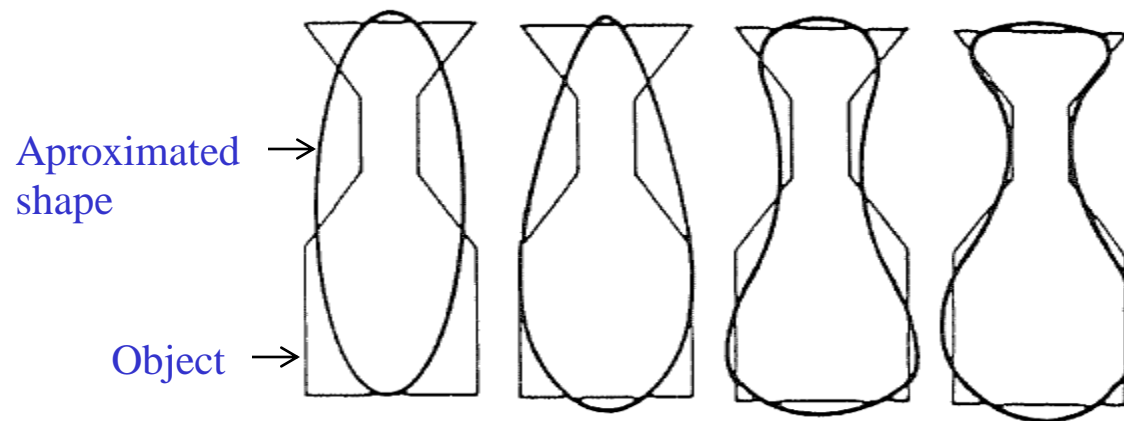
$l = 0$  gives the average value of the boundary points (position/centroid of the shape)

$l > 0$  encodes details

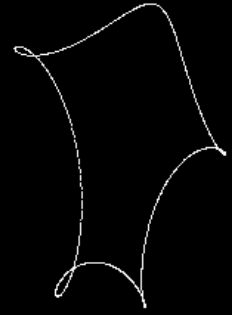
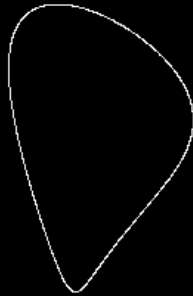
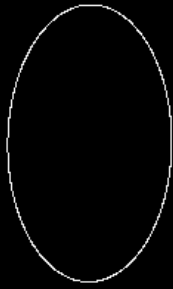
# Reconstruction from $M < N$ coeffs.

$$b[l] = \sum_{k=-M/2}^{M/2} F[k] e^{j \frac{2\pi k l}{N}} \quad l = 0, 1 \dots N-1$$

Reconstructed shape with  $M = 1$  to 4



M=1 to 4



M=5 to 7



N=1257



M=10

M=20

M=30

M=1257

# Variant of Fourier Descriptor

$B[k]$  is **not** invariant to scale, translation, rotation and starting point shift

Ex. Translation by  $b_0 \rightarrow B[k] + b_0\delta[k]$

Why? (check by deriving it mathematically)

