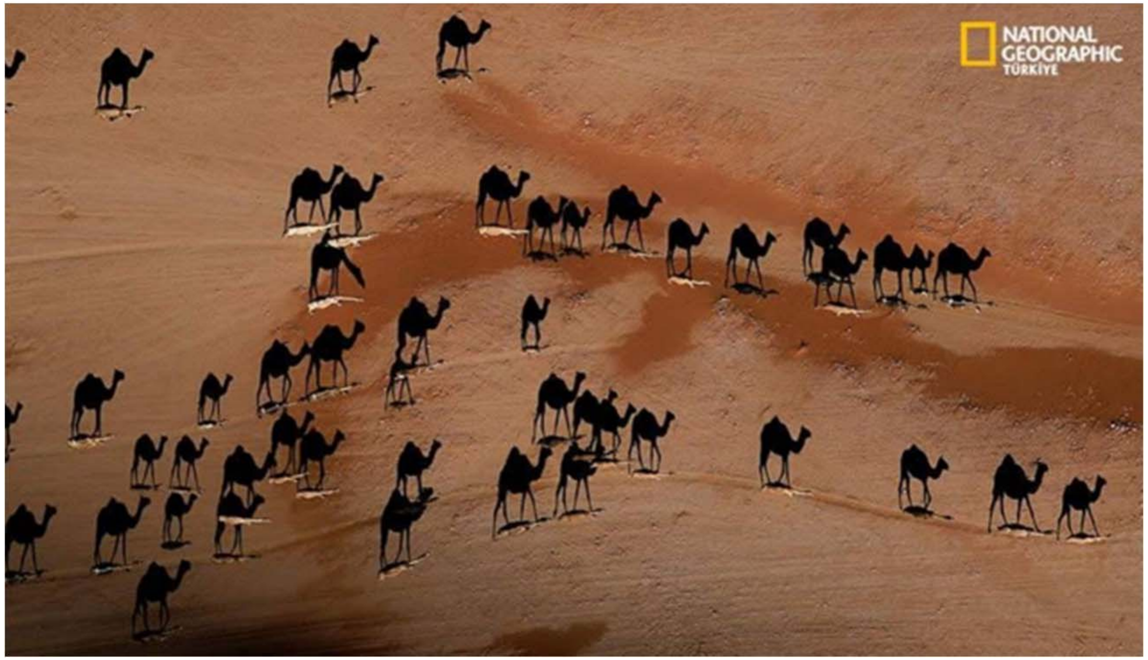
Shape



Shape

- Statistical description
  - Topological
  - Geometrical
- Structural description
- Other methods

Shape. Statistical Description

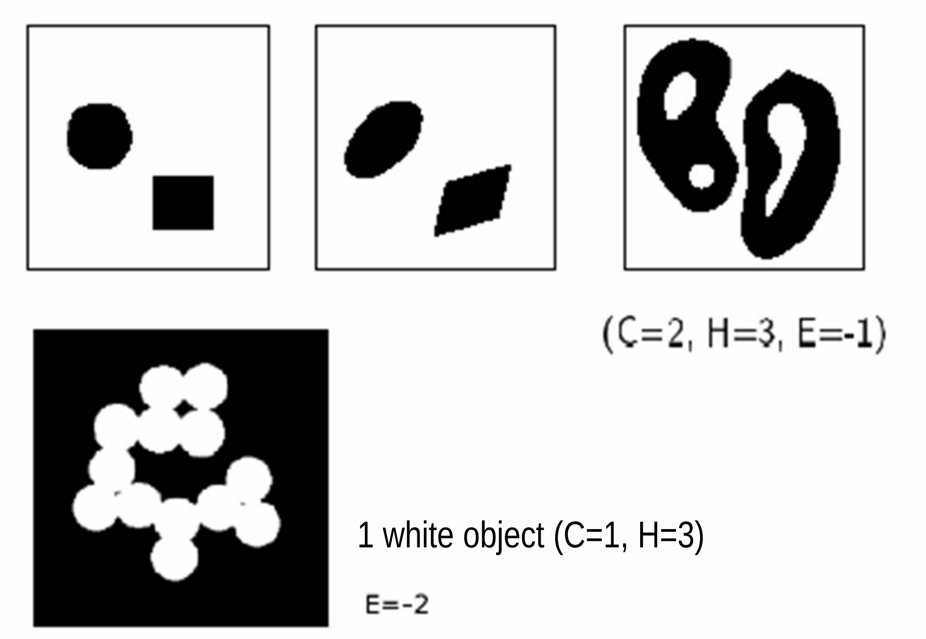
Statistical Description. Different descriptors:

- Topological
  - Number of objects
  - Euler number
  - Bounding box
- Geometric
  - Area, width, perimeters
  - Elongation (excentricity)
  - Compacity
  - Inertia moments
  - Vertical, horizontal or diagonal projections

Shape. Statistical Description

Topological descriptors (Binary images)

- Number of objects (C)
- Number of holes (H)
- Euler Number (E)

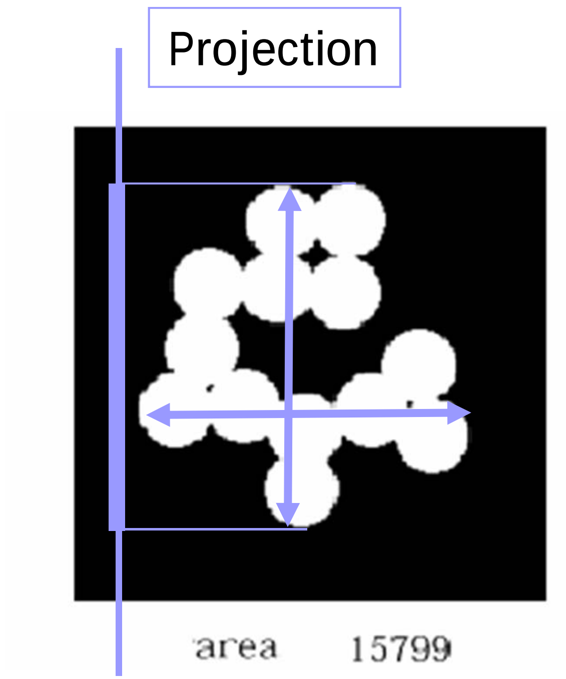


From Jordi Vitrià at the Universitat Autònoma de Barcelona

Shape. Statistical Description

Geometric descriptors

- Area, Perimeter
- Width, Height
- Compacity $\frac{P^2}{(4\pi A)}$
- Elongation: W/H



From Jordi Vitrià at the Universitat Autònoma de Barcelona

Shape. Statistical Description

Inertia Moments

$$m_{ij} = \sum_{x=1}^{N}\sum_{y=1}^{N} f(x,y)\ x^i\ y^j$$

- Area = m_{00}
- $\mu_x = m_{10}/m_{00}$, $\mu_y = m_{01}/m_{00}$

- With this definition, the same shape in a different position will have different moments

Central Moments

$$\mu_{ij} = \sum_{x=1}^{N}\sum_{y=1}^{N} f(x,y)\ (x-\mu_x)^i\ (y-\mu_y)^j$$

Where μ_x i μ_y are the coordinates of the centroid of the shape

Shape. Statistical Description

Central Moments

Center

(μ_x, μ_y)

Variance

μ_{20}/μ_{00} and μ_{02}/μ_{00}

Covariance

$$\frac{1}{\mu_{00}} \begin{bmatrix} \mu_{20} & \mu_{11} \\ \mu_{11} & \mu_{02} \end{bmatrix}$$

