

# Fundamentals of Computer Vision

Unit 7: Feature Description

Jorge Bernal

# Index

01

1.  
Introduction

02

2. Shape  
Descriptors

03

3. Color  
Descriptors

04

4. Texture  
Descriptors

05

5. Motion  
Descriptors

1

# Introduction

# Introduction

## Definition of feature:

- Piece of information that is useful to solve a given task
- Interesting part of the image

## Types of features:

- **Global:** global properties of the whole image
  - Mean grey level, mean colour, main colours, histogram
- **Local:** properties of a part of the image with their own entity
  - Points, edges, regions

# Introduction

- How can we find local features?
  - Feature detection/extraction algorithms
- Detection/Extraction: locate the position of the feature
- **Description: measures that are taken from the detected feature that allow us to distinguish it or compare with others**

# Introduction

- Why do we use features?
  - They have been used with success in several disciplines and applications:
    - Edge detection associated to roads in aerial images
    - Quality control
    - Polyp Detection
  - Interest points play a key role for certain Applications:
    - Tracking
    - 3D reconstruction
  - They are a first step to achieve a robust image representation:
    - Object recognition
    - Scene classification
    - Texture analysis
    - Image search

# Introduction

- Why do we use features?
  - They have been used with success in several disciplines and applications:
    - Edge detection associated to roads in aerial images
    - Quality control
    - Polyp Detection
  - Interest points play a key role for certain Applications:
    - Tracking
    - 3D reconstruction
  - They are a first step to achieve a robust image representation:
    - Object recognition
    - Scene classification
    - Texture analysis
    - Image search

# Introduction: why do we need feature descriptors



A

B

A and B are flat **surfaces** and they are spread over a lot of area. It is **difficult to find the exact** location of these patches.



C

D

C and D are **edges**. You can find an approximate location, but exact location is still difficult. An edge is therefore better feature compared to flat area, but **not good enough**.



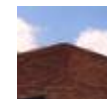
E

F

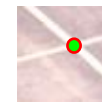
E and F are **corners**. They can be easily found. Because wherever you move this patch, it will look different, then it can be considered as **good features**.



# Introduction: why do we need feature descriptors



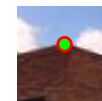
(12,43,54)



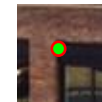
(0,73,14)



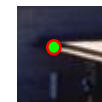
(12,43,0)



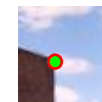
(12,43,54)



(1,0,54)



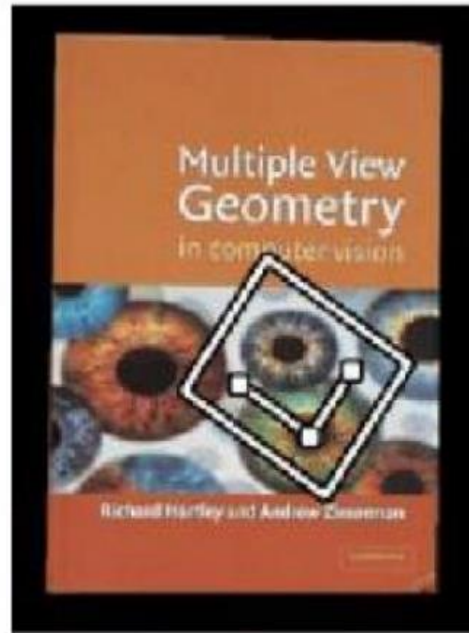
(1,3,5)



(12,23,74)

# Introduction

- Desirable properties:
  - Shift invariant
  - Scale invariant
  - Rotation invariant
  - Contrast invariant



# Introduction

- General approach:
  - Determine the scale where a feature is most stable
  - Determine the orientation of the small patch surrounding this feature point at this scale
  - Characterize a small patch tilted in this orientation and scale with a descriptor
  - The descriptor should be invariant to intensity shift or scaling, and small position shift

2

# Shape Descriptors

# Shape Descriptors

- Shape is, indeed, an important visual cue and it is one of the most used to describe image content.
- But it also has its complications because we can not forget that when we project 3-D objects into a 2-D image we are losing one whole dimension of information, so the 2-D representation of an object gives only a partial representation of it.
- It is highly affected by noise, defects, occlusion or deformation, which can make harder the process of object recognition.

