

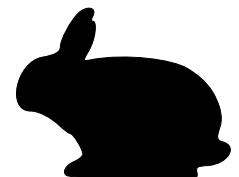
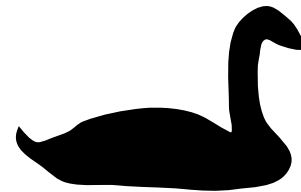


Shape Matching



Shape-Based Recognition

- Humans can recognize many objects based on shape alone
- Fundamental cue for many object categories
- Invariant to photometric variation.

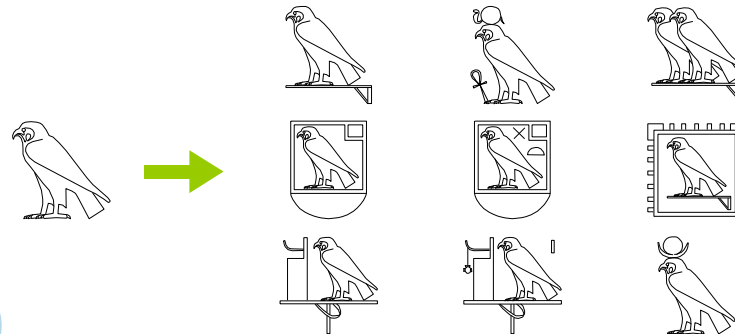
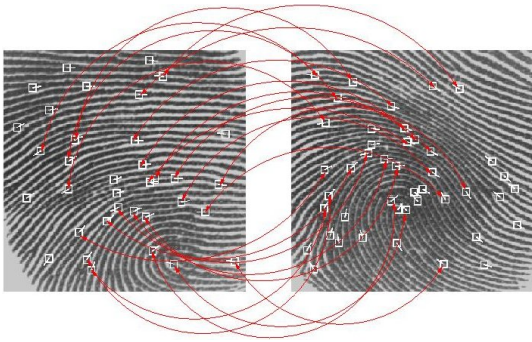


Shapes vs. Intensity Values



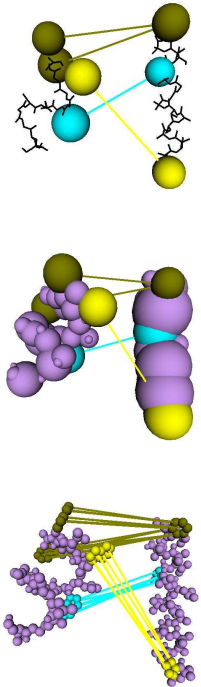
Similar to a human in terms of shape, but very different in terms of pixel values.

- Shape retrieval
- Recognizing object categories
- Fingerprint identification
- Optical Character Recognition (OCR)
- Molecular-biology



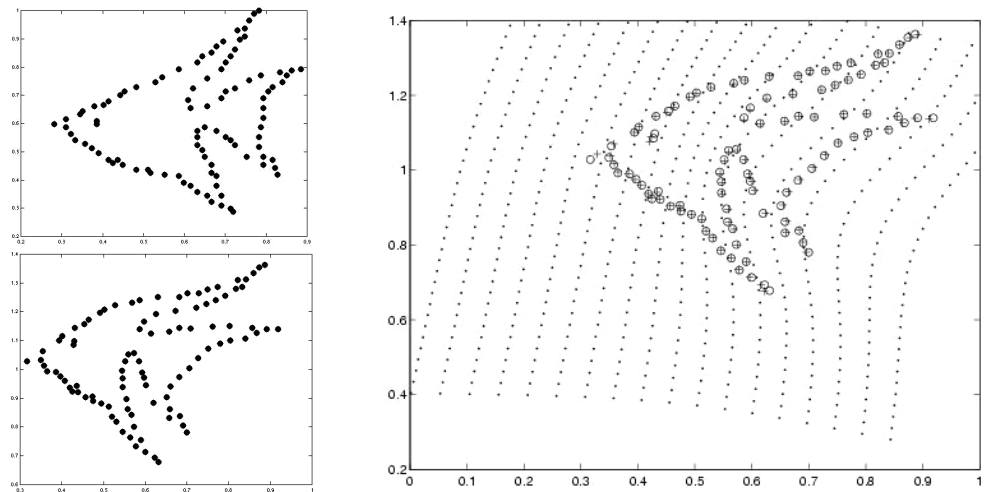
Western
Western

1909
1909



Geometric Transformations

- Often in matching images are allowed to undergo some geometric transformation
- Related but not identical shapes can be deformed into alignment using simple coordinate transformations
- Find the transformations of one image that produce good matches to the other image



Biological Shape

- D'Arcy Thompson: *On Growth and Form*, 1917
 - studied transformations between shapes of organisms

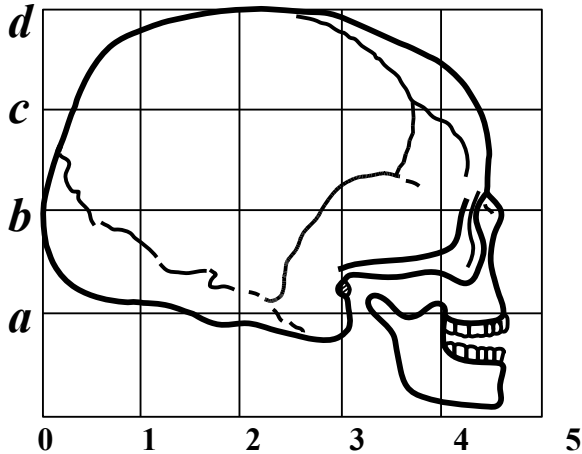


Fig. 177. Human skull

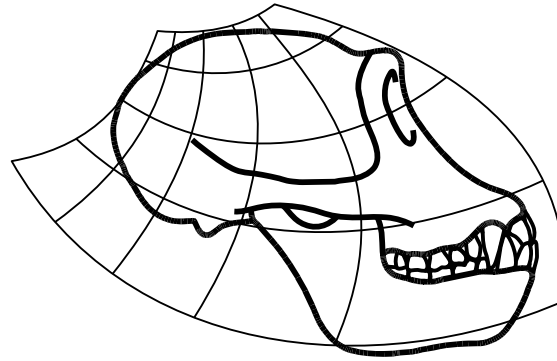


Fig. 179. Skull of chimpanzee.

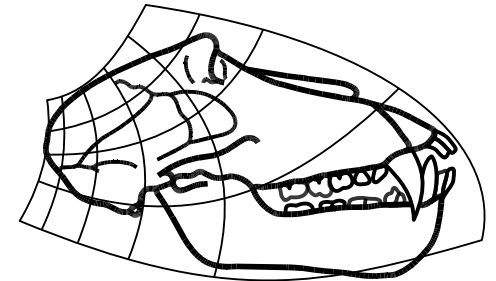
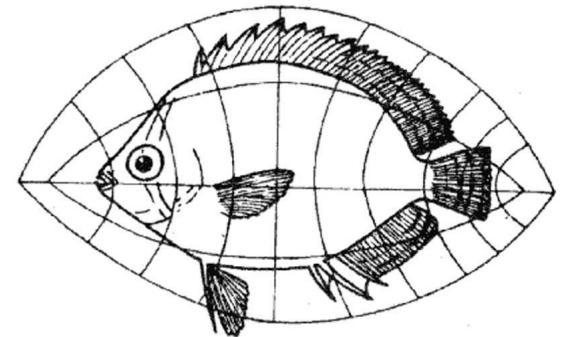
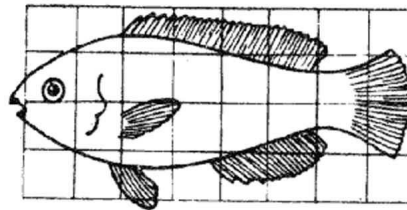
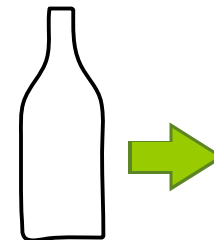
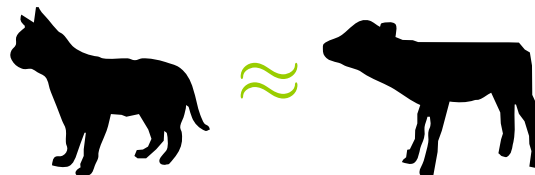


Fig. 180. Skull of baboon.



