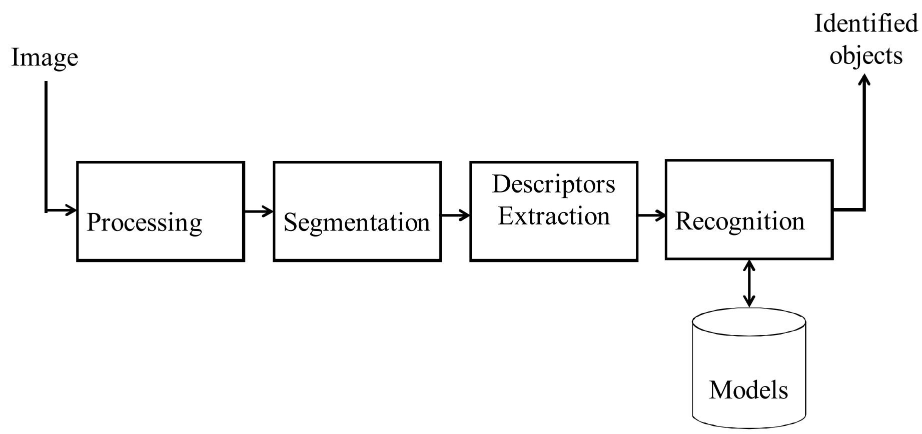
Descripció de Regions

A computer vision system



Introducció

- Volem extraure característiques numèriques de les regions
- Problema: les formes varien.
    - traslació
    - Rotació
    - Resolució
    - Escala
    - Projecció 2D
    - Oclusions

- **labelling** : Les regions s'identifiquen amb etiquetes úniques
- Usarem descriptors basats en contorns i descriptors basats en regions

Types of invariance

Illumination

Types of invariance

Illumination

Scale

Types of invariance

Illumination

Scale

Rotation

Types of invariance

- Illumination
- Scale
- Rotation
- Affine

UPC

Types of invariance

- Illumination
- Scale
- Rotation
- Affine
- Full Perspective

UPC

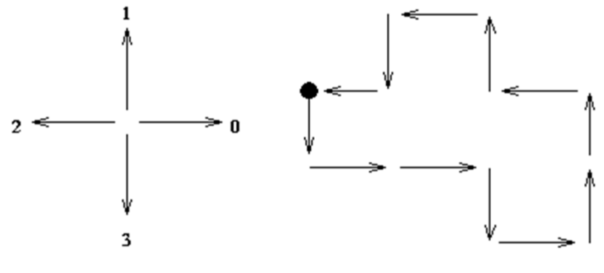
Introducció

- Descriptors basats en contorns:
  - Codis de cadena
  - Propietats geomètriques (perímetre, corbatura...)
  - Descriptors de Fourier
  - Segments (aprox. Poligonals)
  - B-Splines
  - Shape context

-Descriptors basats en regions:
  - Propietats geomètriques (àrea, excentricitat...)
  - Moments estadístics
  - Convex hull
  - Esquelets
  - Descomposició en sub-regions (grafs)

Codis de cadena

- Descriu l'objecte com una seqüència de segments unitaris d'una orientació determinada



- Codi: 3,0,0,3,0,1,1,2,1,2,3,2
- Codi incremental: 1,0,3,1,1,0,1,3,1,1,3,1

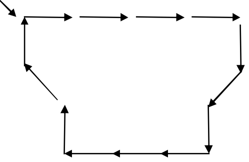
Chain Codes

We need a convention to choose the initial point!

2	3	4
1		5
8	7	6

(1,2) 5 5 5 5 7 8 7 1 1 1 3 2 3

(1,2)

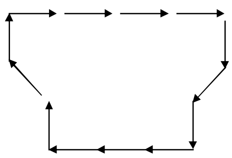


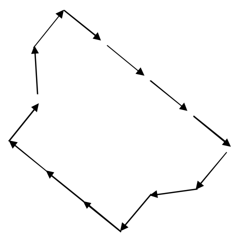
Here the top-left most point was used. Another choice is to write the sequence so it is the circular permutation with the largest (smallest) value: 8 7 1 1 1 3 2 3 5 5 5 5 7

Chain Codes and Rotation

Chain codes can be made rotation invariant by using the derivative of the chain code, also called the DIFFERENCE code:

2	3	4
1		5
8	7	6





8 7 1 1 1 3 2 3 5 5 5 5 7

1 6 0 0 6 1 7 6 0 0 0 6 7

8 2 2 2 4 3 5 6 6 6 6 8 1

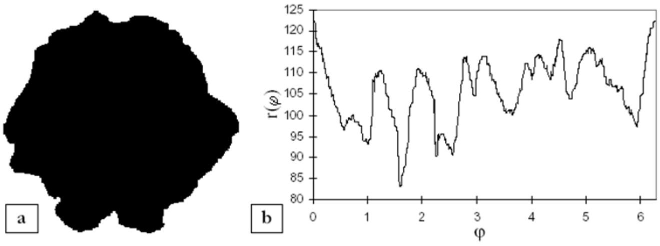
6 0 0 6 1 7 6 0 0 0 6 7 1

Largest permutation

7 6 0 0 0 6 7 1 6 0 0 6 1

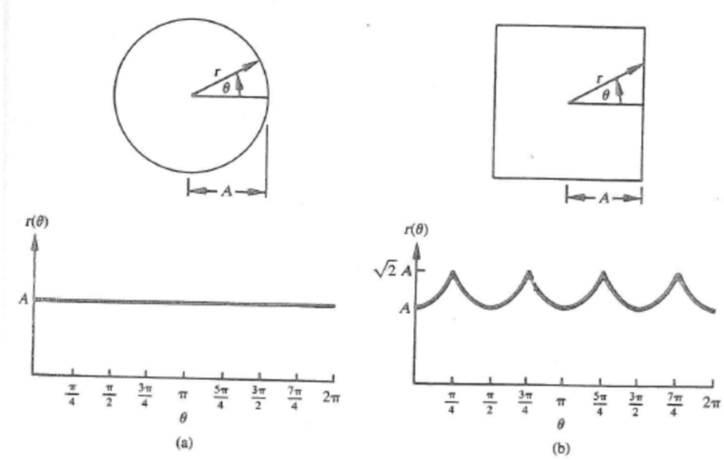
Propietats geomètriques del contorn

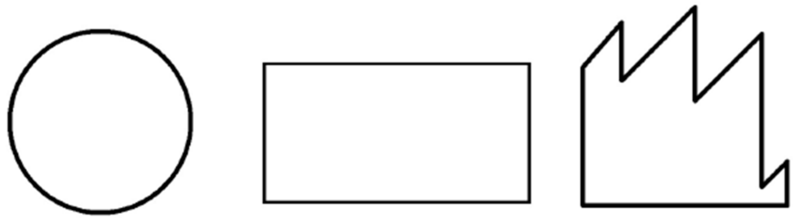
- **Perímetre**. Els passos horitzontals i verticals del codi de Freeman sumen 1 unitat. Els diagonals √2
- **Corbatura**. Rati entre el perímetre i el nº de canvis de direcció del contorn
- **Transformació r(γ)**. Seqüència de les distàncies dels píxels del contorn al centre de l'objecte.



Signatures

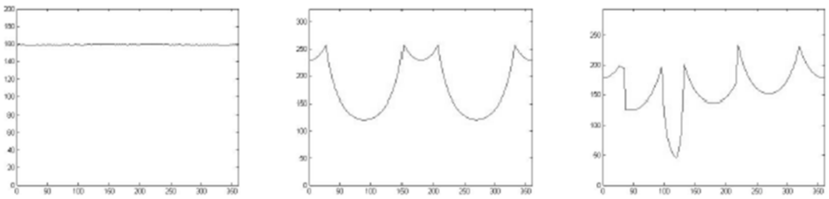
- ρ(θ)





(a) Cercle (b) Rectangle (c) Punxes

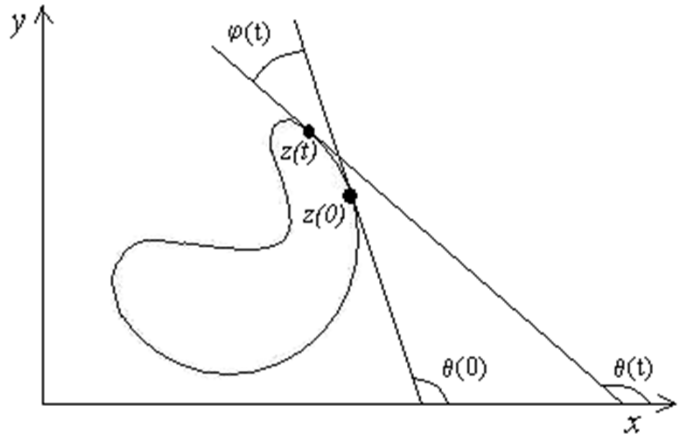
Figura 1: Algunes imatges utilitzades en les proves



(a) Cercle (b) Rectangle (c) Punxes

Figura 2: Contorn per *polar signature*

Slope density function



Slope Density Function

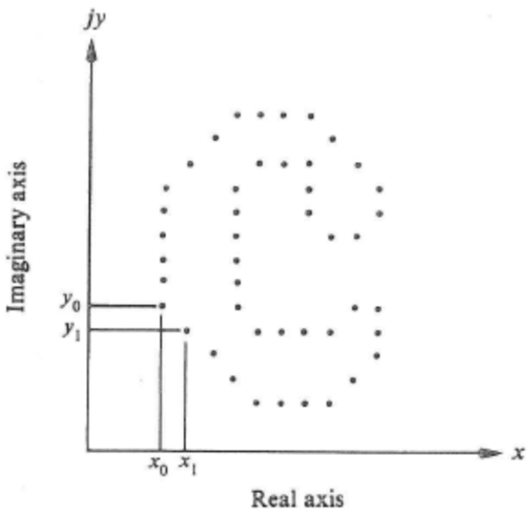
- Ψ-s histogram

Good descriptor. Responds strongly to boundary sections with constant tangent angles.

Useful to:

- ☐Find the rotation of a known contour in the image (by correlation)
- ☐Object recognition

Fourier Descriptor



N points (x,y)

N complex numbers

2D→ 1D

Background

Any function that periodically repeats itself can be expressed as the sum of sines and/or cosines of different frequencies, each multiplied by a different coefficient (Fourier series).

Even functions that are not periodic (but whose area under the curve is finite) can be expressed as the integral of sines and/or cosines multiplied by a weighting function (Fourier transform).

Background

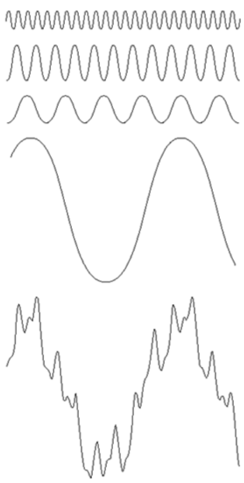


FIGURE 4.1 The function at the bottom is the sum of the four functions above it. Fourier's idea in 1807 that periodic functions could be represented as a weighted sum of sines and cosines was met with skepticism.