# Shape Descriptors

- Assumption: the object whose shape we want to describe has been segmented (or, at least, somehow separated) from the image so we have a binary image patch which contains the object.
- Two groups:
  - Contour-based: we extract features only from the contour of the shape.
  - Region-based: we use the whole shape region.
- Each group is also subdivided into structural approaches (representing the shape by segments/sections) or global approaches (represent the shape as a whole).

# Shape Descriptors

- Contour-based Shape Descriptors (Global):
  - Simple descriptors:
    - Area
    - Eccentricity
    - Axis orientation
    - Radius of the principal axis



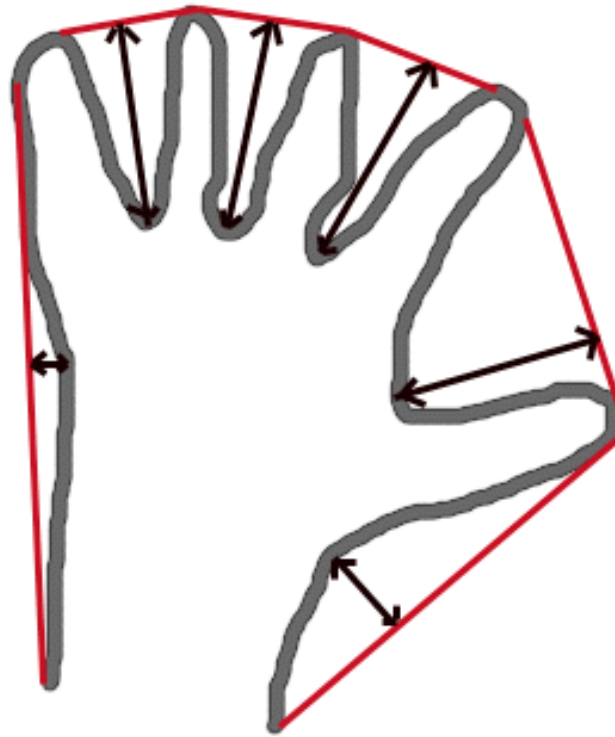
# Shape Descriptors

- Contour-based Shape Descriptors (Global):
  - Convex Hull:
    - One region is considered as convex only if by taking any two points of it the segment that binds them is inside the region. Convex Hull is defined as the minimal convex region.
    - Before dividing the contour in segments, it is smoothed to avoid some non-desired effects such as hysterical responses to noise. At last the whole shape will be represented as a chain of concavities.



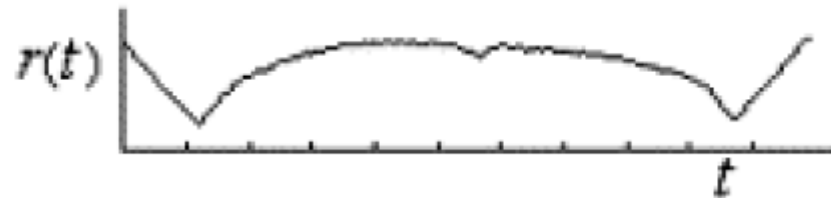
# Shape Descriptors

- Contour-based Shape Descriptors (Global):
  - Convex Hull:



# Shape Descriptors

- Contour-based Shape Descriptors (Global):
  - Shape signature:
    - This method represents the shape of an object by means of a uni-dimensional function which is extracted from the points belonging to the contour of the shape.
    - There are several possible Shape Signatures such as the centroidal profile, shape radii, complex coordinates, distance to the centroid, tangent or accumulative angle, curvature, arc length, etc.