Related Problems

- Shape representation and decomposition
- Finding a set of correspondences between shapes
- Transforming one shape into another
- Measuring the similarity between shapes
- Shape localization and model alignment
- Finding a shape similar to a model in a cluttered image



References

- **Shape Matching and Object Recognition Using Shape Contexts**, by S. Belongie, J. Malik, and J. Puzicha. Transactions on Pattern Analysis and Machine Intelligence (PAMI), 2002.
 - **Recognizing Objects in Adversarial Clutter: Breaking a Visual CAPTCHA**, by G. Mori and J. Malik, in Proceedings IEEE Computer Vision and Pattern Recognition (CVPR), 2003.
 - **Using the Inner-Distance for Classification of Articulated Shapes**, by H. Ling and D. Jacobs, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2005.
 - **Comparing Images Using the Hausdorff Distance**, by D. Huttenlocher, G. Klanderman, and W. Rucklidge, Transactions on Pattern Analysis and Machine Intelligence (PAMI), 1993.
 - **A Boundary-Fragment-Model for Object Detection**, by A. Opelt, A. Pinz, and A. Zisserman, Proceedings of the European Conference on Computer Vision (ECCV), 2006.
 - **Hierarchical Matching of Deformable Shapes**, by P. Felzenszwalb and J. Schwartz, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2007
- 

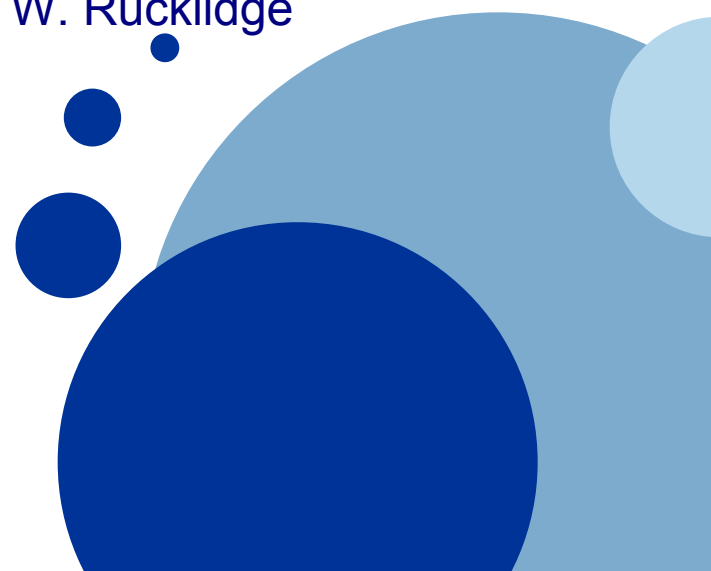
Outline

- Shape Distance and Correspondence
 - *Hausdorff Distance*
 - Shape Context
 - Inner Distance
- Hierarchical Approach
 - Hierarchical Matching
- Machine Learning Approach
 - Boundary Fragment Model


Comparing Images Using the Hausdorff Distance

1993

D. Huttenlocher, G. Klanderman, and W. Rucklidge



Overview

- Use Hausdorff distance to compare images to a model
 - Fast and simple approach
 - Tolerant of small position errors
 - Model is only allowed to translate with respect to the image
 - Can be extended to allow rotation and scale
- 

Hausdorff Distance

- A means of determining the resemblance of one point set to another
- Examines the fraction of points in one set that lie near points in the other set

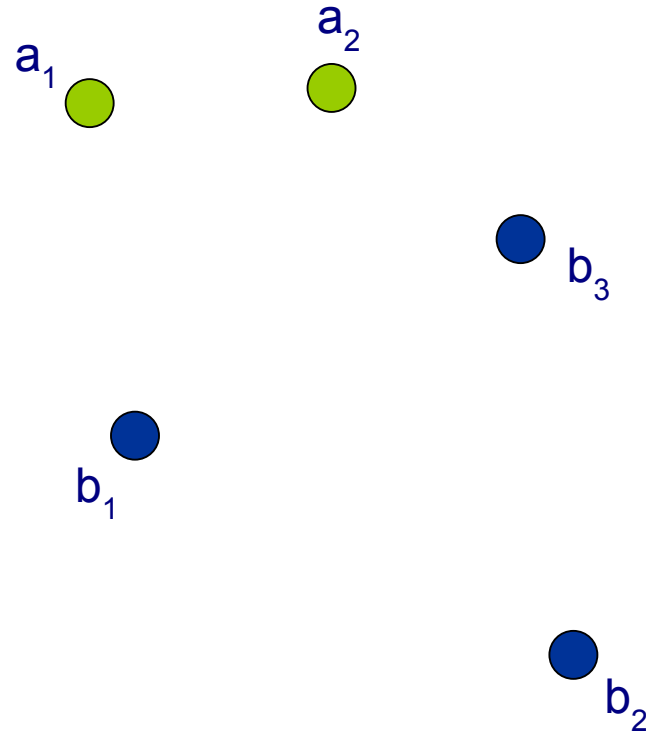
$$H(A, B) = \max \{h(A, B), h(B, A)\}$$

$$h(A, B) = \max_{a \in A} \left\{ \min_{b \in B} \{d(a, b)\} \right\}$$


Hausdorff Distance

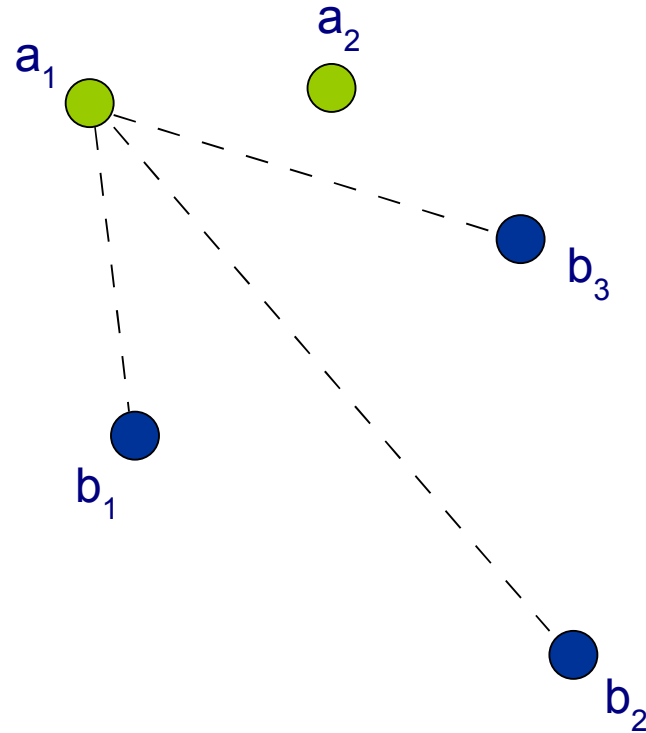
Example

Given two sets of points
A and B, find $h(A,B)$



Example

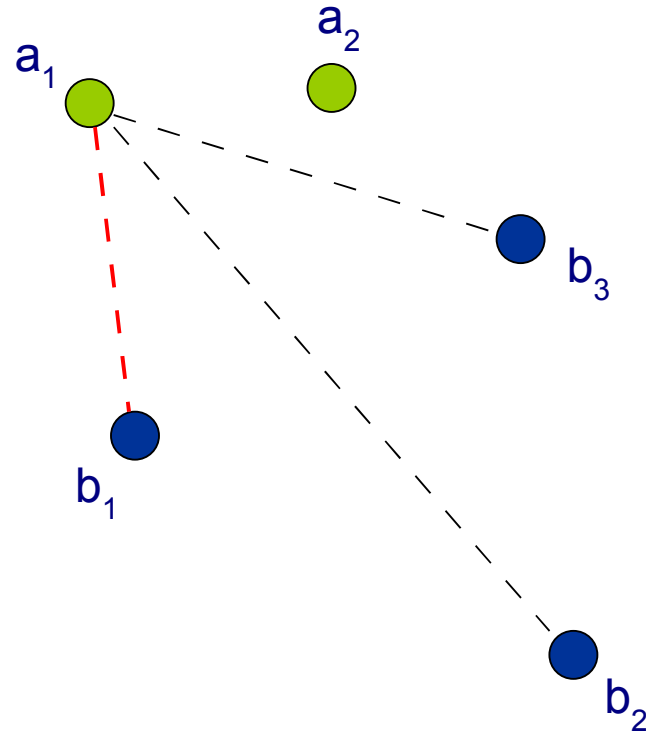
Compute the distance
between a_1 and each b_j