The **frequency domain** refers to the plane of the two dimensional discrete Fourier transform of an image.

The purpose of the Fourier transform is to represent a signal as a linear combination of sinusoidal signals of various frequencies.

Introduction to the Fourier Transform and the Frequency Domain

The one-dimensional Fourier transform and its inverse

Fourier transform (discrete case) DTC

$$F(u) = \frac{1}{M}\sum_{x=0}^{M-1} f(x)e^{-j2\pi ux/M} \quad \text{for } u = 0,1,2,\ldots,M-1$$

Inverse Fourier transform:

$$f(x) = \sum_{u=0}^{M-1} F(u)e^{j2\pi ux/M} \quad \text{for } x = 0,1,2,\ldots,M-1$$

Fourier Descriptors

Fourier transform of the signature $s(t)$

$$u_n = \frac{1}{N}\sum_{t=0}^{N-1} s(t)\exp\left(\frac{-j2\pi nt}{N}\right)$$

u_n, $n = 0, 1, \ldots, N-1$, are called FD denoted as FD_n

Normalised FD

$$\mathbf{f} = \left[\frac{|FD_1|}{|FD_0|}, \frac{|FD_2|}{|FD_0|}, \ldots, \frac{|FD_m|}{|FD_0|}\right]$$

Where $m=N/2$ for central distance, curvature and angular function

$m=N$ for complex coordinates

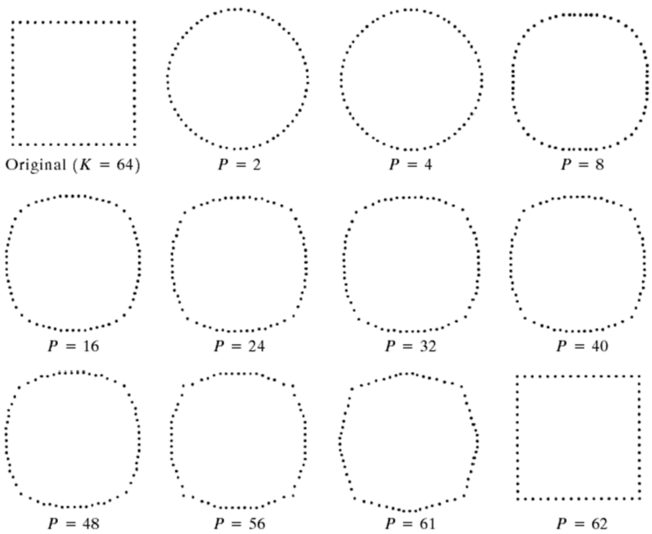
Fourier Descriptors

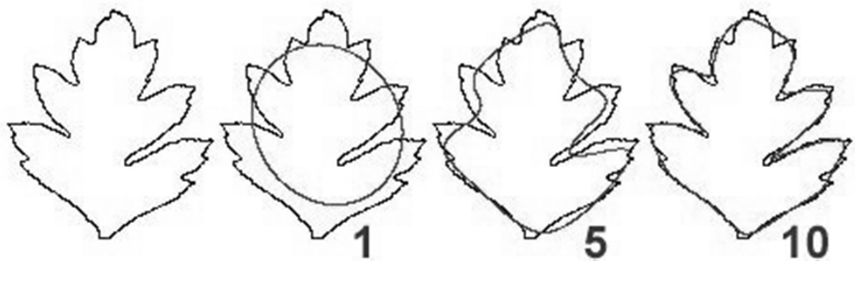
This is a way of using the Fourier transform to analyze the shape of a boundary.

- The x-y coordinates of the boundary are treated as the real and imaginary parts of a complex number.
- Then the list of coordinates is Fourier transformed using the DFT.
- The Fourier coefficients are called the Fourier descriptors.
- The basic shape of the region is determined by the first several coefficients, which represent lower frequencies.
- Higher frequency terms provide information on the fine detail of the boundary.

Fourier Descriptors

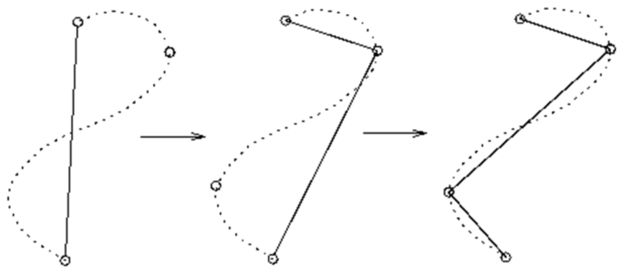
FIGURE 11.14 Examples of reconstruction from Fourier descriptors. P is the number of Fourier coefficients used in the reconstruction of the boundary.