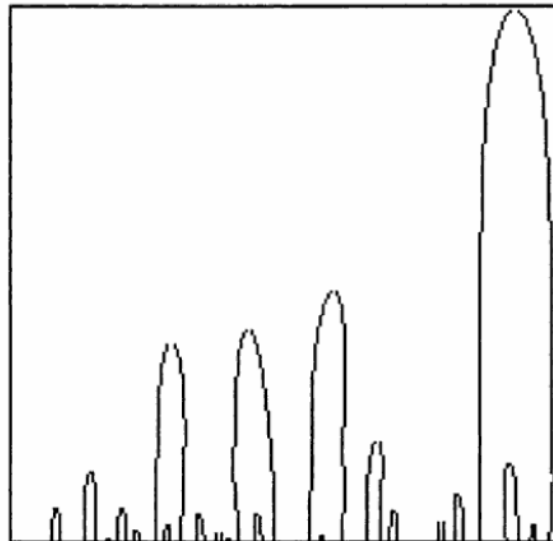


# Shape Descriptors

- Contour-based Shape Descriptors (Global):
  - Shape signature:
    - Shape Signatures are usually normalized for translation and scale invariance.
    - In order to compensate for orientation changes, shift matching is needed to find the best matching between two shapes. Most of the signature matching is normalized to shift matching in 1-D space, however, some signature matching requires shift matching in 2-D space, such as the matching of centroidal profiles.
  - ☹ Shape Signatures are sensitive to noise, and slight changes in the boundary can cause large errors in matching.

# Shape Descriptors

- Contour-based Shape Descriptors (Global):
  - Curvature scale space:
    - Several arch-shaped contours representing the inflection points of the shape
    - The maxima of these contours are used to represent a shape

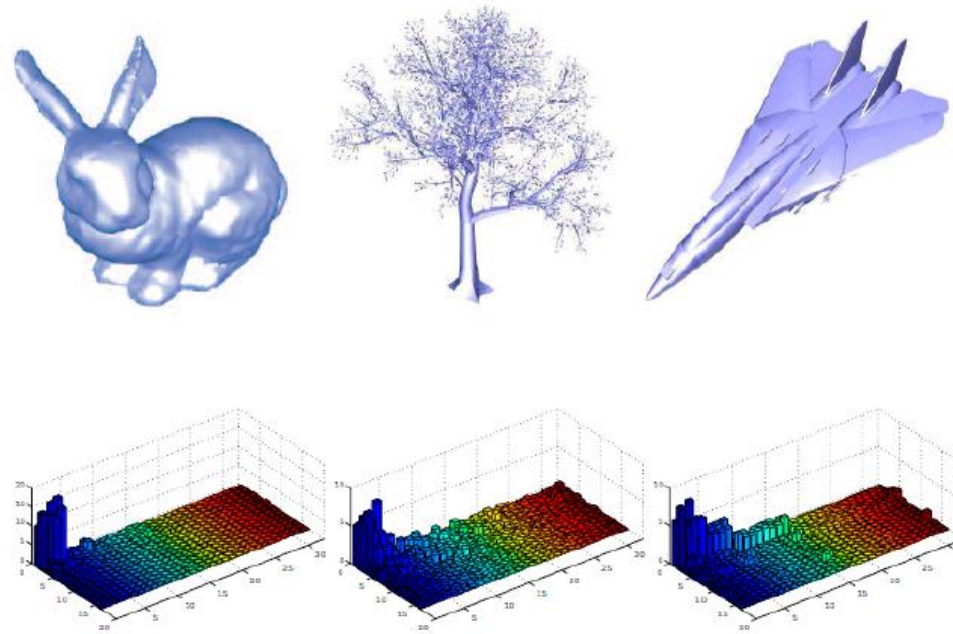


# Shape Descriptors

- Contour-based Shape Descriptors (Global):
  - Wavelet Transform:
    - Hierarchical descriptor of planar curves which is able to decompose a curve in several scales.
    - Higher scale components convey more general information and those with lower scale have more local and detailed information.
    - The descriptor also has some interesting properties like multi-resolution representation, is invariant and it keeps the unicity, stability and spatial location properties

# Shape Descriptors

- Contour-based Shape Descriptors (Global):
  - Wavelet Transform:

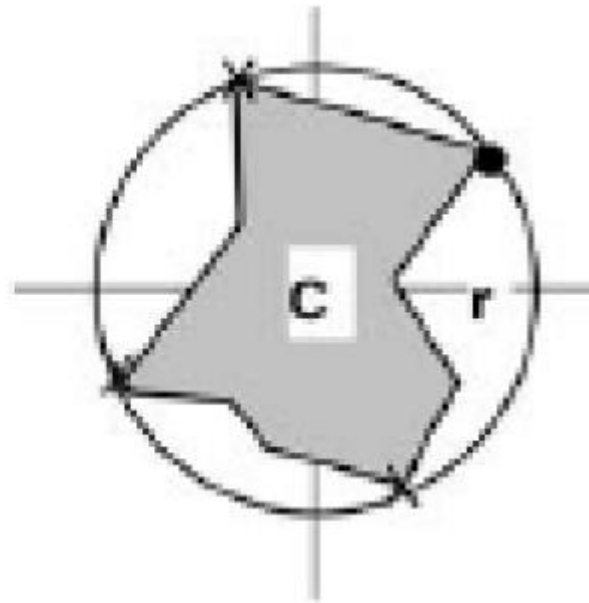
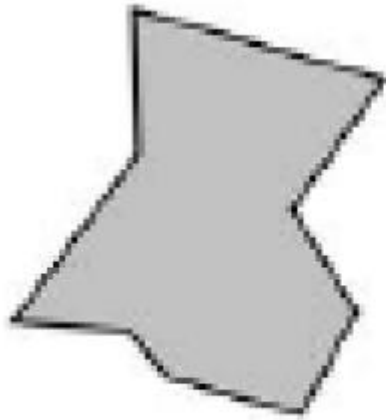