Hausdorff Distance

Example

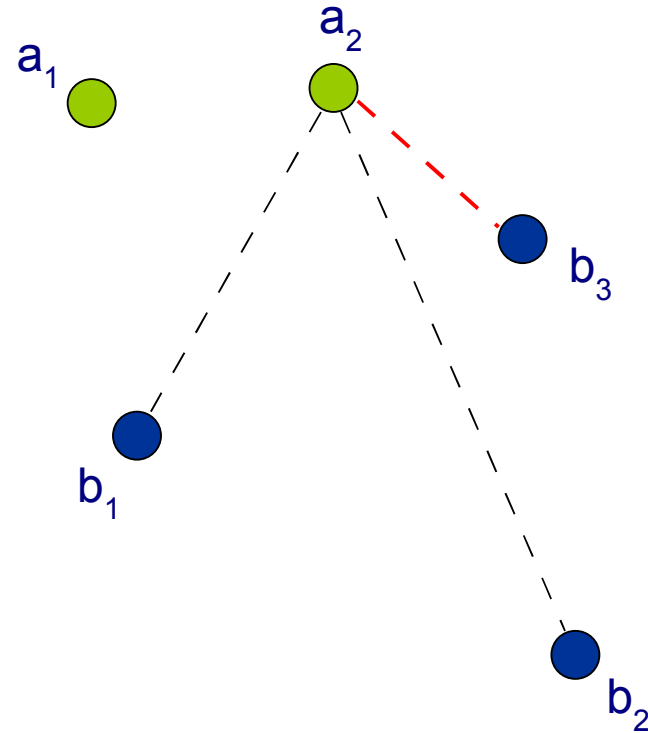
Keep the shortest



Hausdorff Distance

Example

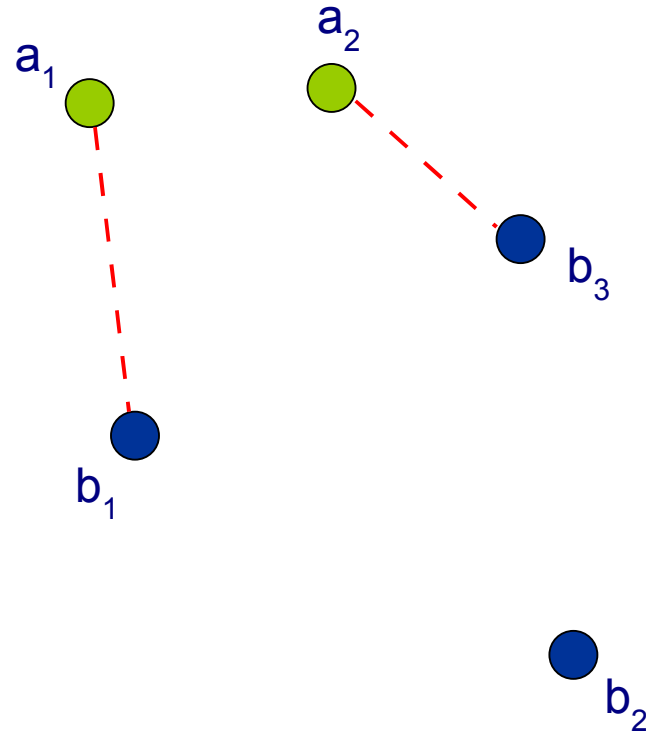
Do the same for a_2



Hausdorff Distance

Example

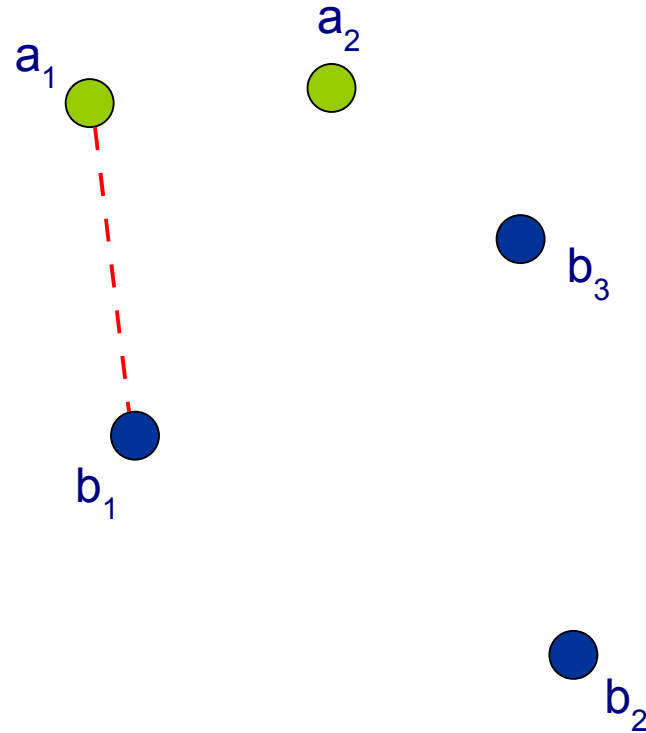
Find the largest of these two distances



Hausdorff Distance

Example

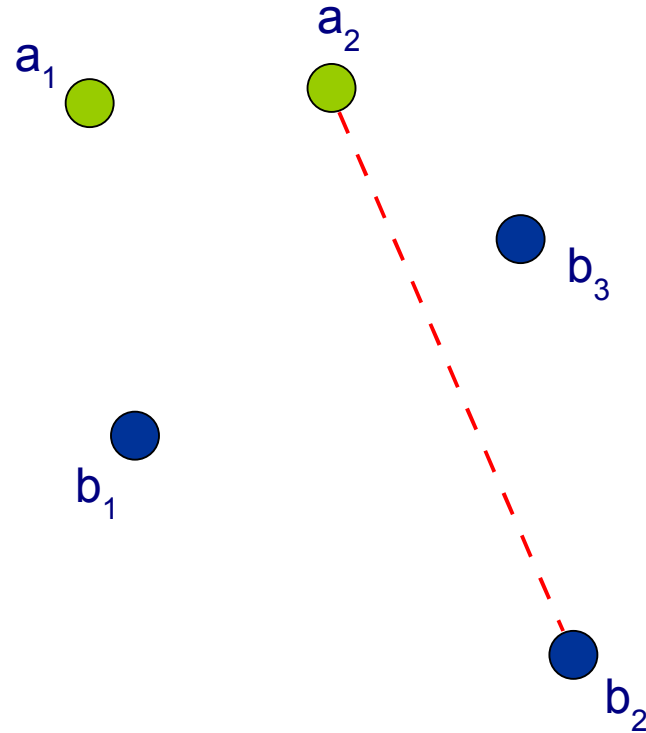
This is $h(A,B)$



Hausdorff Distance

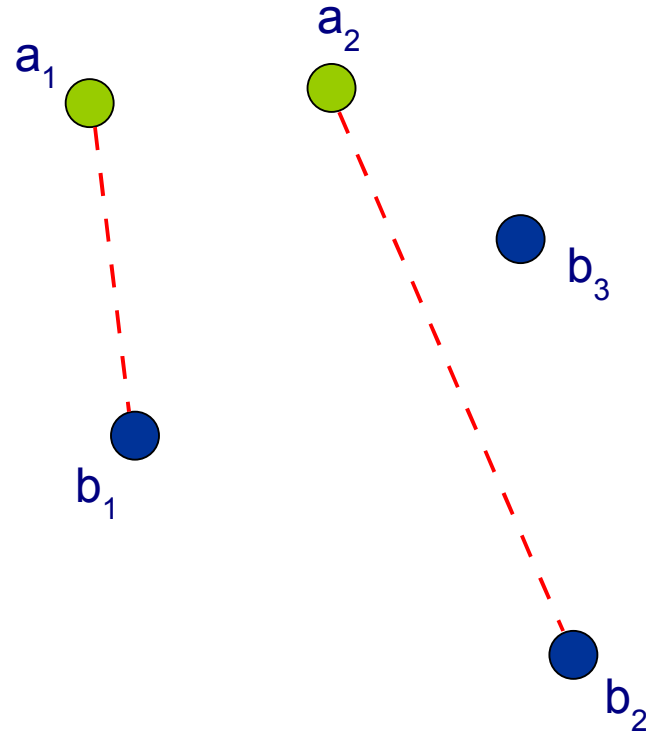
Example

This is $h(B,A)$



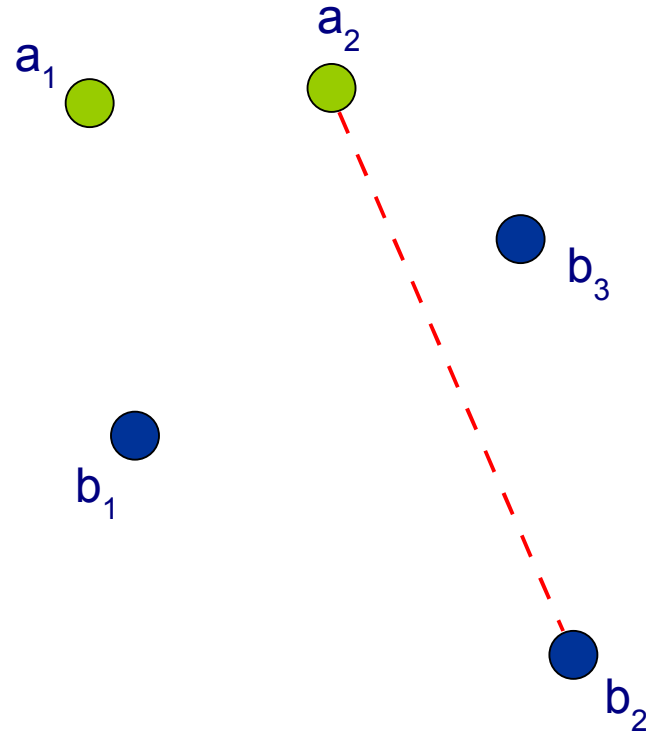
Example

$$H(A,B) = \max(h(A,B), h(B,A))$$



Example

This is $H(A,B)$



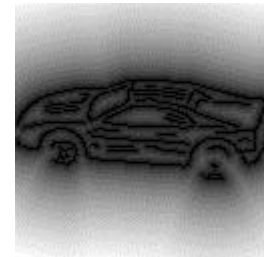
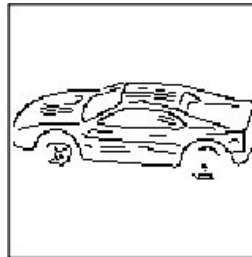
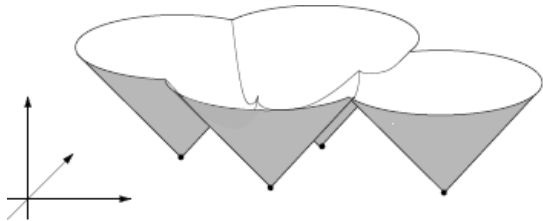