1
5
10

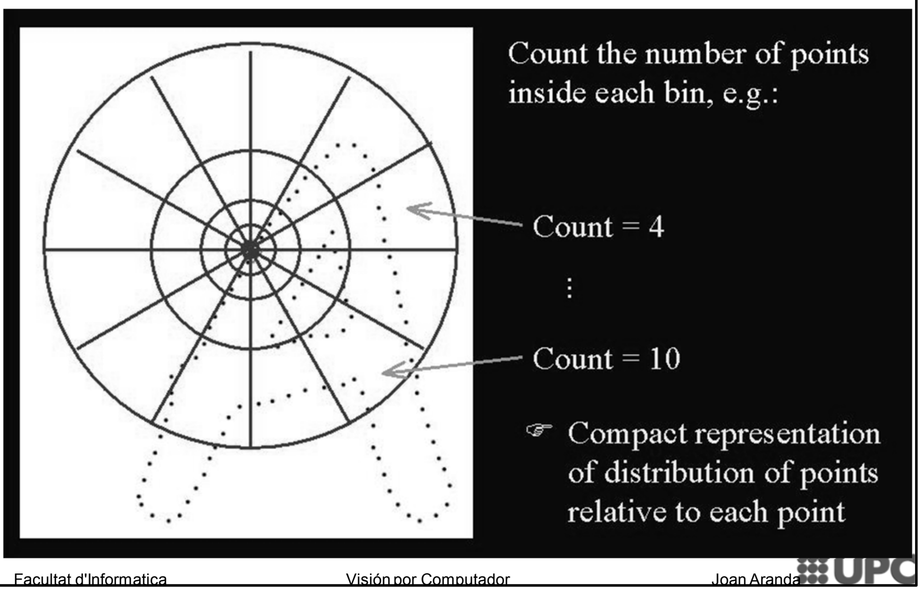
Aproximacions poligonals

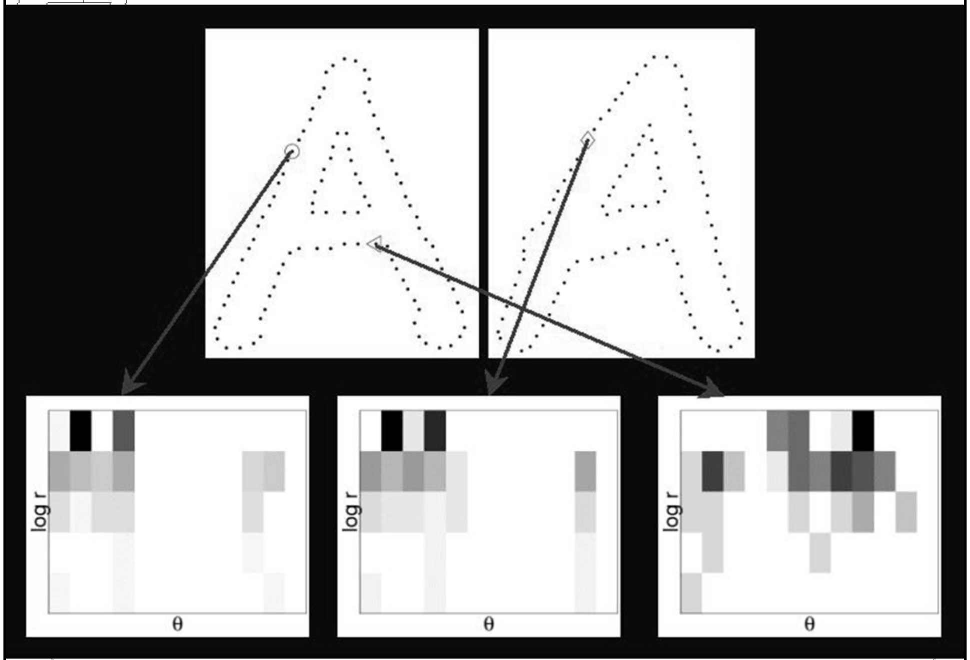
- Representa la regió com un polígon.
- Usem els vèrtexs de la regió per construir el polígon