To achieve these, one can

- drop the phase and the  $l = 0$  term
- do a normalisation

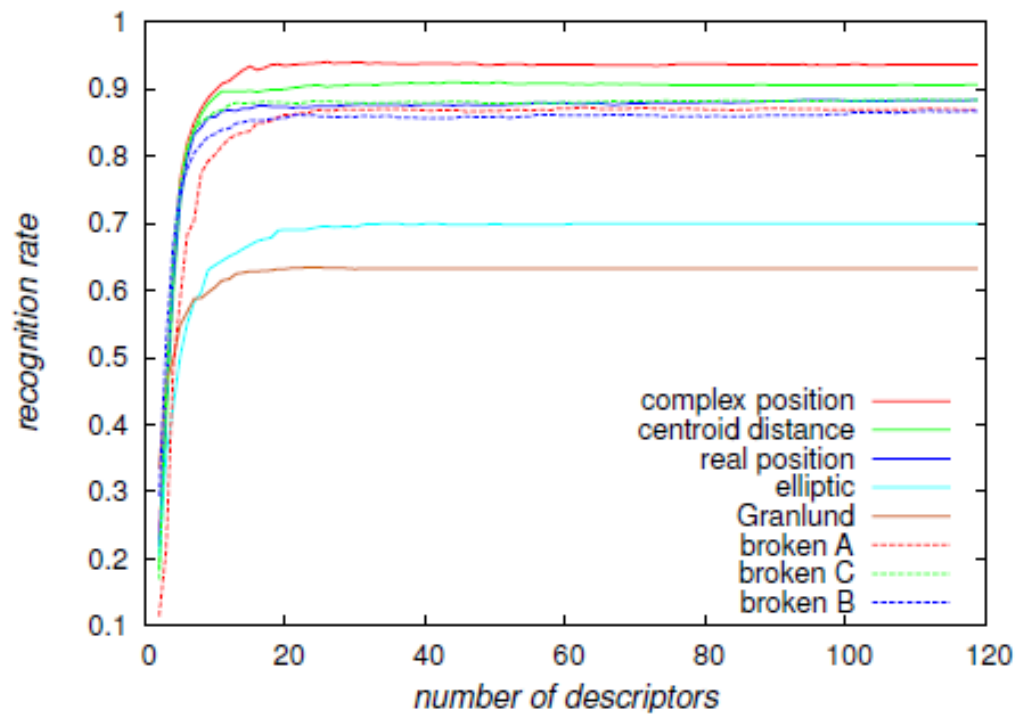
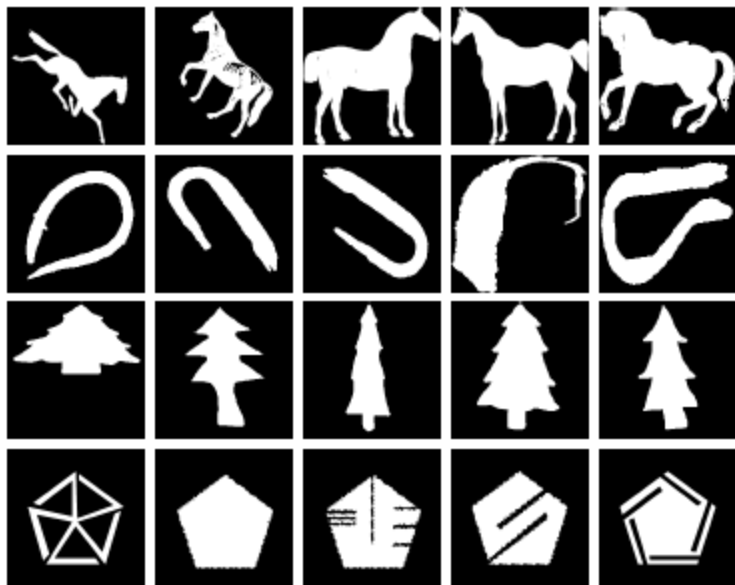
## Normalised magnitude form of FD

$$C[k] = \frac{|B[k]|}{\max\{|B[k]|\}} \quad k = 1, (N-1), 2, (N-2) \dots$$

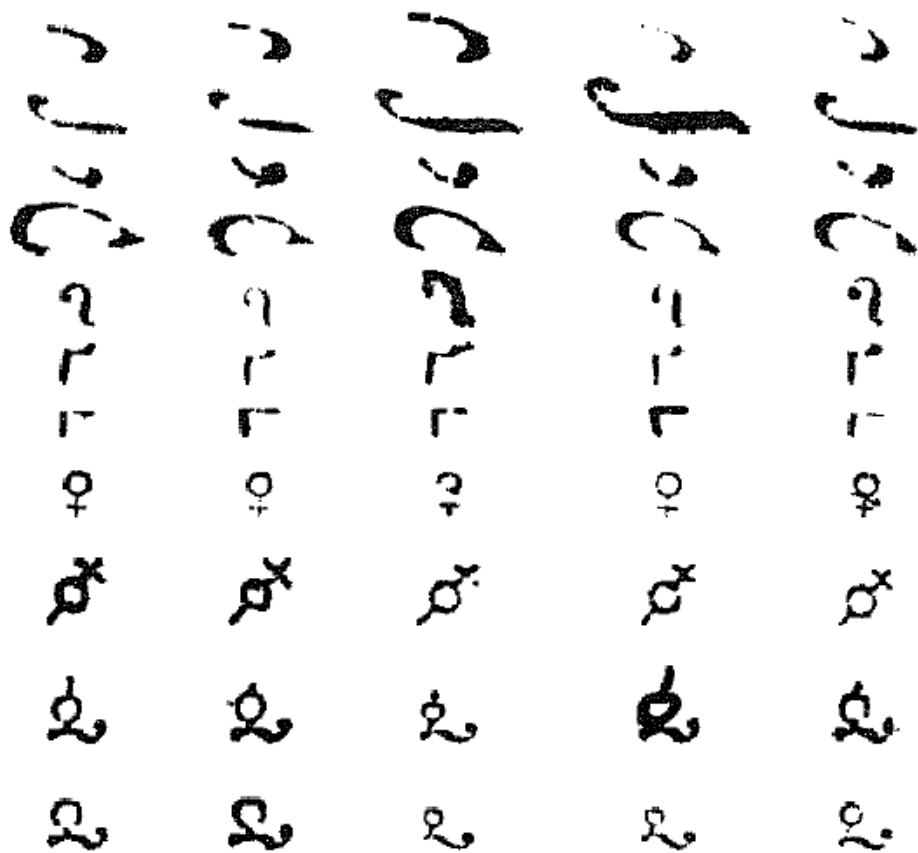
# Fourier descriptors..contd.