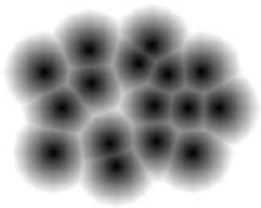
Generalization

- Hausdorff distance is very sensitive to even one outlier in A or B
- Use k^{th} ranked distance instead of the maximal distance
- Match if $h_k(A, B) < \delta$
 - k is how many points of the model need to be near points of the image
 - δ is how near these points need to be

$$h_k(A, B) = \min_{a \in A} \left\{ k^{\text{th}} \min_{b \in B} \{d(a, b)\} \right\}$$

Distance Transforms

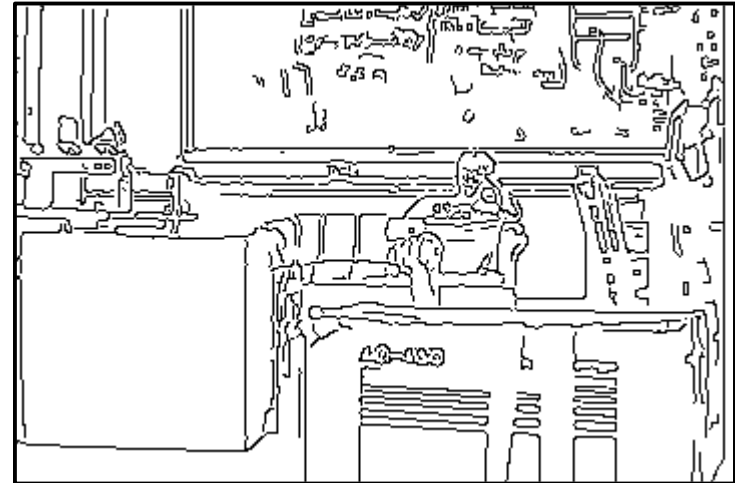
- Processing can be sped up by probing a precomputed Voronoi surface
- A Voronoi surface defines the distance from any location in B to the nearest point
- Can be efficiently computed using dynamic programming in linear time