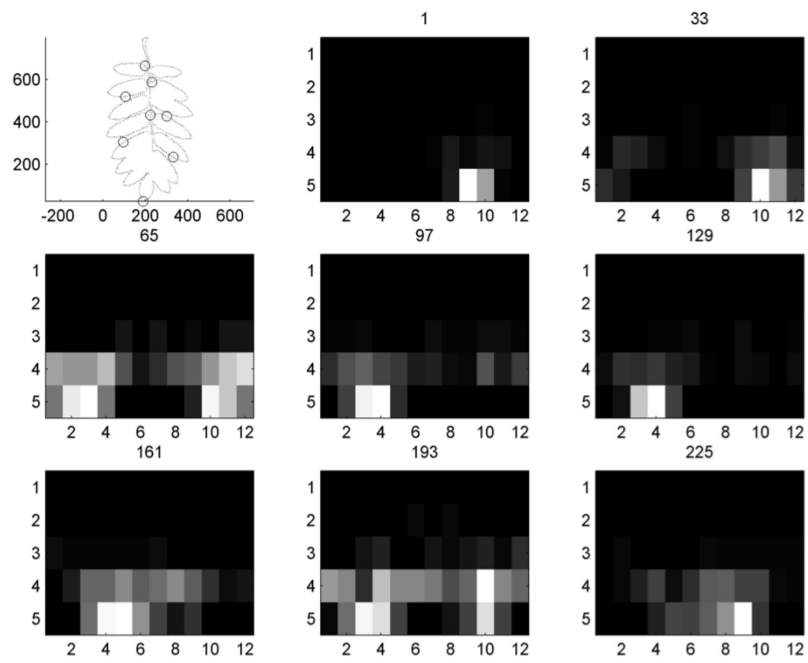


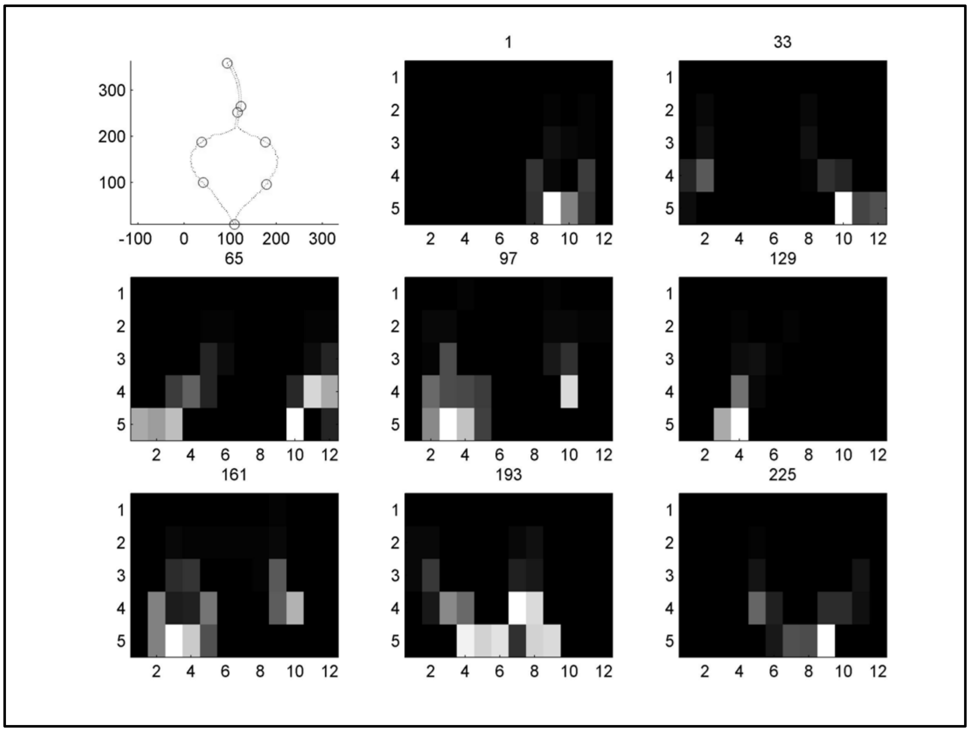
- En comptes de segments rectilinis també s'usen B-splines

Shape Context




log r
θ
log r
θ
log r
θ


600
400
200
-200 0 200 400 600
1
33
65
97
129
161
193
225
2 4 6 8 10 12



1
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97
129
161
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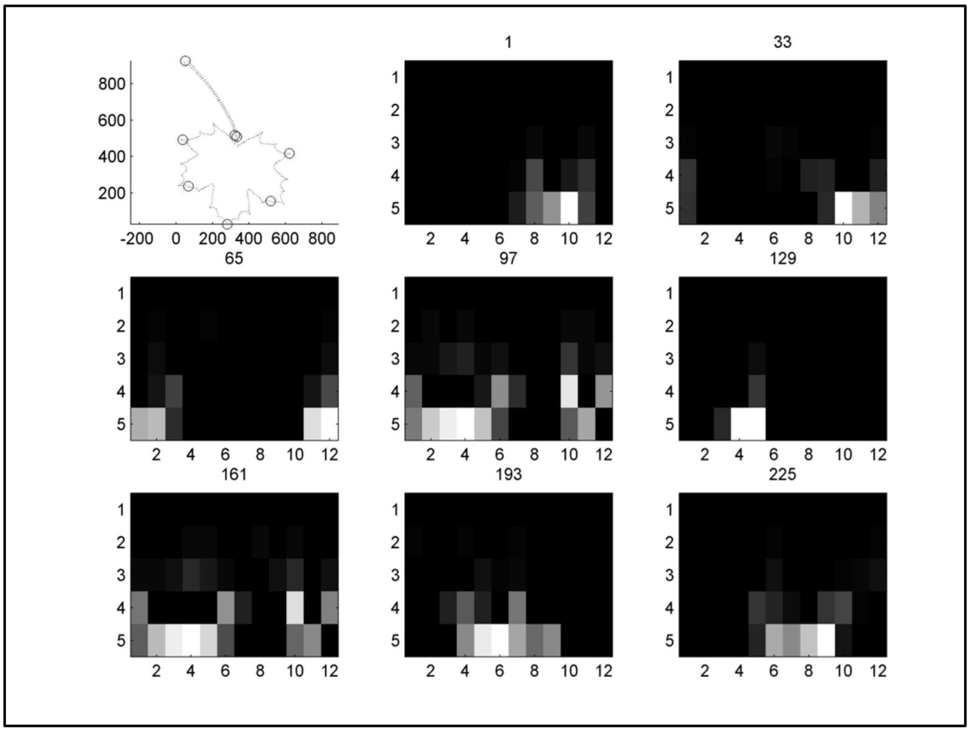
225