Eccentricity

$$\frac{\lambda_1}{\lambda_2}$$

Orientation

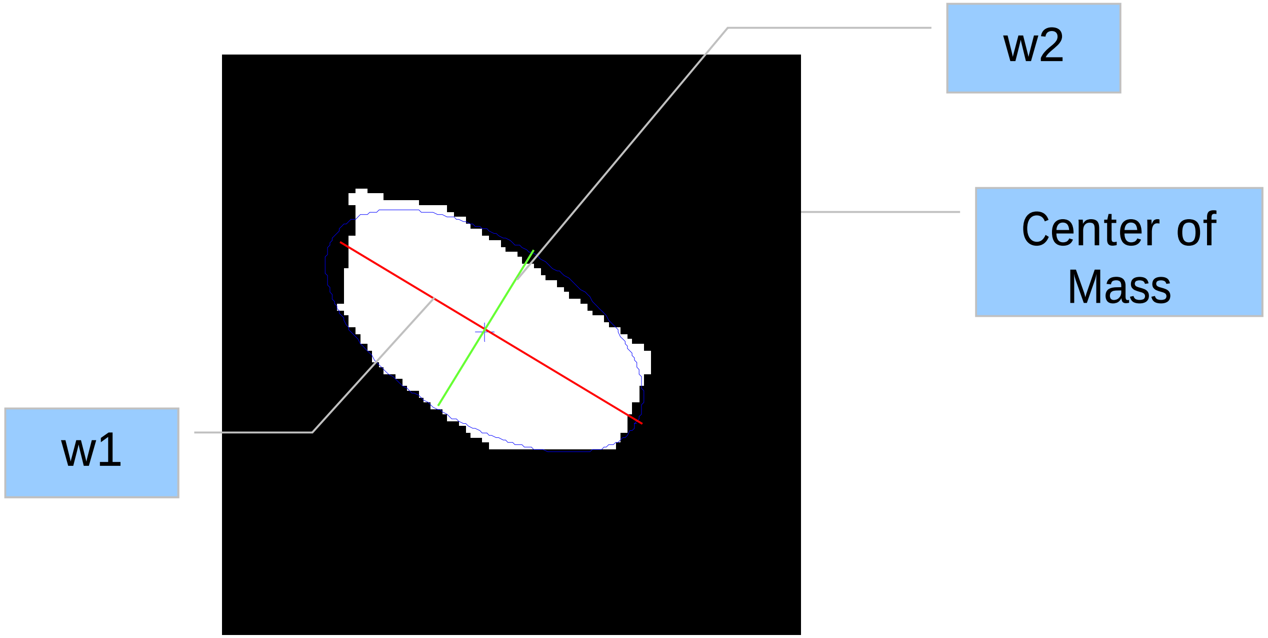
$$\frac{v_1}{||v_1||}$$

or $\theta = \frac{1}{2}\tan^{-1}\frac{2\mu_{11}}{\mu_{20}-\mu_{02}}$

Shape. Statistical Description

Example of Central Moments

- Principal axes are related to the eigenvectors and eigenvalues of the covariance matrix



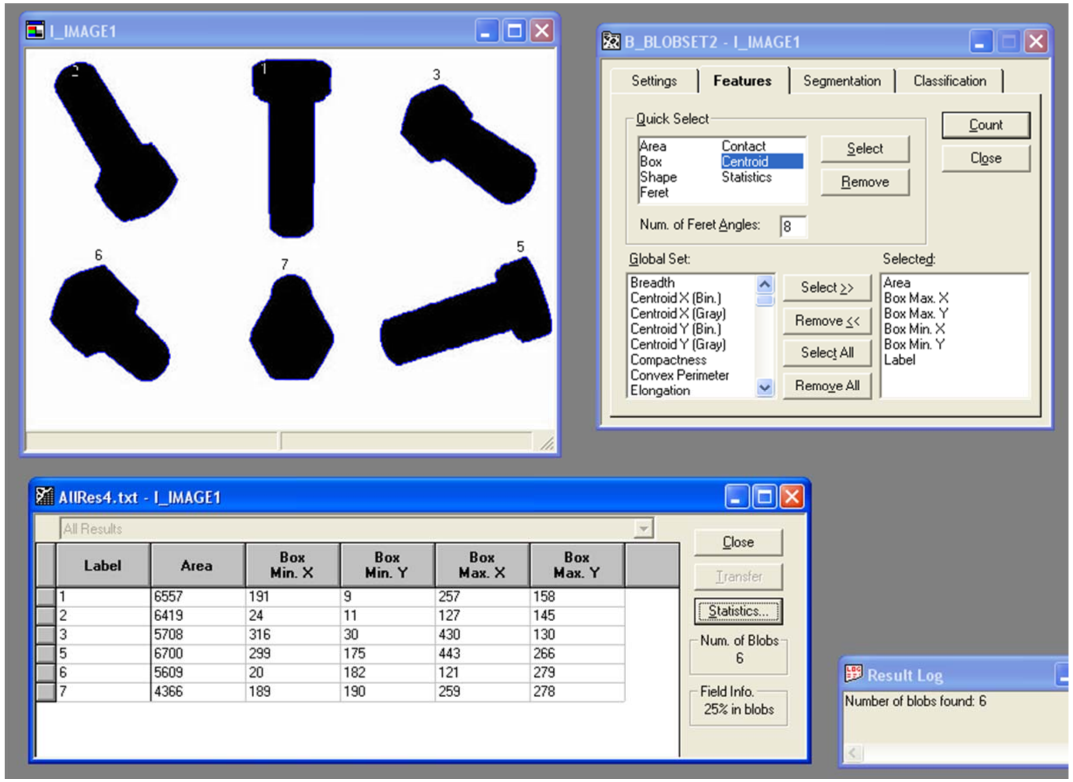
Shape. Statistical Description

Invariant moments

Moments that are not affected by specific transformations

- Translation: Central moments
- Rotation: eigenvalues of the covariance matrix
- Scale: ratio between eigenvalues

Shape. Statistical Description



Label	Area	Box Min. X	Box Min. Y	Box Max. X	Box Max. Y
1	6557	191	9	257	158
2	6419	24	11	127	145
3	5708	316	30	430	130
5	6700	299	175	443	266
6	5609	20	182	121	279
7	4366	189	190	259	278

- Shape representation using a vector of numerical characteristics
- Similarity between shapes is defined as distance metric in the feature space

Shape

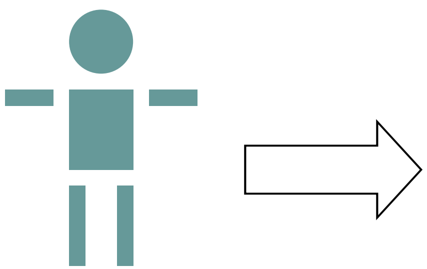
- Statistical description
  - Topological
  - Geometrical
- Other methods
  - Structural description
  - Salient Points
  - PDM

Shape. Structural Description

Statistical description: shape representation using a vector of numerical characteristics. Similarity between shapes is defined as distance metric in the feature space

Structural description: explicit or implicit representation of the structure of an object, where structure is the hierarchical and relational organisation of lower level characteristics

Example



Shape $\boldsymbol{F}$

Statistical Desc.: $\boldsymbol{F}$ = (#components, height, width)

Structural Desc:

LeftLeg, RightLeg: VERTICAL RECTANGLE;

LeftArm, RightArm: HORITZONTAL RECTANGLE;

body: SQUARE;

head: CERCLE;

$\boldsymbol{F} = \text{head} \Uparrow (\text{LeftArm} \Leftrightarrow (\text{body} \Uparrow (\text{LeftLeg} \Leftrightarrow \text{RightLeg})) \Leftrightarrow \text{RightArm})$

Shape. Structural Description

Structural shape description can be split into two categories based on the model used for description:

- Syntactical description:
  - Representation using *formal grammar*
  - Recognition is performed using a parser

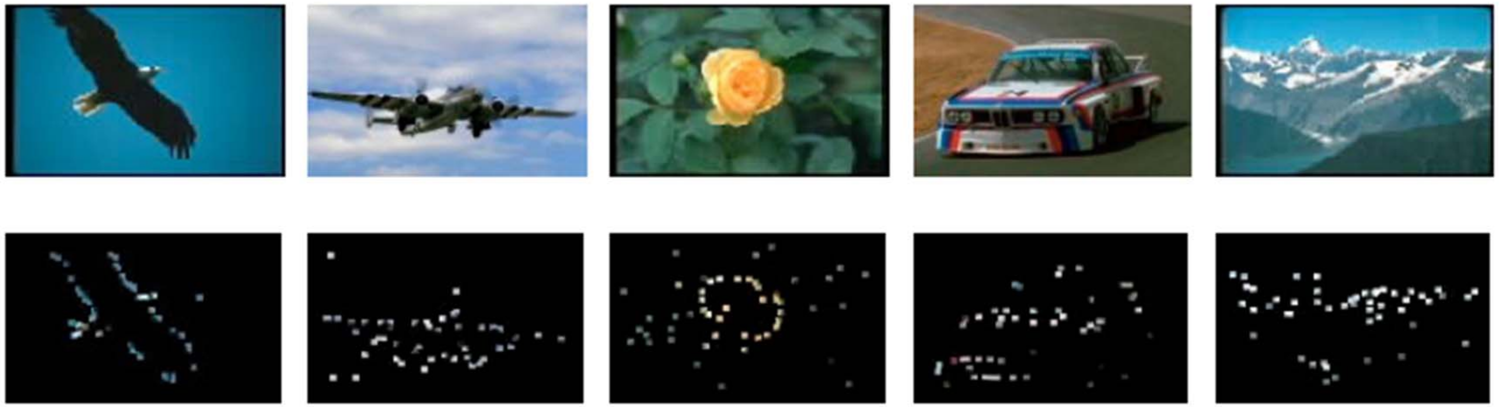
- Structural prototypes:
  - Explicit Representation using structural definitions such as strings and graphs
  - Recognition is performed by stating the matching using an implicit distance (or similarity) function

Shape. Salient Points

Salient Points

A shape can also be described by a set of salient points

- Methods
  - Edge Corners
  - Wavelets
  - Edge Curvature
  - Etc..

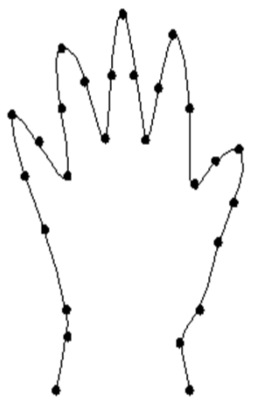


Extracted from Michael S. Lew

Shape. PDM

PDM (Point Distribution model / Statistical Shape model)

- Describe a shape from studying the statistical variation of characteristic points from a set of training images of this shape

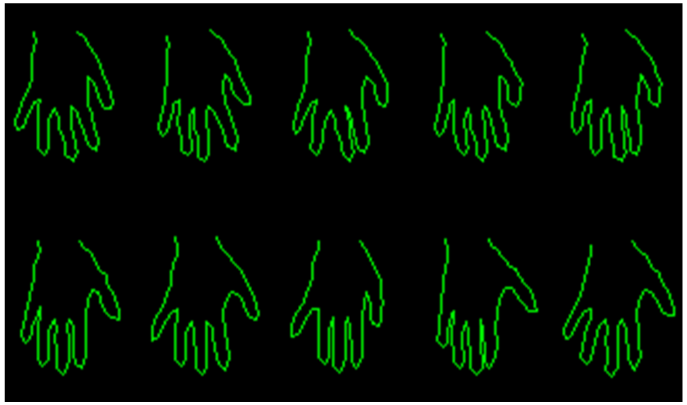


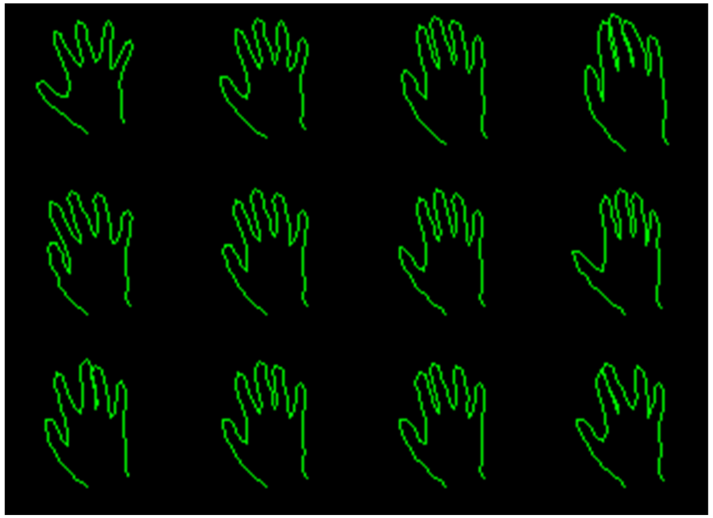
- Overview
  - Align the training set
  - Obtain a mean shape
  - Compute the variance of the training set
  - Extract eigenvectors and eigenvalues of the covariance
  - The shape can be modeled by taking only the eigenvectors with the larger eigevalues (account for most of the variation)

Examples extracted from Tim Cootes

Shape. PDM

PDM. Hand Example





Shape (summary)

- Difficulty to extract reliable shape information from the region
- The selection of a shape feature depends on the many factors
  - Is invariance needed?
  - How complex is the scene/shape?
  - Nature of noise?



Shape Context

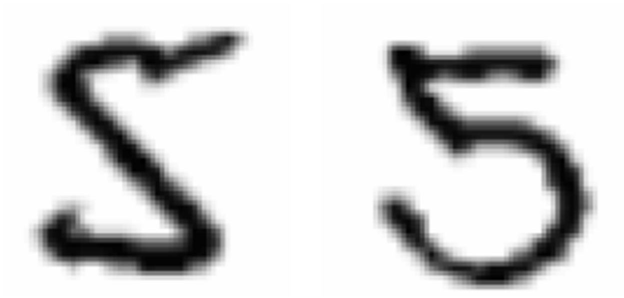
By:

Carlos J. Becker

Sophia Bano

Motivation

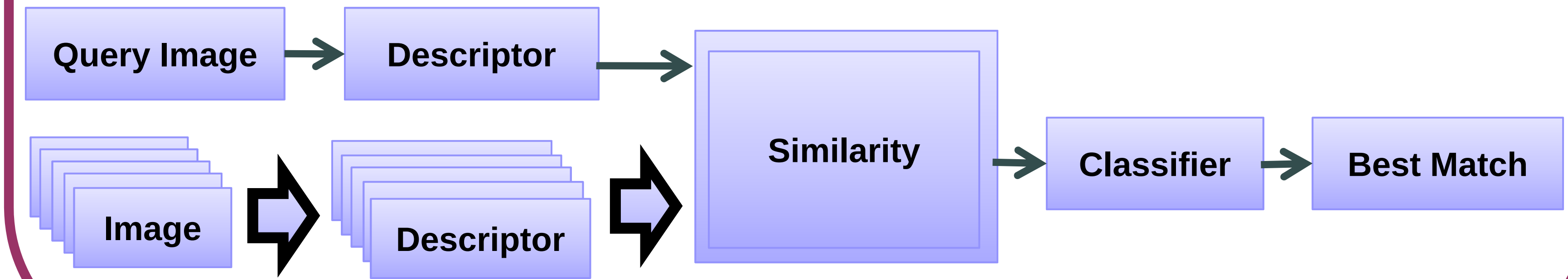
- Shape matching



- Object Recognition based on shapes

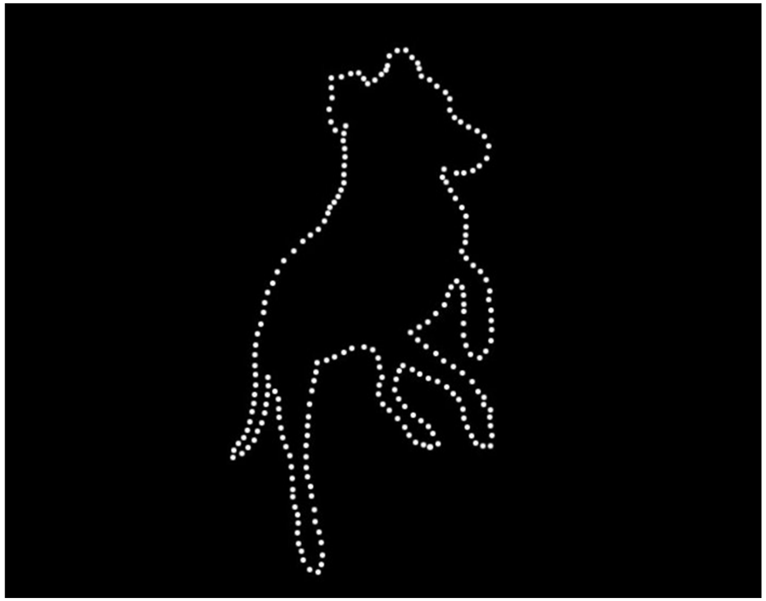
Motivation

- Classification Problem, we need:
  - Descriptor
    - Characterization
  - Similarity between two descriptors (i.e Distance)
    - Matching



Shape Representation

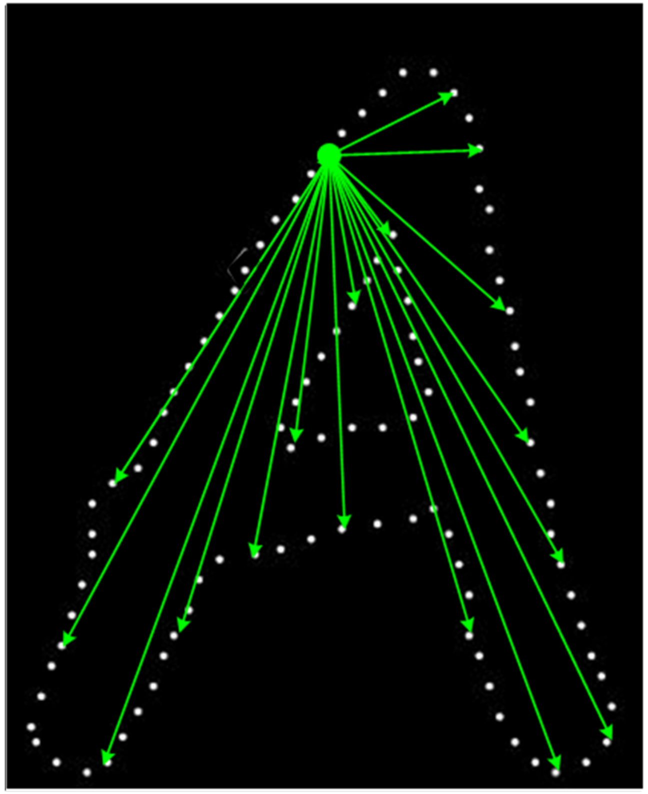
- Set of points taken from external and internal contour of the object



- Points could or could not represent key points in the image (corners/edges/etc)

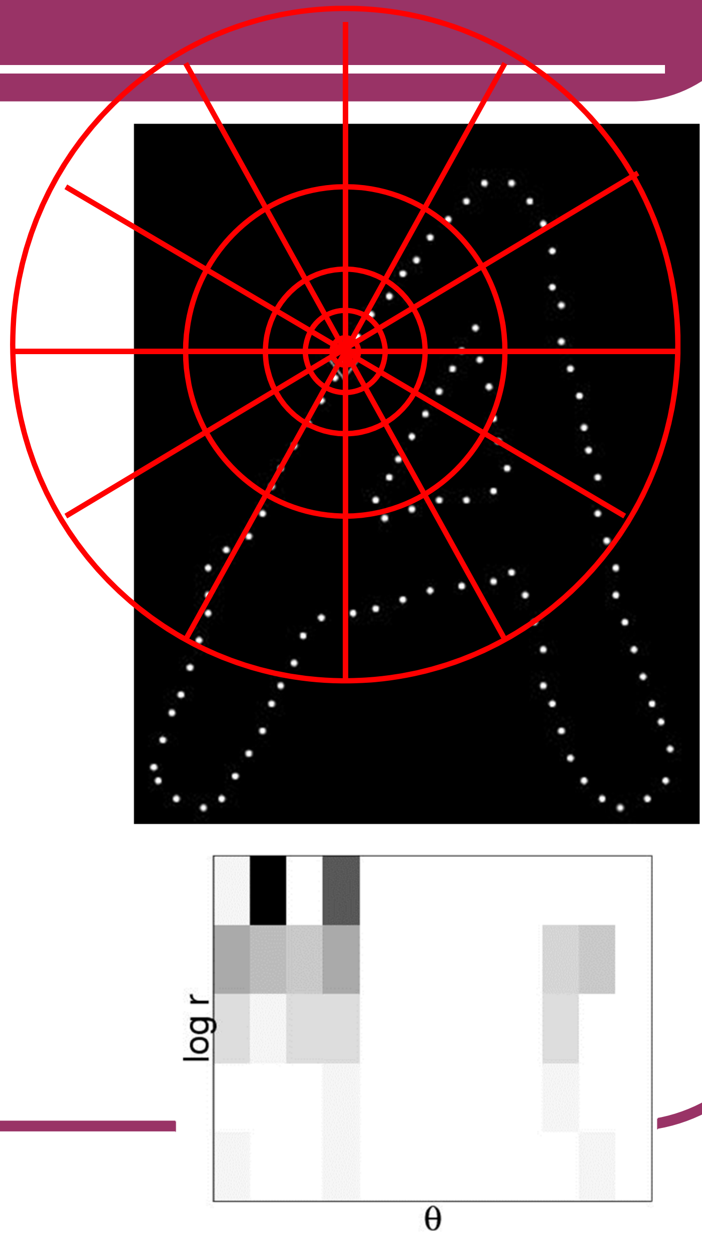
Shape Context

- Novel shape Descriptor
  - Describes the relationship between each point of shape contour with rest of points
    - Histogram Representation
  - All the information is relative to the contour points.
  - Rich Descriptor