- Very popular for representing shape
- Many variants exist
  - All aimed at invariance+ improving discriminating power
- Dalitz *et al.* (Eurasip J of Sig proc. 2013) propose one aimed at handling ‘broken’ shapes
  - Uses the radial distance  $r[k]$  from centroid and a distance transform to encode shape

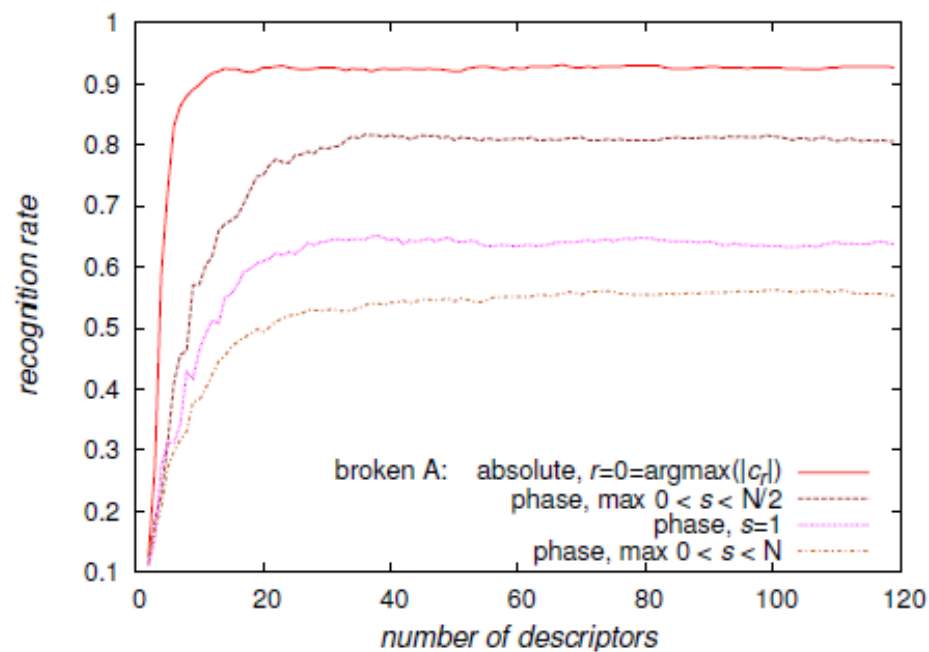
# MPEG-7 CE-1 dataset



# Neumes (broken shapes) dataset



Old music notation



Recognition vs number of descriptors

# Region descriptors

## Basic ones:

- *Area*  $A$  – total number of object pixels
- *Perimeter*  $P$  – total number of boundary pixels
- *Compactness* –  $A/(P^2/4\pi)$ 
  - denominator is the area of a circle with perimeter  $P$ ; max for a circular object
- *Dispersion* – major chord length/area
  - simpler defn: max radius/min radius



# Moments (statistical)

Describes the layout of the object pixels

- **Moments**

$$m_{pq} = \sum_x \sum_y x^p y^q I[x, y]$$

- $m_{00}$  = area under the shape  $I$

- *Centroid*:  $[\bar{x}, \bar{y}] = [\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}}]$

- **Centralised moments**  $\mu_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q I[x, y]$

- to attain invariance to translation

- measure of skewness in  $x$ -direction:  $\frac{\mu_{30}}{\sqrt{(m_{20})^3}}$

- measure of skewness in  $y$ -direction  $\frac{\mu_{03}}{\sqrt{(m_{02})^3}}$

# Moment invariants

- Central moments are combined to create 7 moment invariants to attain invariance to
  - Translation
  - Rotation
  - Reflection

# Orthogonal moments

- **Zernike polynomials**

- set of orthogonal polynomials defined on a disc

- Start with orthogonal basis functions (in polar coords):

$$V_{nm}(\rho, \theta) = R_{n,m} e^{jm\theta};$$

$$n > 0; \quad |m| \leq n; \quad n - |m| \text{ is even}$$

$$R_{n,m}(\rho) = \sum_{s=0}^{(n-|m|)/2} (-1)^s \cdot \frac{(n-s)!}{s! \left(\frac{n+|m|}{2} - s\right)! \left(\frac{n-|m|}{2} - s\right)!} \rho^{n-2s}$$

# Zernike moments

- Find the projection of the image onto the polynomials defined onto a disc i.e.  $(x^2 + y^2) = 1$

$$A_{nm} = \frac{n+1}{\pi} \sum_x \sum_y I(x, y) V_{nm}^*(\rho, \theta)$$

- If we use  $|A_{nm}|$  the moments are rotationally invariant
- Have been used in retrieval, quantify mass volume, classify malignant/benign masses based on shape,