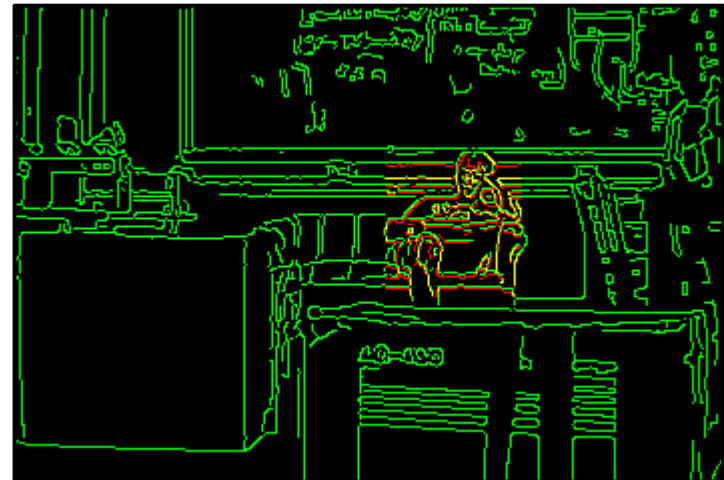
Example: Matching



Model



Edges



Match

Hausdorff Distance

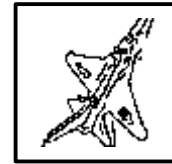
Example: Matching



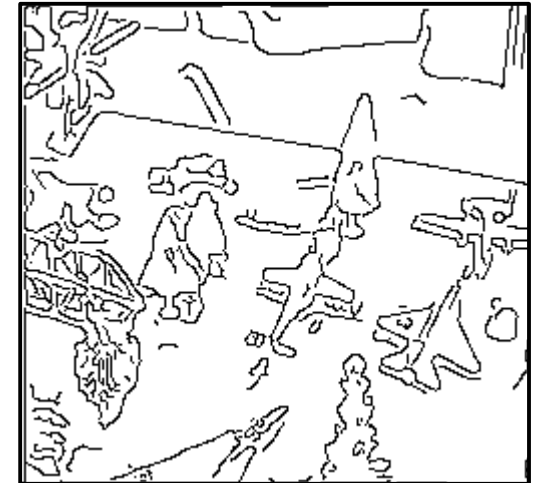
Model



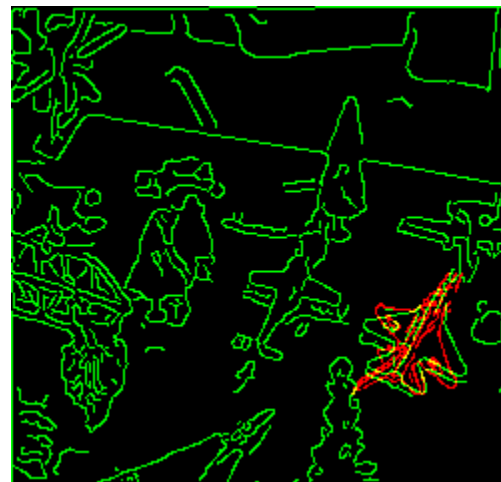
Image



Model



Edges



Match

Outline

- Shape Distance and Correspondence
 - Hausdorff Distance
 - *Shape Context*
 - Inner Distance
- Hierarchical Approach
 - Hierarchical Matching
- Machine Learning Approach
 - Boundary Fragment Model

Shape Matching and Object Recognition Using Shape Contexts

2002

S. Belongie, J. Malik, and J. Puzicha

A series of overlapping blue circles of various sizes in the bottom-right corner, ranging from dark blue to light blue.

Overview

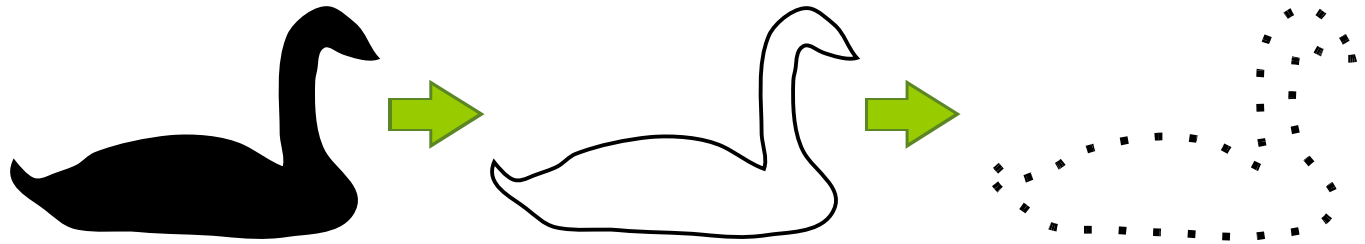
- 1) Solve for correspondences between points on the two shapes
 - Using shape contexts
- 2) Use the correspondences to estimate an aligning transform
 - Using regularized thin-plate splines
- 3) Compute the distance between the two shapes

Related Work: Deformable Templates

- **The Representation and Matching of Pictorial Structures**, by Fischler & Elschlager (1973)
- **Structural image restoration through deformable templates**, by Grenander et al. (1991)
- **Deformable Templates for Face Recognition**, by Yuille (1991)
- **Distortion invariant object recognition in the dynamic linkarchitecture**, by von der Malsburg (1993)

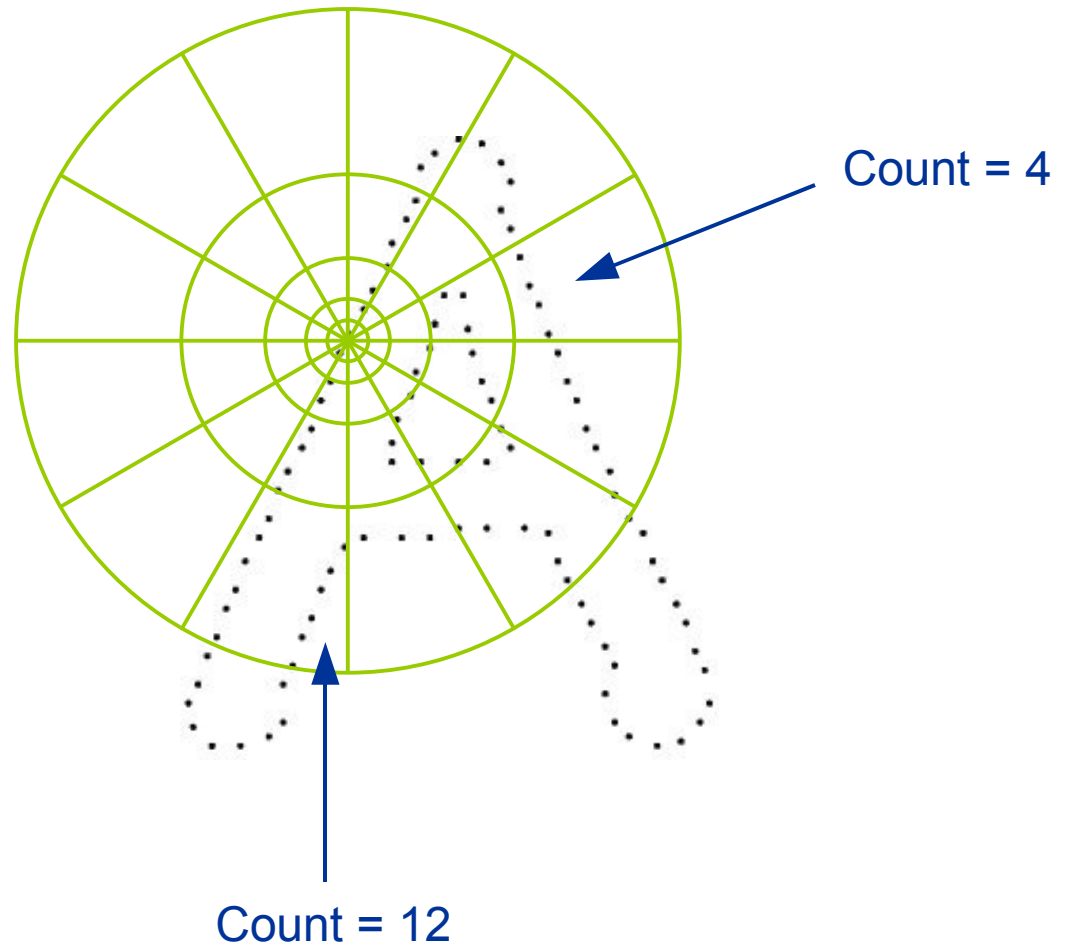
Sampling Points

- A shape is represented by a set of points sampled from the edges of the object



Shape Context: Log-Polar Histograms

Count the number of points inside each bin.