1
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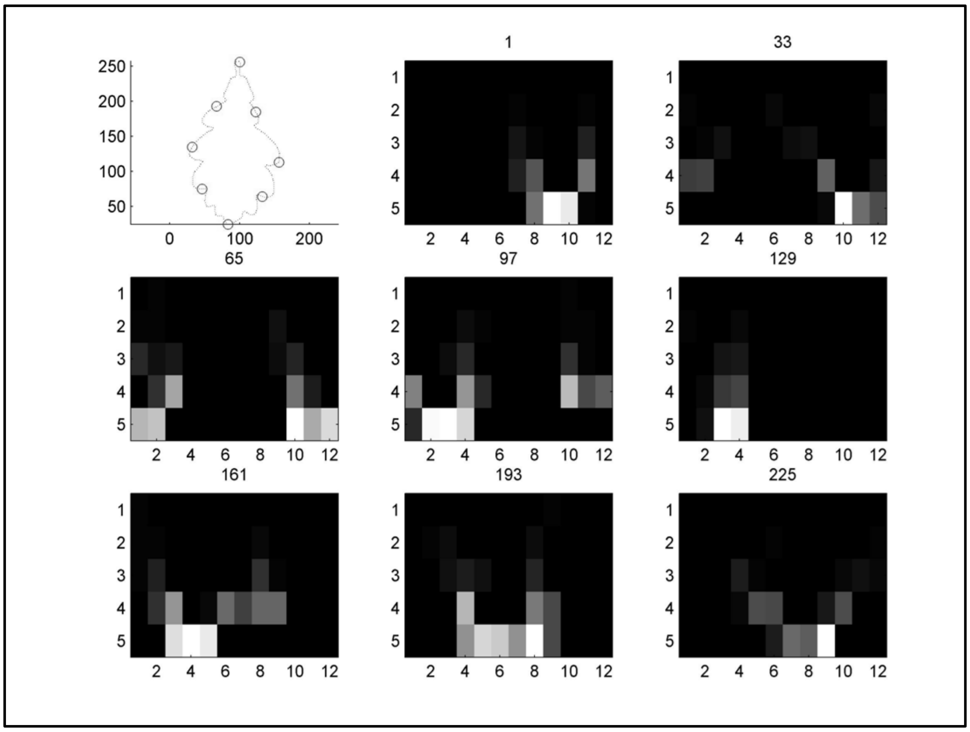
65
97
129
161
193
225



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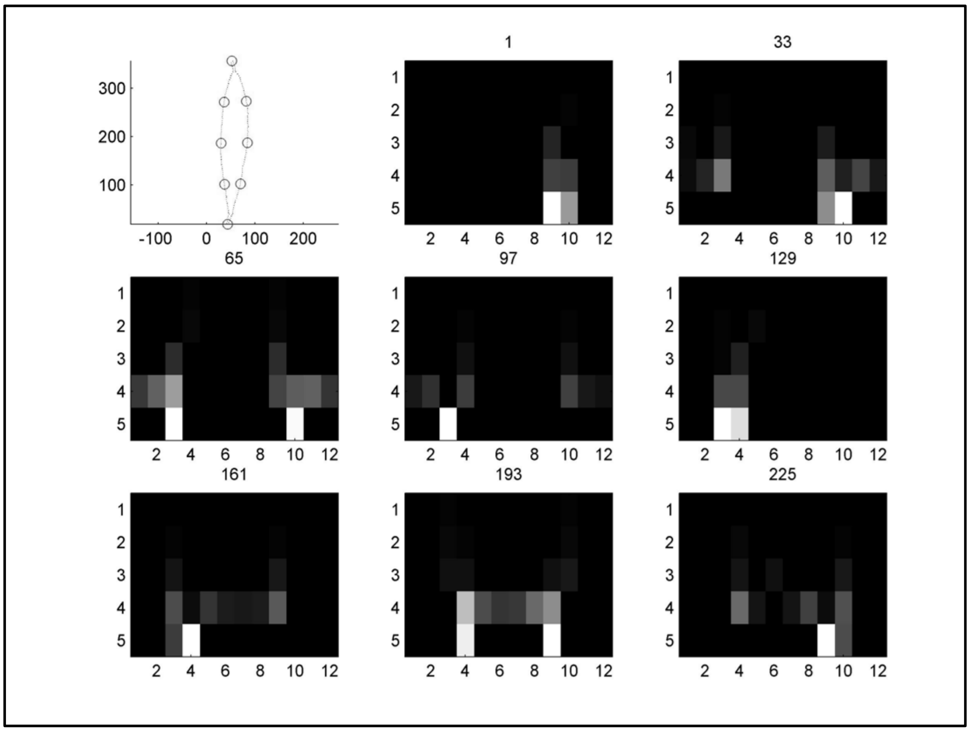
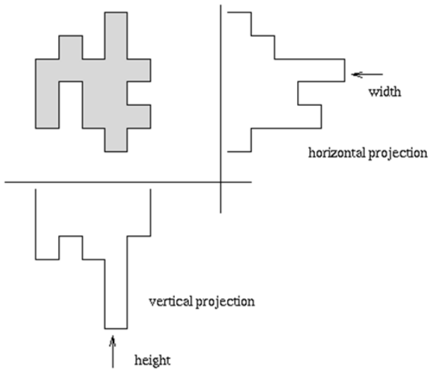


1
33
65
97
129
161
193
225

Propietats geomètriques de les regions

- **Àrea**: comptatge del nº de píxels
- **Projeccions:** Comptatge del nº de píxels en la projecció vertical i horitzontal



- **Excentricitat:** **rati eix major / eix menor**

Propietats geomètriques de les regions

- **Elongació**: Rati entre el llarg i l'ample del rectangle envolvent
- **Rectangularitat:** Rati entre l'àrea de la regió i la del rectangle envolvent
- **Compacitat:** perimetre^2/Àrea. La forma més compacta és el cercle.