Shape Context

- Relationship between points is summarized in a Histogram
  - Polar coordinates
    - Angle
    - Distance
  - Distance taken as log r
    - More sensitive to positions closer to the point than farther



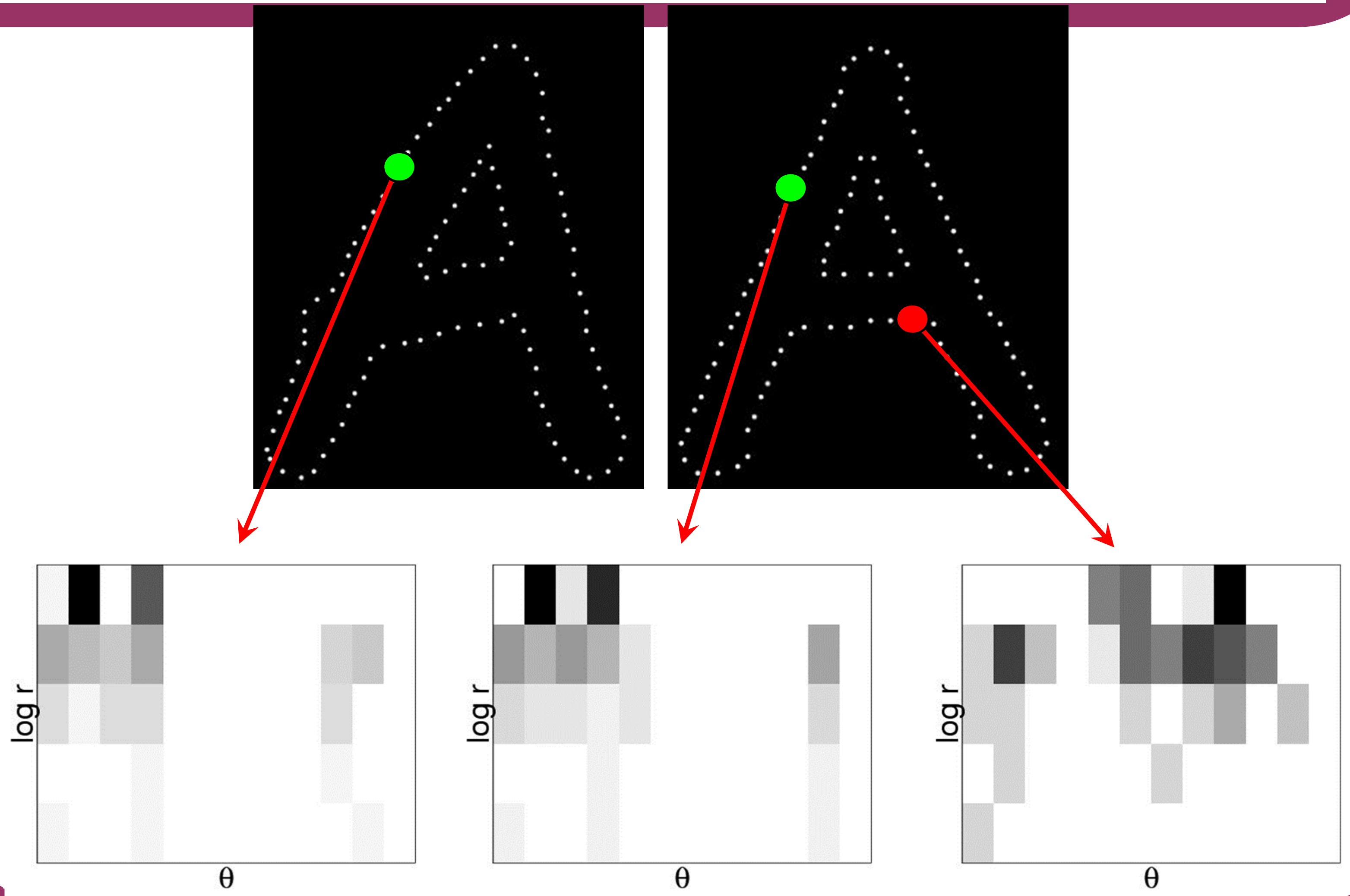
Shape Context

Shape Context Properties

- Invariant to Translation
- Invariant to Scaling
- Can be made invariant to Rotation
- Robust to
  - Small nonlinear transformations
  - Occlusions
  - Presences of outliers

- A blurry or noisy image could lead to a wrong representation of its shape

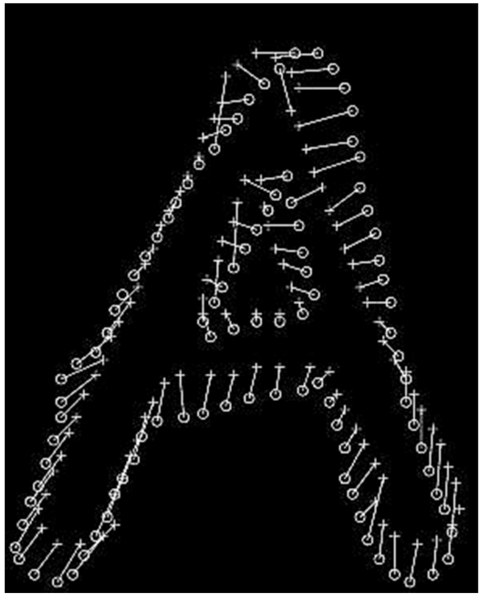
Two shapes: which is the best match?



Two shapes: which is the best match?

- We are comparing histograms
  - **Chi-Square Test** to determine the matching cost:

$$C_{ij} = C(p_i, q_j) = \frac{1}{2}\sum_{k=1}^{K}\frac{[h_i(k) - h_j(k)]^2}{h_i(k) + h_j(k)}$$

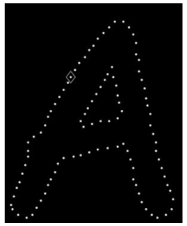


- But we want to minimize the total cost:
  - **Bipartite Matching** using Hungarian method is applied

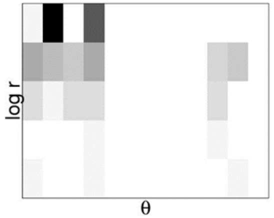
$$H(\pi) = \sum_i C(p_i, q_{\pi(i)})$$

Matching with Shape Context

Query Image

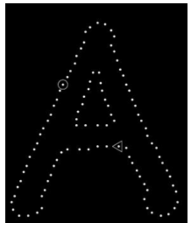


Shape
(N points)

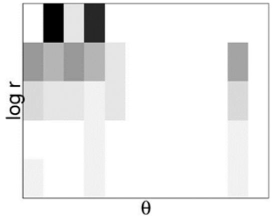


Shape Context
(N histograms)

Reference Image



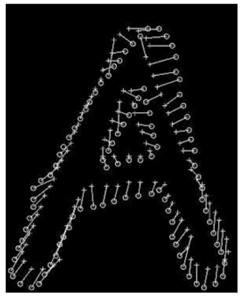
Shape
(N points)