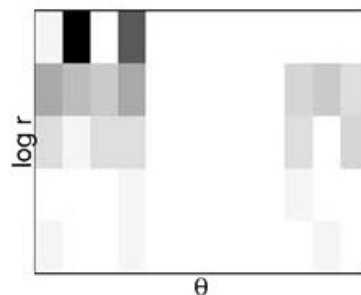
Example: Shape Contexts



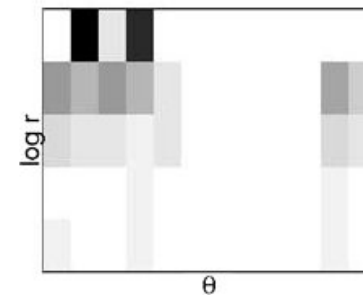
a)



b)



c)



d)

Point Correspondences

- Compute matching costs $C(p_i, p_j)$ using Chi Squared distance:

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

- Minimize the total cost of matching, such that matching is 1-to-1

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

[Jonker & Volgenant, 1987]

Example: Point Correspondences



a)



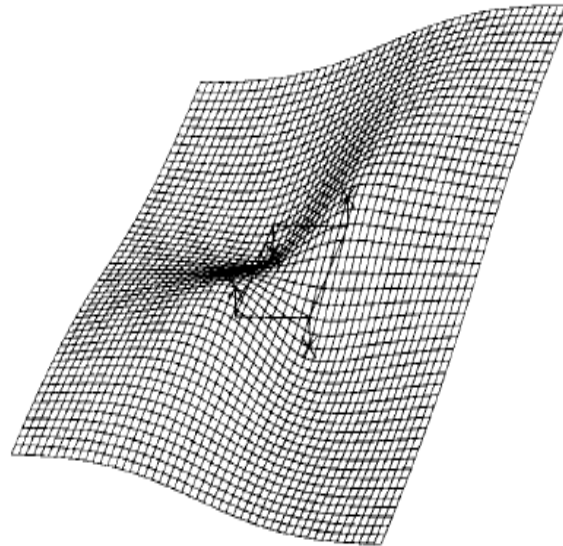
b)



c)

Thin Plate Spline Model

- The name “thin plate spline” refers to a physical analogy involving the bending of a thin sheet of metal
- The 2D generalization of the 1D cubic spline
- Contains the affine model as a special case



Minimizing Bend Energy

- The Thin Plate Spline interpolation has the form:

$$f(x, y) = \underbrace{a_1 + a_x x + a_y y}_{\text{global affine transform}} + \underbrace{\sum_{i=1}^n w_i U(\|(x_i, y_i) - (x, y)\|)}_{\text{local non-linear transformations}}$$

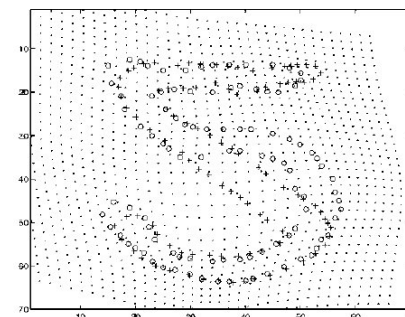
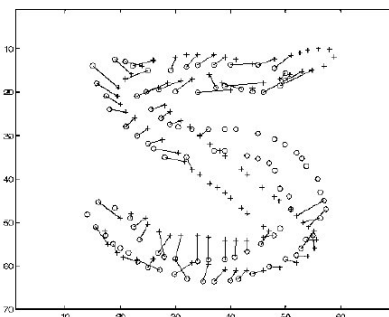
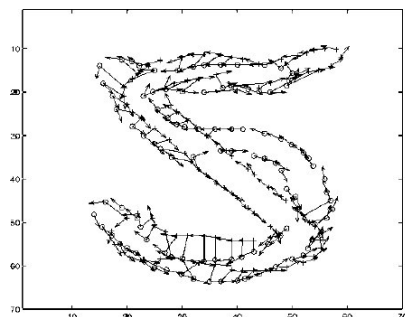
where, $U(r) = r^2 \log r^2$

- Select a and w to minimize the bend energy:

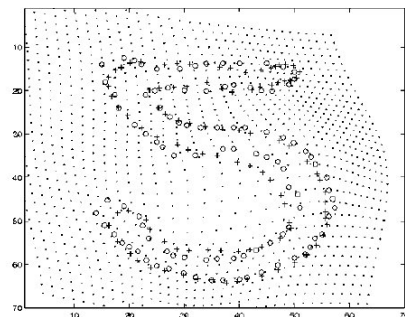
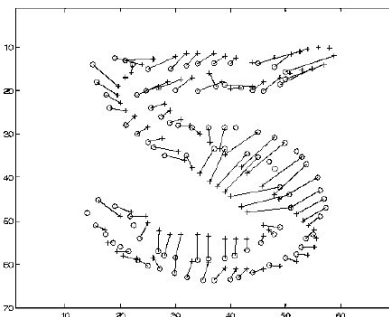
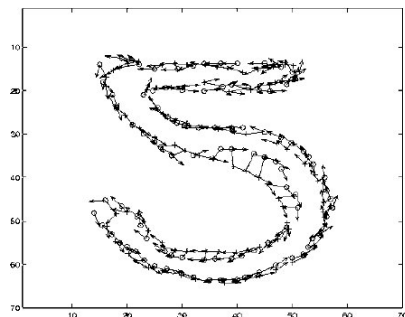
$$I(f) = \int \int_{\mathbb{R}^2} \left(\frac{\partial^2 f}{\partial x^2} \right)^2 + 2 \left(\frac{\partial^2 f}{\partial x \partial y} \right)^2 + 2 \left(\frac{\partial^2 f}{\partial y^2} \right)^2 dx dy$$

Example: Matching and Transformation

a)



b)



Terms in Similarity Score

- Shape Context difference, \mathcal{D}_{sc}
- Local Image appearance difference, \mathcal{D}_{ac}
 - Orientation
 - Gray-level correlation in Gaussian window
 - ... (many more possible)
- Bending energy, \mathcal{D}_{be}

$$\mathcal{D}_{sc} + 1.6 * \mathcal{D}_{ac} + 0.3 * \mathcal{D}_{be}$$

Shape Context Results

Query

Similarity Scores



0.086



0.108



0.109



0.066



0.073



0.077



0.046



0.107



0.114



0.117



0.121



0.129



0.096



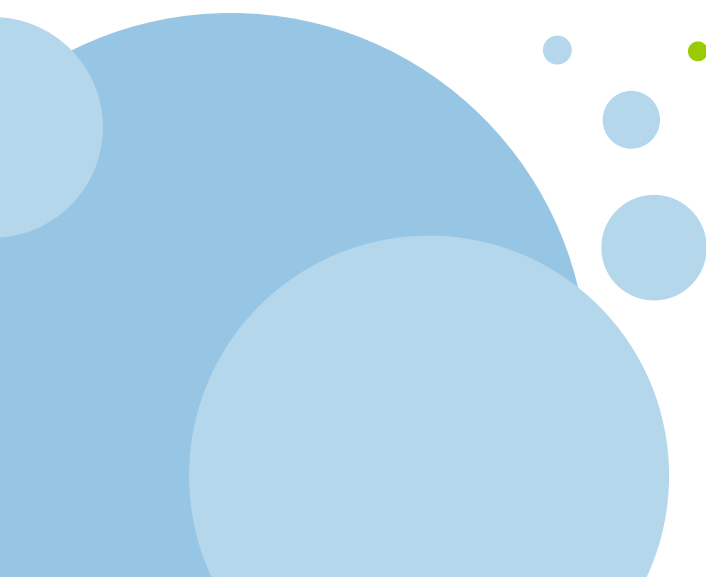
0.147



0.153

Outline

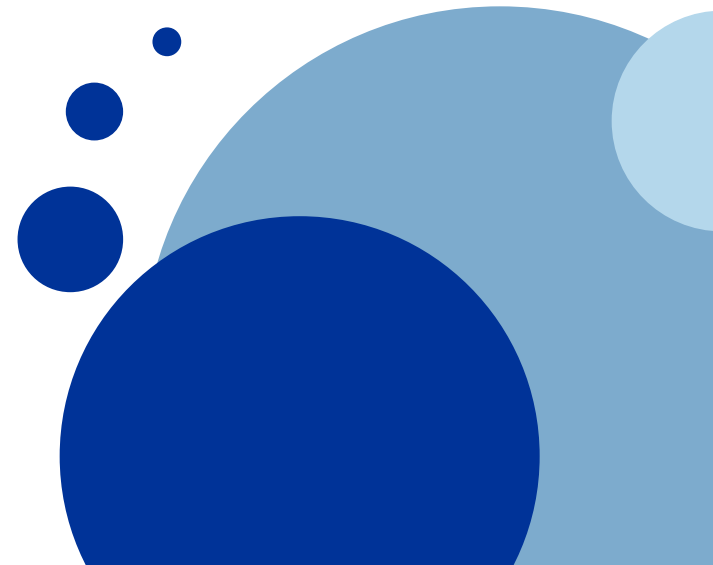
- Shape Distance and Correspondence
 - Hausdorff Distance
 - Shape Context
 - *Inner Distance*
- Hierarchical Approach
 - Hierarchical Matching
- Machine Learning Approach
 - Boundary Fragment Model