# Shape Descriptors

- Contour-based Shape Descriptors (Global):
  - Minimum Boundary Circle-based:
    - Features are extracted from the minimum circle that surrounds the object (that is, the circle that touches its further borders)
    - We can obtain the following: center coordinates, radius, minimum circle crossing points, angle sequence of these crossing points, vertex angle sequence and angle sequence starting point.
    - Rotation, translation and scale invariant which makes it a good candidate

# Shape Descriptors

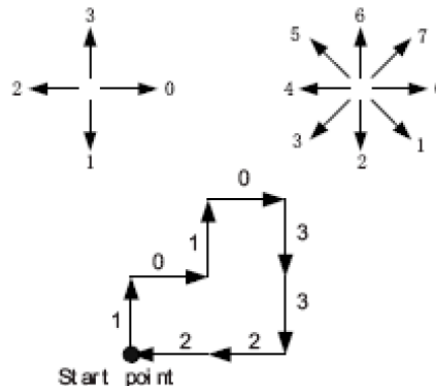
- Contour-based Shape Descriptors (Global):
  - Minimum Boundary Circle-based:





# Shape Descriptors

- Contour-based Shape Descriptors (Structural):
  - Chain code:
    - Codifying lines into a determinate code.
    - The nodes that surround a certain point (or central node) are enumerated counter-clockwise in ascending order from inside to outside.
    - A chain will consist of an ordered link sequence. The inverse and the length of the chain can also be calculated.

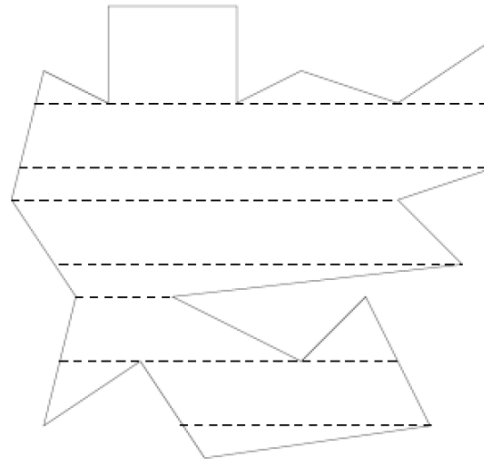


# Shape Descriptors

- Contour-based Shape Descriptors (Structural):
  - Chain code:
    - 😊 Translation invariance, potential scale and rotation invariance
    - 😞 Depends on the starting point

# Shape Descriptors

- Contour-based Shape Descriptors (Structural):
  - Polygon Decomposition:
    - The contour of the shape is divided in approximated segments or polygons, using as primitives the vertex of these polygons.
    - For each primitive the feature extracted consists of a chain of four elements (inner angle, distance to the next vertex and x and y coordinates).



# Shape Descriptors

- Contour-based Shape Descriptors (Structural):
  - Polygon Decomposition:
    - ☹️ Not rotation, translation or scale invariant
    - Similarity can be calculated using Edit Distance

# Shape Descriptors

- Contour-based Shape Descriptors (Structural):
  - Shape context:
    - It is intended to be a way of describing shapes oriented to measure shape similarity and recover of point correspondences
    - To get this, and by using polar coordinates, vectors from the chosen point to every point of the frontier/contour are calculated.
    - The length and orientation of these vectors are quantified so a histogram can be created and then used to represent this point. The histogram of each point is flattened and concatenated to be part of the context of the certain shape

# Shape Descriptors

- Contour-based Shape Descriptors (Structural):
  - Shape context:

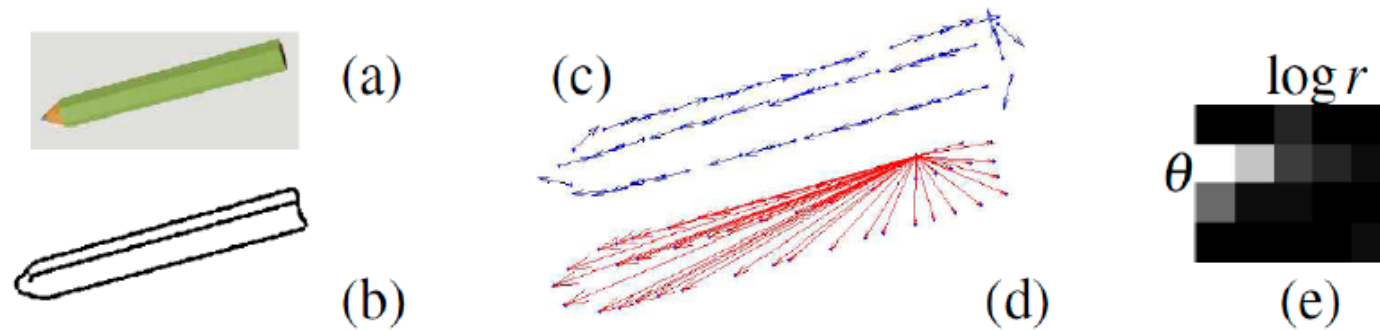


Figure 4.10: Example for deriving the shape context descriptor for the image of a pencil. (a) Input image of the pencil. (b) Contour of the pencil derived using the Canny operator. (c) Sampled points of the contour. (d) All vectors from one point to all the other sample points. (e) Histogram with four angle and five log-radius bins comprising the vectors depicted in (d)[61].

# Shape Descriptors

- Contour-based Shape Descriptors (Structural):
  - Shape context:
    - ☺ Potential translation, scale and rotation invariance
    - ☹ Affected by noise

# Shape Descriptors

- Contour-based Shape Descriptors (Structural):
  - Chamfer:
    - Find a model within an image. First, we have to find weak and noisy edges and then remove them from the image.
    - Next, transformation distance of the remaining pixels has to be calculated.
    - The value of this pixel according to this transformation is proportional to the distance of this pixel to the nearest edge pixel.
    - This model is then shifted around the already transformed image and
    - in each shift position the sum of distances up to the model is calculated. The shift position with less accumulative sum is taken as the best correspondence to the model.

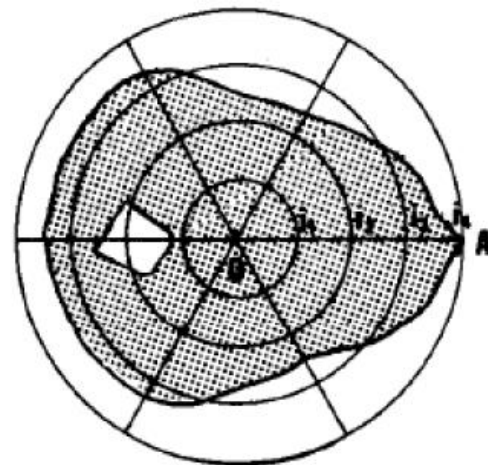


# Shape Descriptors

- Region-based Shape Descriptors (Global):
  - Zernike Moments:
    - Zernike moments are rotation invariant and robust to noise, so if we use a descriptor based in these moments, it will inherit this characteristics.
    - The input image has to be binarized
    - ☺ Rotation invariant, robust to noise
    - ☹ Image coordinates have to be transformed, not efficient

# Shape Descriptors

- Region-based Shape Descriptors (Global):
  - Shape matrix:
    - A shape is transformed into a matrix by polar quantization of the shape
    - Translation, rotation and scale invariant



(a)

	0	1	2	3	4
0	1	1	1	1	1
1	1	1	1	0	0
2	1	1	1	1	0
3	1	1	0	1	0
4	1	1	1	1	0
5	1	1	1	0	0

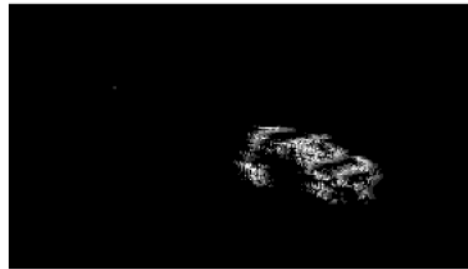
(b)