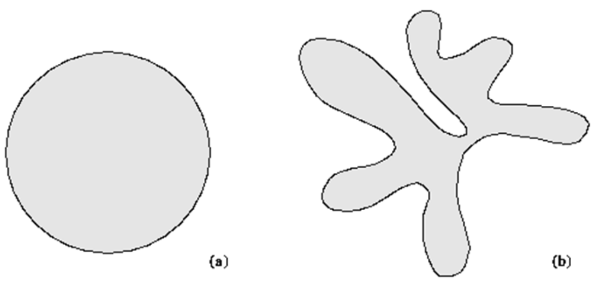
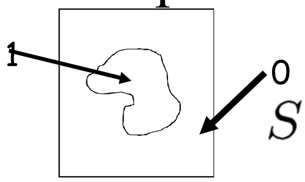


Figure 6.25 *Compactness: (a) Compact, (b) non-compact.*

Shape recognition by Moments



$$S = \{(x, y) | f(x, y) = 1\}$$

Given a pair of non-negative integers (j,k) the *digital* (j,k)th *moment* of S is given by:

$$M_{jk}(S) = \sum_{(x,y) \in S} x^j y^k$$

Càlcul de l'eix principal d'inèrcia

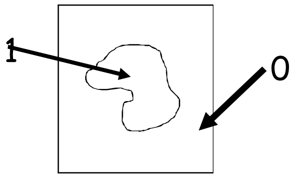
$$\theta = \arctan\left(\frac{M_{xx} - M_{yy} + \sqrt{(M_{xx} - M_{yy})^2 + 4M_{xy}^2}}{2M_{xy}} \right)$$

$$M_{xx} = \sum_i x_i^2 - \frac{(\sum_i x_i)^2}{A}$$

$$M_{yy} = \sum_i y_i^2 - \frac{(\sum_i y_i)^2}{A}$$

$$M_{xy} = \sum_i x_i y_i - \frac{\sum_i x_i \sum_i y_i}{A}$$

Shape recognition by Moments



$$S = \{(x, y) | f(x, y) = 1\}$$

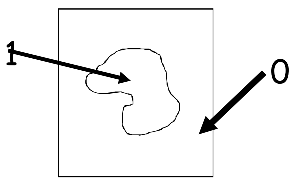
$$M_{jk}(S) = \sum_{(x,y) \in S} x^j y^k$$

Example:

$$M_{oo}(S) = \sum_{(x,y) \in S} x^0 y^0 = \sum_{(x,y) \in S} 1 = \#(S)$$

Area of S !!

Shape recognition by Moments



$$S = \{(x, y) | f(x, y) = 1\}$$

$$M_{jk}(S) = \sum_{(x,y) \in S} x^j y^k$$

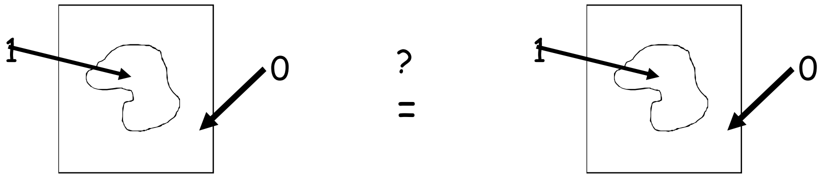
Example:

$$M_{10}(S) = \sum_{(x,y) \in S} x^1 y^0 = \sum_{(x,y) \in S} x \qquad M_{01}(S) = \sum_{(x,y) \in S} x^0 y^1 = \sum_{(x,y) \in S} y$$

$$\frac{M_{10}(S)}{M_{oo}(S)} = \frac{\sum_{(x,y) \in S} x}{\#(S)} = \bar{x} \qquad \frac{M_{01}(S)}{M_{oo}(S)} = \frac{\sum_{(x,y) \in S} y}{\#(S)} = \bar{y}$$

Center of gravity of S !!

Shape recognition by Moments

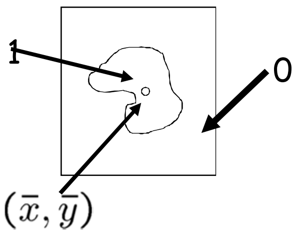


Recognition could be done by comparing moments

However, moments M_{jk} are not invariant under:

- Translation
- Scaling
- Rotation
- Skewing

Central Moments



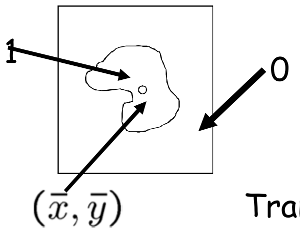
$$S = \{(x, y) | f(x, y) = 1\}$$

$$\bar{x} = \frac{M_{10}(S)}{M_{oo}(S)} \qquad \bar{y} = \frac{M_{01}(S)}{M_{oo}(S)}$$

Given a pair of non-negative integers (j,k) the *central* (j,k)th *moment* of S is given by:

$$\mu_{jk}(S) = \sum_{(x,y) \in S} (x - \bar{x})^j (y - \bar{y})^k$$

Central Moments

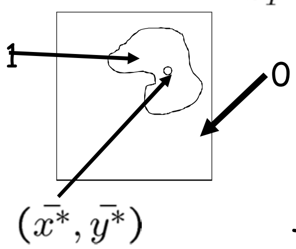


$$S = \{(x,y) | f(x,y) = 1\}$$

$$\mu_{jk}(S) = \sum_{(x,y)\in S} (x-\bar{x})^j (y-\bar{y})^k$$

Translation by T = (a,b) :

$$S_T = \{(x^*, y^*) | x^* = x + a, y^* = y + b, (x,y) \in S\}$$

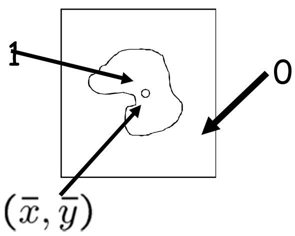


$$\bar{x^*} = \frac{M_{10}(S_T)}{M_{oo}(S_T)} = \bar{x} + a \qquad \bar{y^*} = \frac{M_{01}(S_T)}{M_{oo}(S_T)} = \bar{y} + b$$

$$\mu_{jk}(S_T) = \mu_{jk}(S)$$

Translation INVARIANT!