Using the Inner-Distance for Classification of Articulated Shapes

2005

H. Ling and D. Jacobs

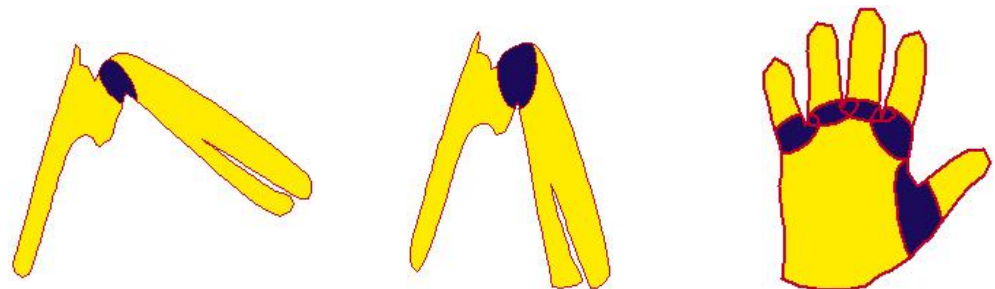


Overview

- Its difficult to capture the part structure of complex shapes with existing shape matching methods
 - Replace euclidean distance with the inner-distance
 - Insensitive to shape articulations
 - Often more discriminative for complex shapes
 - An extension to shape contexts
- 

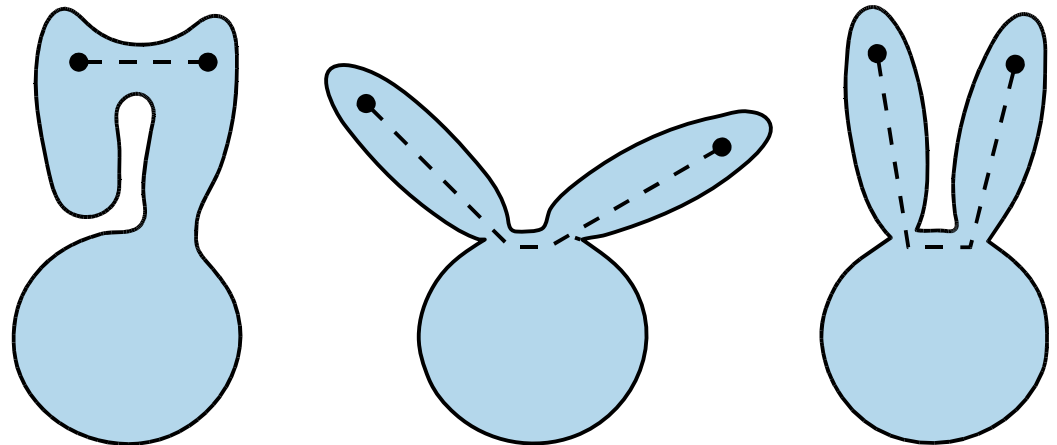
Model of Articulated Objects

- 1) An object can be decomposed into a number of parts
- 2) Junctions between parts are relatively small with respect to the parts they connect
- 3) Articulation on the object is rigid with respect to any part, but can be non-rigid on the junctions
- 4) An object that has been articulated can be articulated back to its original form



The Inner-Distance

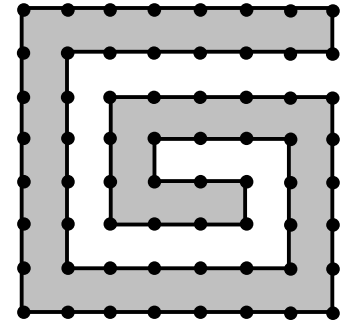
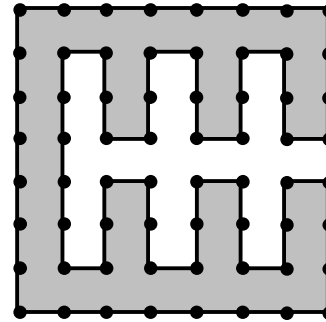
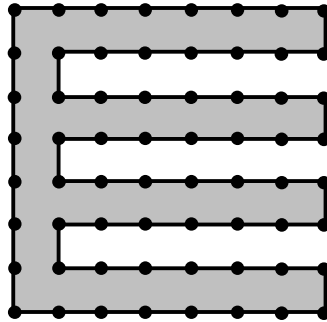
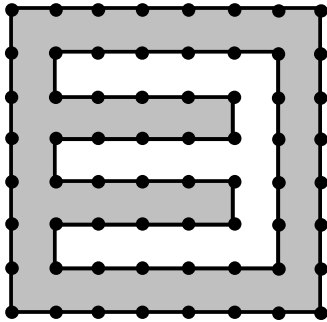
- The length of the shortest path between landmark points within the shape silhouette
- For convex shapes, the inner-distance reduces to the Euclidean distance
- Inner-Distance changes only due to deformations of the junctions





**Inner
Distance**

Inner-Distance vs Euclidean Distance



Computing the Inner-Distance

1) Build a graph on the sampled points

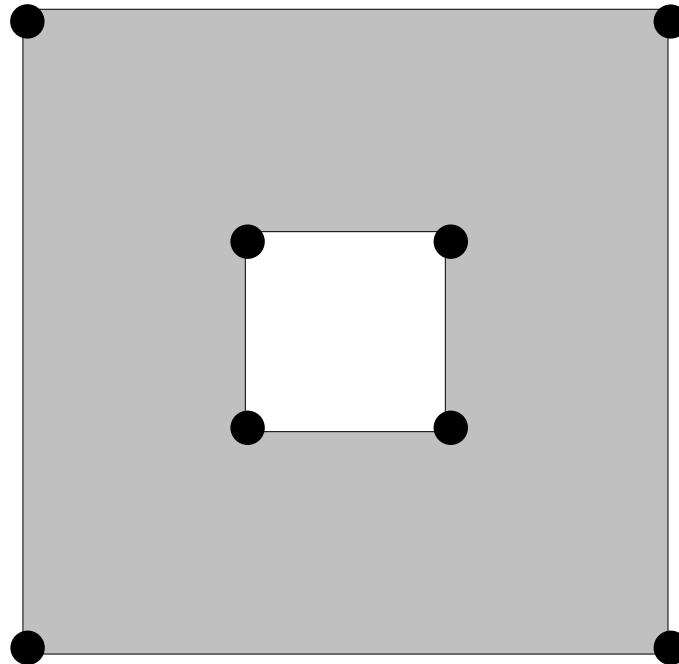
- For each pair of points x, y .
 1. If line segment between them existed entirely within the object
 2. Build an edge connecting x and y with weight