# Shape Descriptors

- Region-based Shape Descriptors (Global):
  - Grid-based descriptor:
    - Grid of cells is superimposed over a shape and this grid is scanned from side to side, giving a bitmap as a result.
    - The cells that cover the shape of the object are set to 1 and the rest, to 0. The difference between the two shapes can be calculated as the number of cells in the grids which are covered by one shape and not the other and hence the sum of 1's in the result of the exclusive-or of the two binary numbers.
    - Not rotation or scale invariant (needs normalization)

# Shape Descriptors

- Region-based Shape Descriptors (Global):
  - Grid-based descriptor:



The Sustained temporal change.



The grid with cellsize  $\lambda = 4$ .



The grid with cellsize  $\lambda = 8$ .



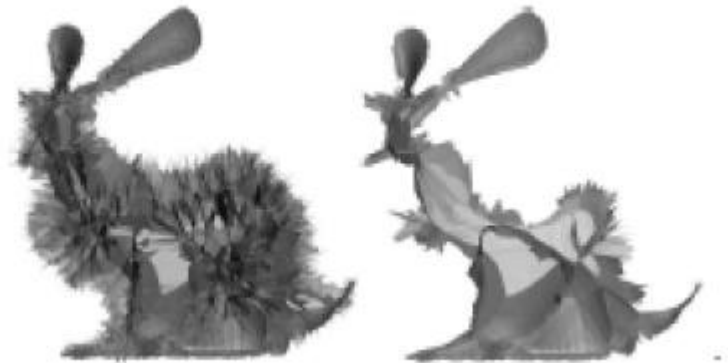
The grid with cellsize  $\lambda = 16$ .

# Shape Descriptors

- Region-based Shape Descriptors (Global):
  - Angular Radial Partitioning:
    - Transforms the image data into a new structure that supports measurement of the similarity between images in an effective, easy and efficient manner with emphasis on capturing scale and rotation invariant properties.
    - Needs of the calculation of the normalized edge image
    - This image is partitioned into  $M$  (number of radial partitions) and  $N$  (number of angular partitions)

# Shape Descriptors

- Region-based Shape Descriptors (Structural):
  - Skeleton:
    - Connected contour of medial lines along the different parts of an object.
    - One of the ways to calculate the Skeleton of an image is by using the Medial Axis Transform (MAT), where the Medial Axis is the geometric place where the centers of the maximum discs that fit into the shape coincide.
    - The Skeleton can be decomposed in segments and represented as a graph.



# Shape Descriptors

- Region-based Shape Descriptors (Global):
  - Angular Radial Partitioning:



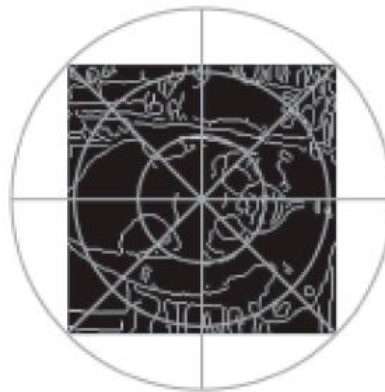
a



b



c



d

# Shape Descriptors

Descriptor	Type	Rotation invariant	Translation invariant	Scale invariant
Shape signature	Contour-based Global	Not direct	After normalization	After normalization
Convex Hull	Contour-based Global	Yes	Yes	Yes
Wavelet Transform	Contour-based Global	No	No	Yes
Minimum Boundary Circle	Contour-based Global	Yes	Yes	Yes
Chain Code	Contour-based Structural	Possible	No	Yes
Polygons Decomposition	Contour-based Structural	No	No	No
Shape Context	Contour-based Structural	Possible	Possible	Possible
Chamfer	Contour-based Structural	No	Yes	Yes



# Shape Descriptors

Descriptor	Type	Rotation invariant	Translation invariant	Scale invariant
Zernike Moments	Region-based Global	Yes	No	No
Shape Matrix	Region-based Global	Yes	Yes	Yes
ARP	Region-based Global	No	No	Yes
Grid-based	Region-based Global	Possible	No	No
Skeleton	Region-based Structural	Yes	No	Yes

# Fundamentals of Computer Vision

Unit 7: Feature Description

Jorge Bernal