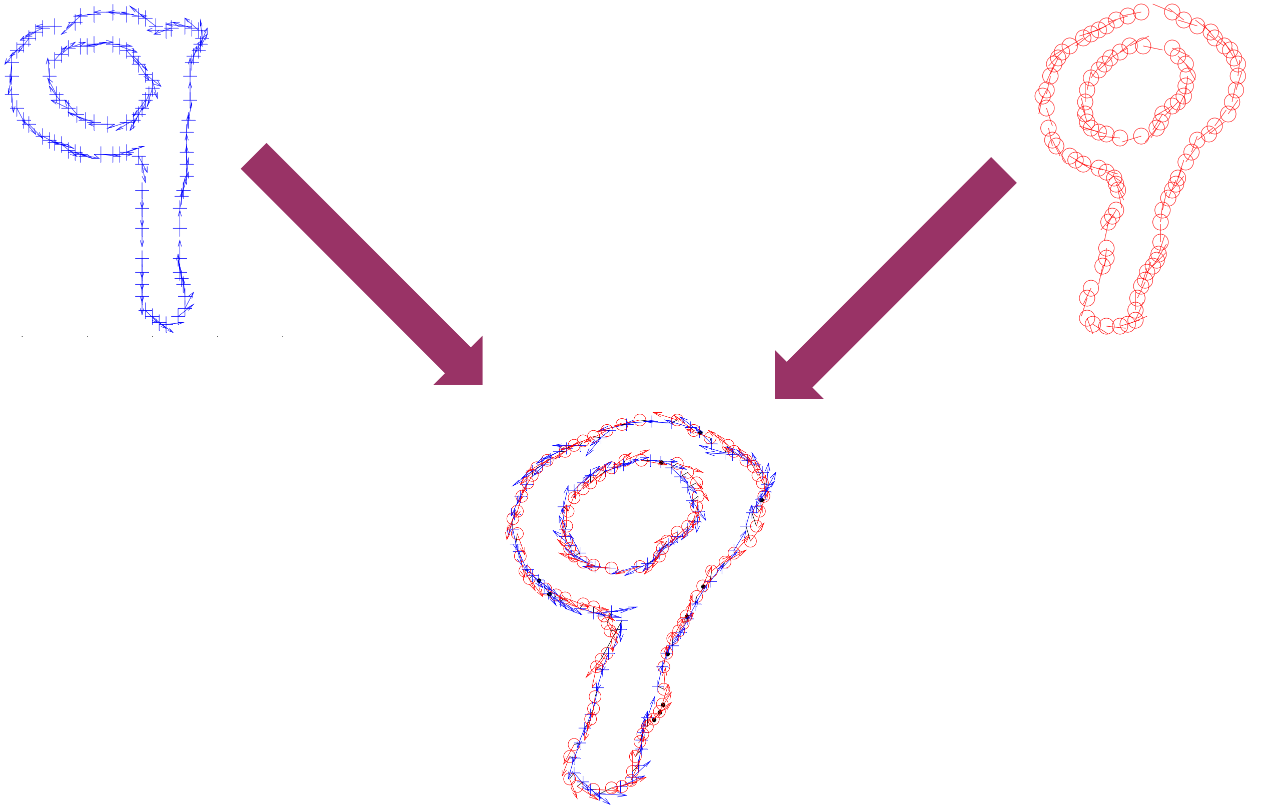
Shape Context
(N histograms)

Correspondence
(Matching cost)

Matching



Matching Example



Matching

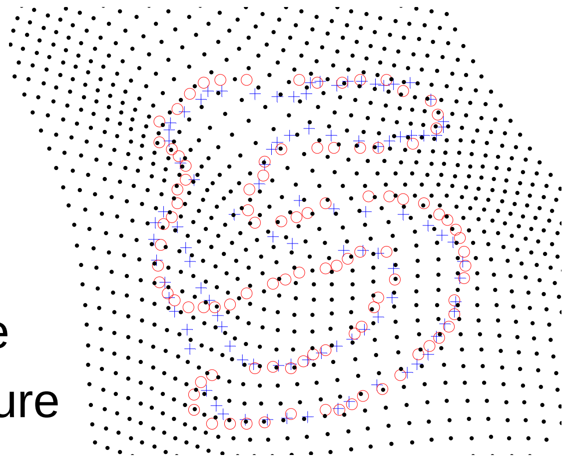
So Far……..

- We have our Shape Descriptor
- We know how to solve the correspondence between two Shape Descriptors:

- This will minimize the total matching cost, regardless of how similar or not the shape descriptors are:

Similarity Measure

- We need a measure of similarity
  - How much can we deform a shape to match it with reference shape?
  - Spatial transformation of points $(x', y') = T(x, y)$

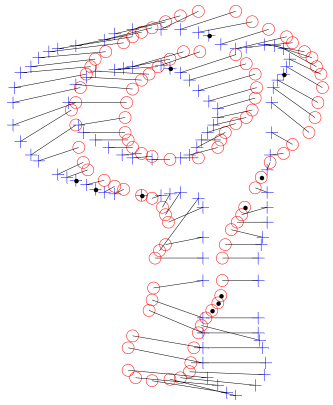


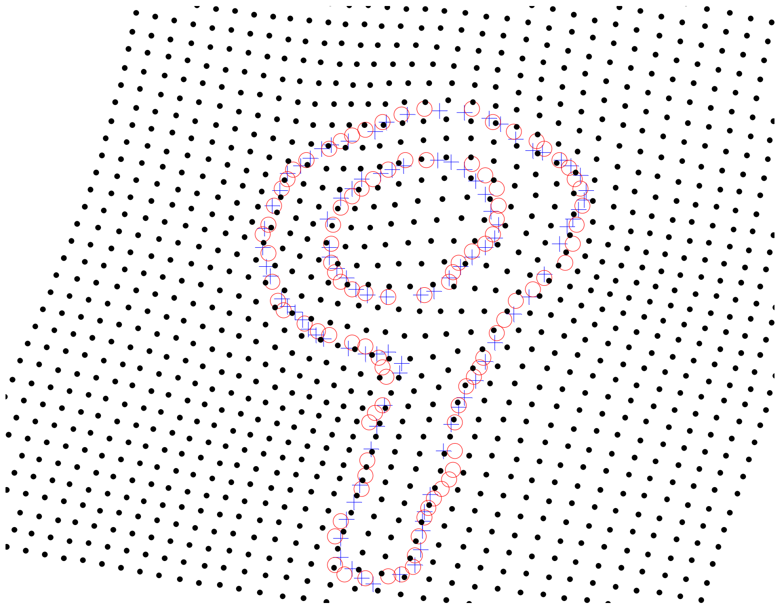
  - Thin-Plate Spline chosen
    - Affine transformation is a special case
    - Able to express organic growth in nature
    - Non-linear transformation

Thin Plate Spline (TPS)

- TPS parameter estimation is fairly easy to do
- Physical analogy to bending a thin sheet of metal
- Bending Energy expresses the ‘effort’ needed to ‘bend’ the space during the transformation
  - GREAT AS DISIMILARITY MEASURE