Normalized Moments



$$S = \{(x,y) | f(x,y) = 1\}$$

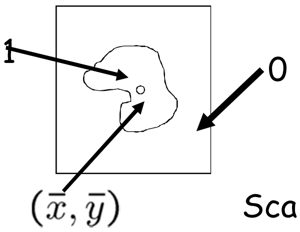
$$\mu_{jk}(S) = \sum_{(x,y)\in S} (x-\bar{x})^j (y-\bar{y})^k$$

$$\sigma_x = \sqrt{\frac{\mu_{20}(S)}{M_{oo}(S)}} \qquad \sigma_y = \sqrt{\frac{\mu_{02}(S)}{M_{oo}(S)}}$$

Given a pair of non-negative integers (j,k) the *normalized* (j,k)th *moment* of S is given by:

$$m_{jk}(S) = \sum_{(x,y)\in S} \left(\frac{x-\bar{x}}{\sigma_x}\right)^j \left(\frac{y-\bar{y}}{\sigma_y}\right)^k$$

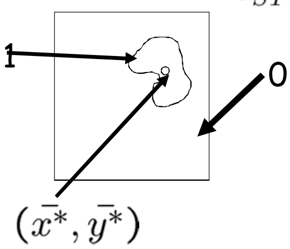
Normalized Moments



$$S = \{(x,y) | f(x,y) = 1\}$$

Scaling by (a,c) and translating by T = (b,d) :

$$S_{ST} = \{(x^*, y^*) | x^* = ax + b, y^* = cy + d, (x,y) \in S\}$$



$$m_{jk}(S_{ST}) = m_{jk}(S)$$

Scaling and translation INVARIANT!

Convex Hull

- Forma convexa més petita que engloba a la regió

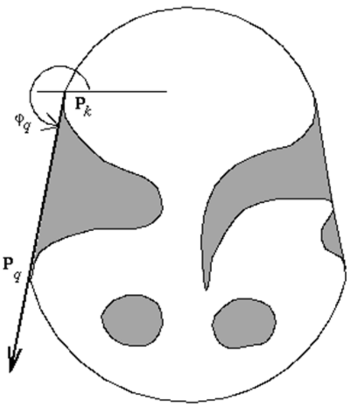
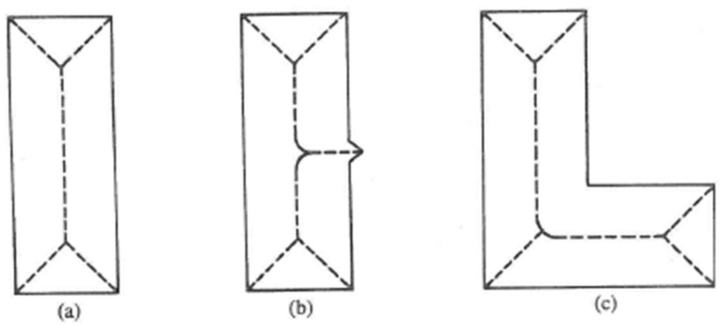


Figure 6.26 *Convex hull.*

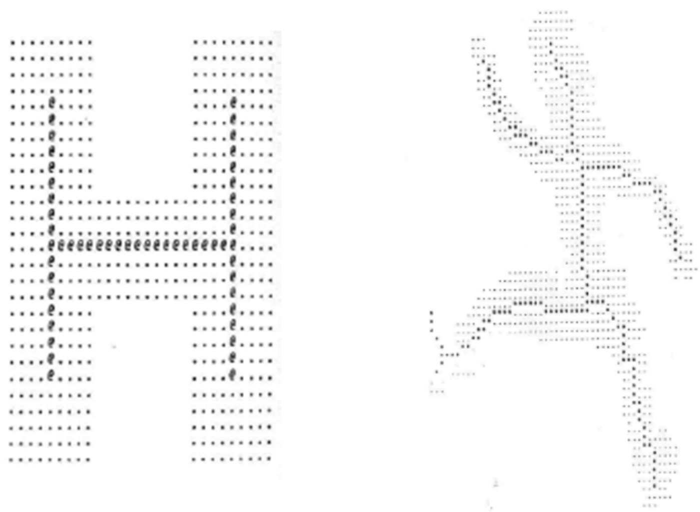
Region Skeletons

Thinning algorithms



Medial axes of three simple regions.

ZHANG & SUEN algorithm

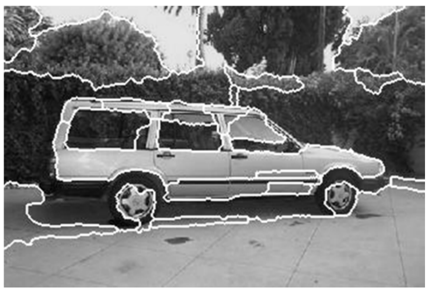


Representations using Parts

- Divide the shape into sub-parts and represent the object by:
  - Its parts
  - Attributes of the parts
  - Relationships among parts
- Main problem:
  - What is a part?

What is a part?

- Convex regions
- "Near-convex" parts
- Functional-based parts
- Segmentation-based parts



Característiques de nivell de gris

- S'usen estadístics senzills:
  - Màxim
  - Mínim
  - Mitjana
  - Desviació
  - Histogrames
  - Matrius de co-ocurrència

- També es solen usar característiques de textura

Limitacions dels descriptors de formes

- Són massa depenents de la segmentació
- Són massa sensibles al soroll
- Són massa sensibles a les oclusions
- No és trivial fer-los invariants