TPS Result



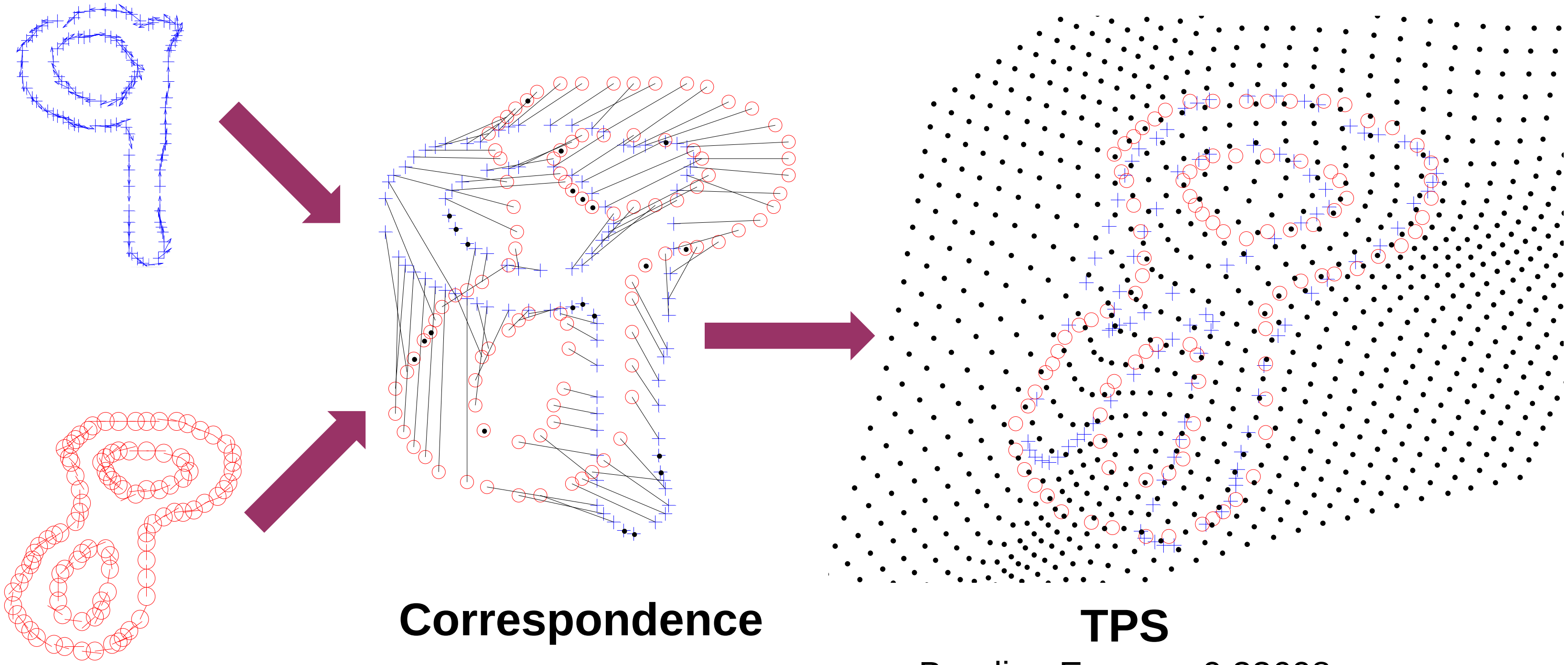


Correspondence

TPS

Bending Energy= 0.070513

TPS Result



Correspondence

TPS

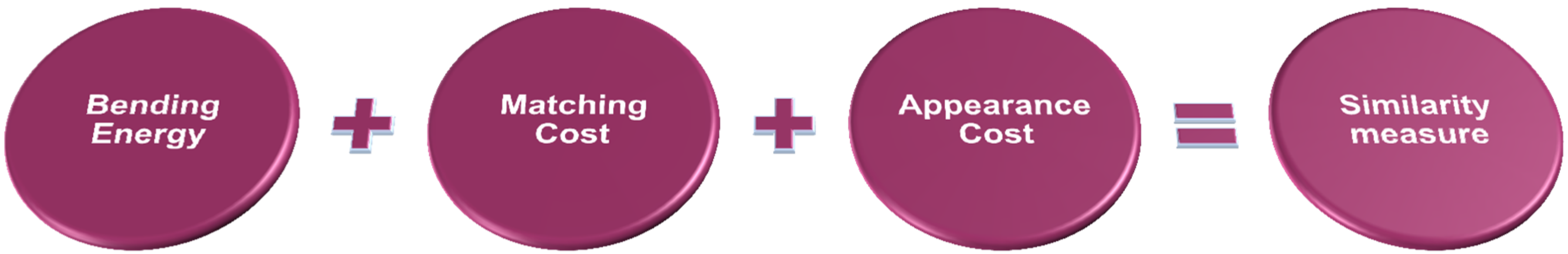
Bending Energy= 0.33608

Similarity Measure

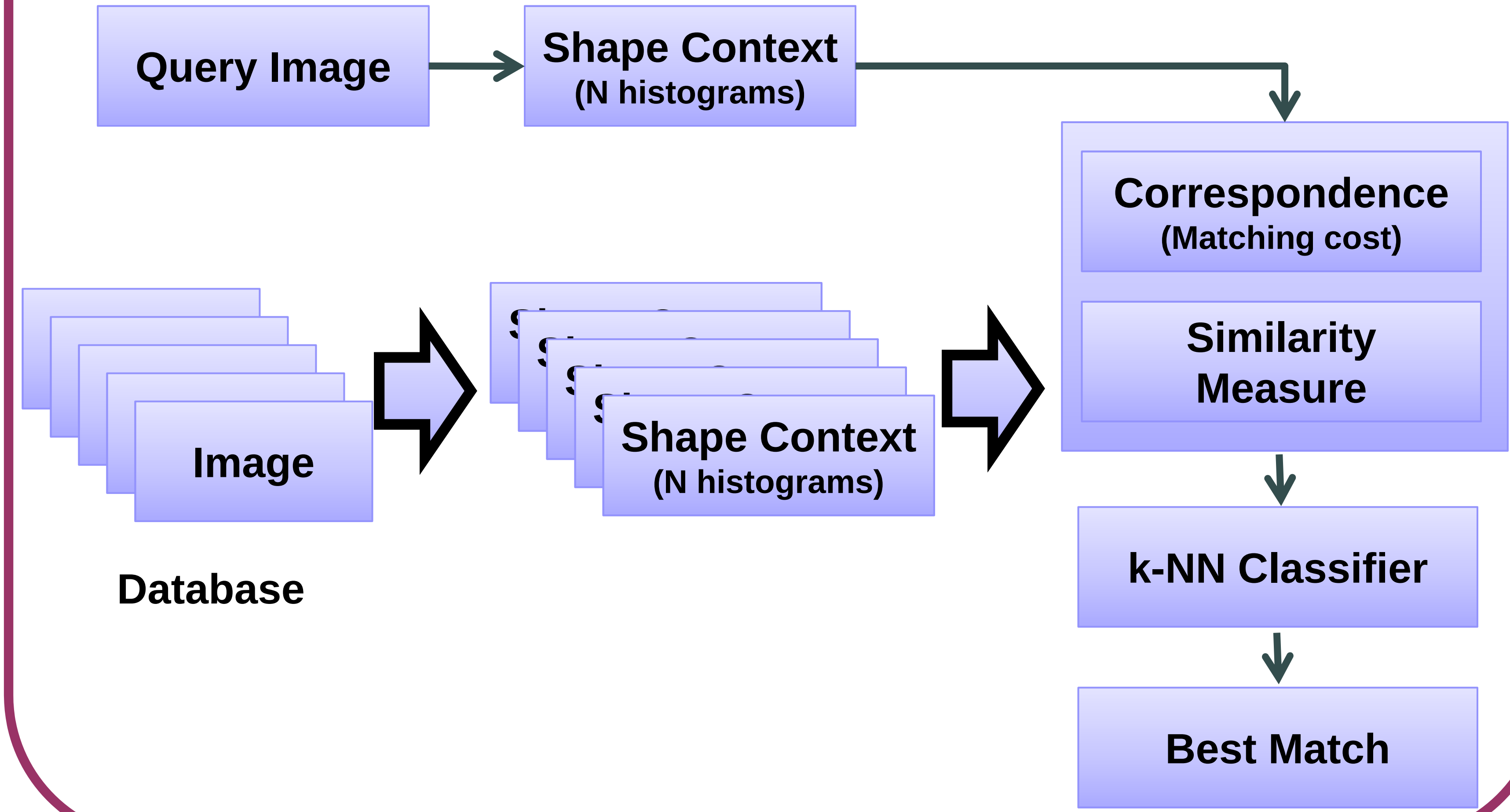
- In order to provide a consistent distance measure, three similarity measures are merged:
  - **TPS Bending Energy**
  - **Matching Cost**

    How well TPS matches one shape into the other
  - **Appearance Cost**

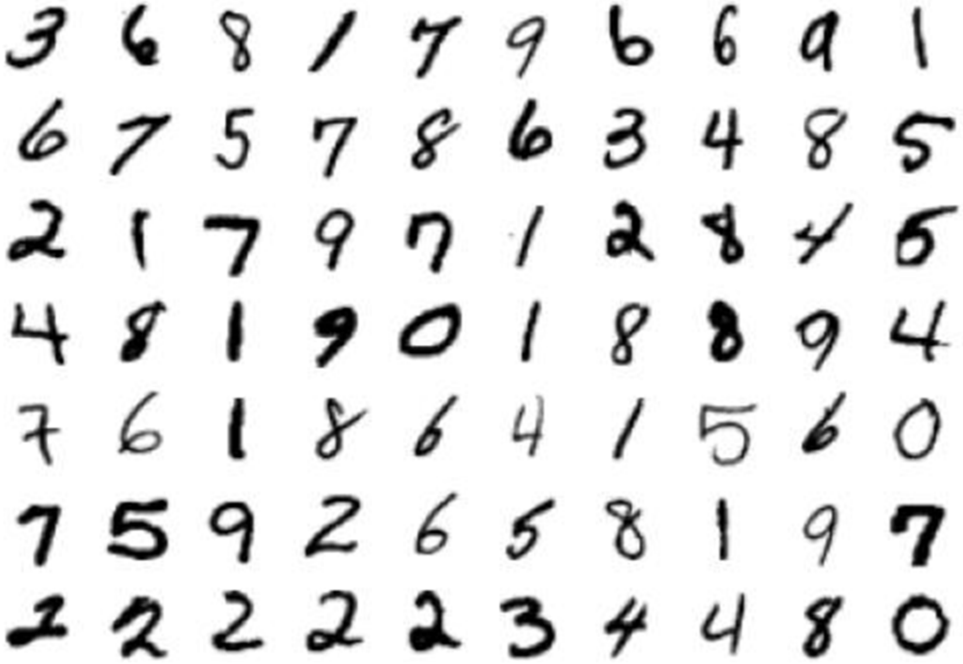
    Taking into account brightness difference around shape points



Classification Process



Results (MNIST Database)

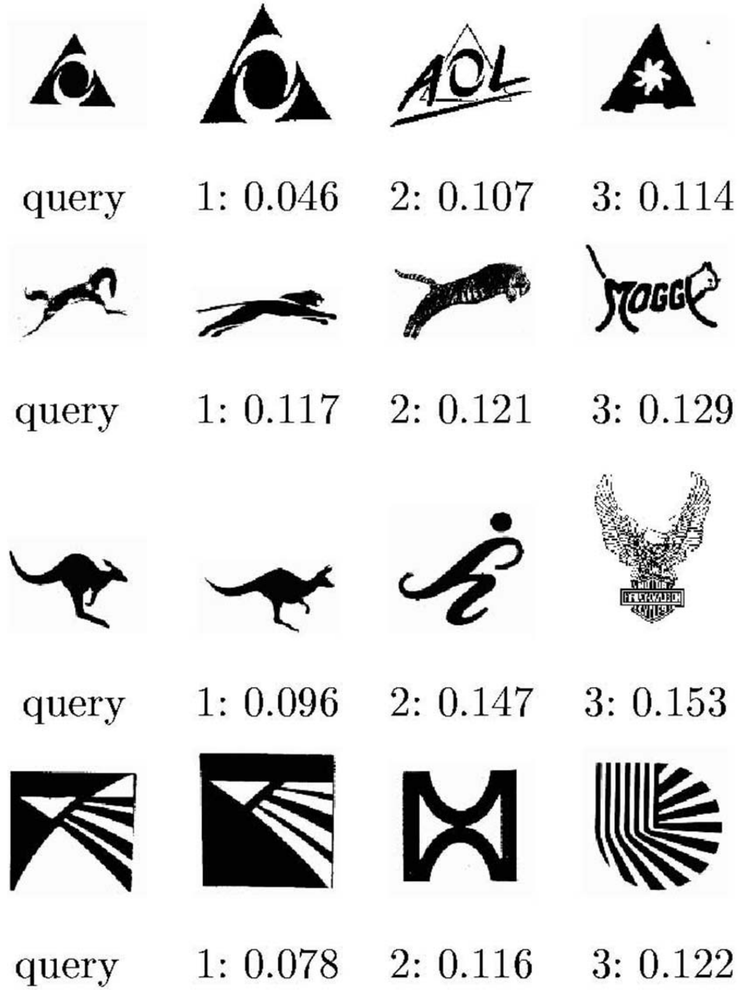


- Shape Representation
  - 100 points sampled from canny edge detector
- Error Rate 0.63% with a database of 20,000 images

Results (Trademark Retrieval)

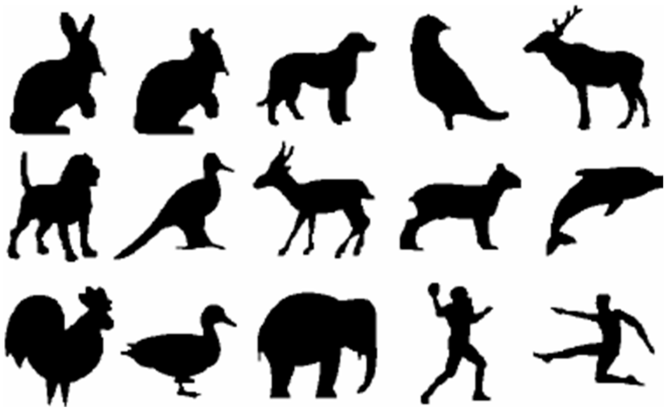
- Database
  - 300 trademarks
- Shape Representation
  - 300 points
- Affine Transformation

- No visually similar trademark has been missed.



Results

MPEG-7 Shape Silhouette



COIL-20 3D Object Recognition

- Shape Context out performed the accuracy of many existing techniques, some conceptually and computationally more complicated and expensive

Conclusions

- Estimation of shape similarity and correspondence based on a novel descriptor **THE SHAPE CONTEXT**

- Shape Context is
  - Simple and intuitive shape descriptor which is easy to apply
  - Rich descriptor, greatly improving point set registration, shape matching, shape recognition
  - Invariance to several common image transformations (translation, scale, rotation, occlusions)

- Main disadvantage: a blurry, diffuse or extremely noisy image may lead to an incorrect representation of its shape (i.e.: canny)
- Problems in cluttered background

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