$$w = ||x - y||$$

2) Apply a shortest path algorithm on the graph

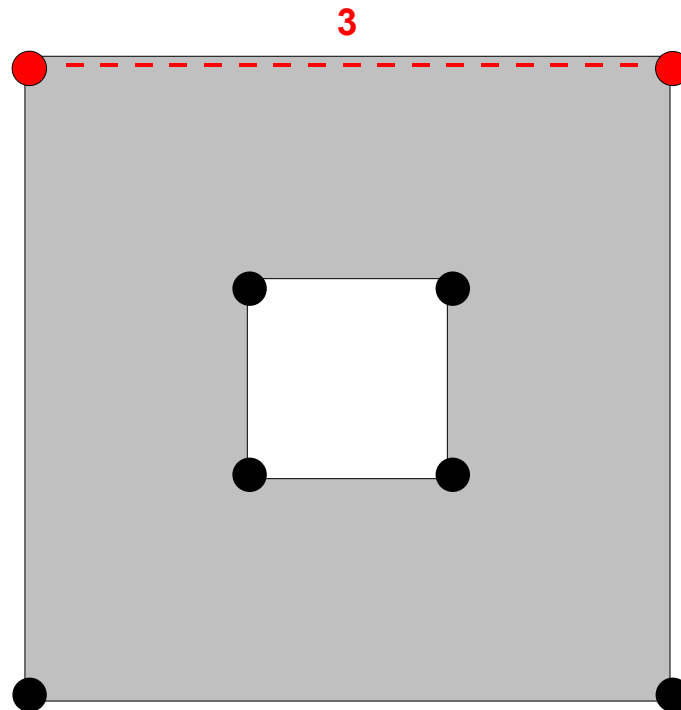
Inner
Distance

Example: Inner Distance



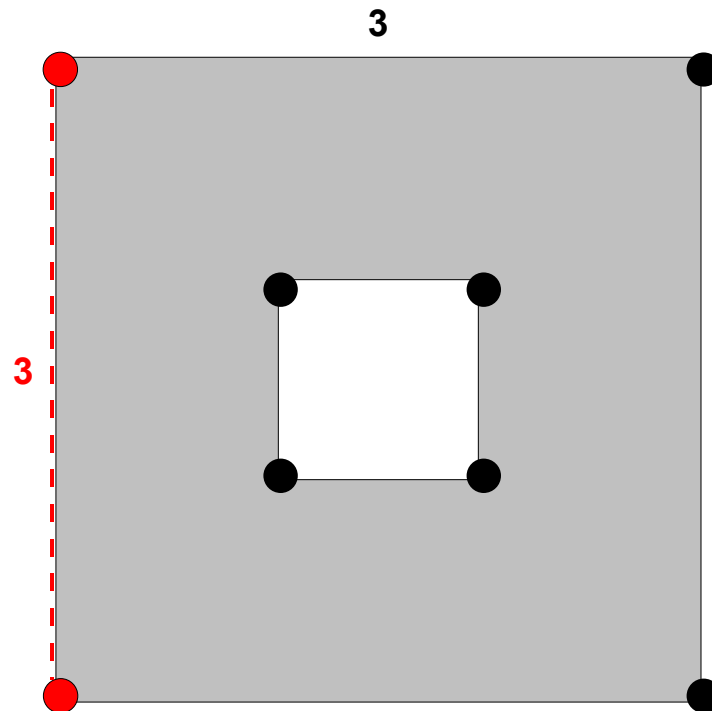
Inner Distance

Example: Inner Distance



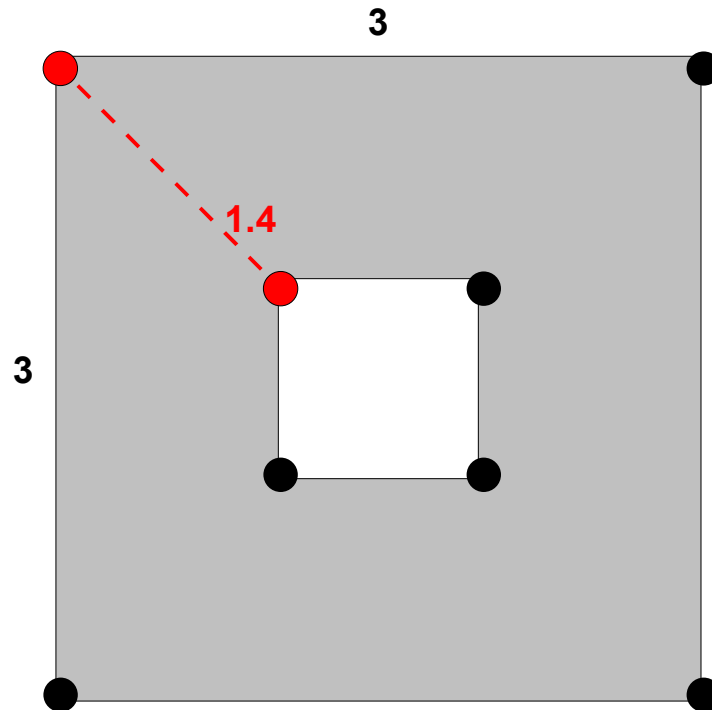
Inner Distance

Example: Inner Distance



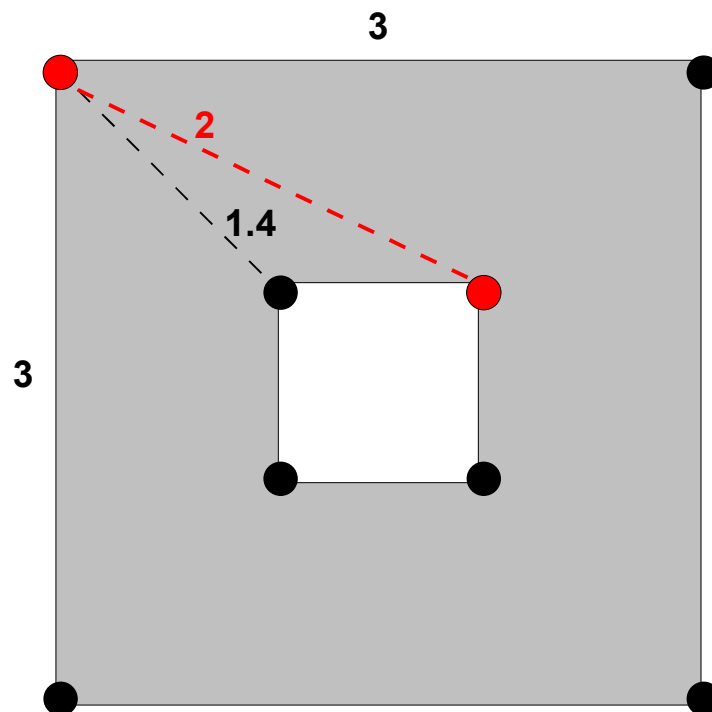
Inner Distance

Example: Inner Distance



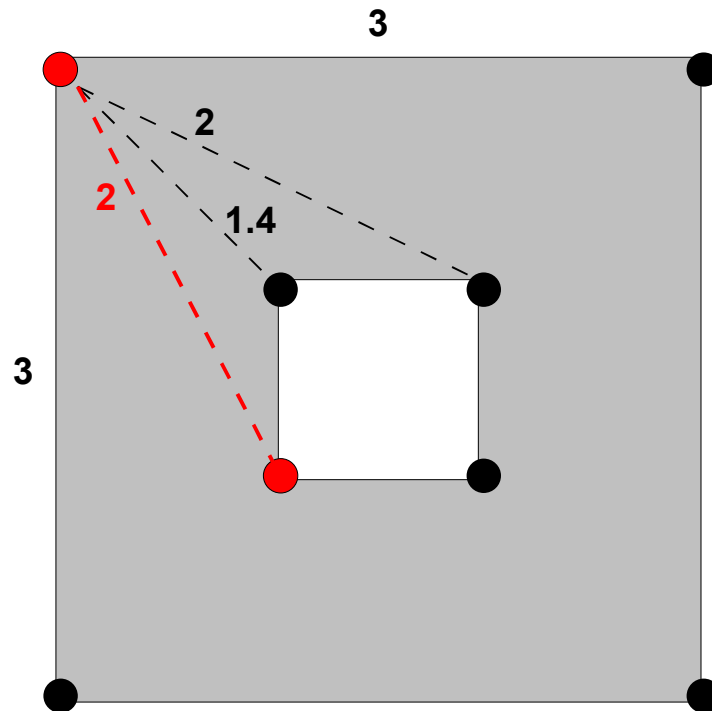
Inner Distance

Example: Inner Distance



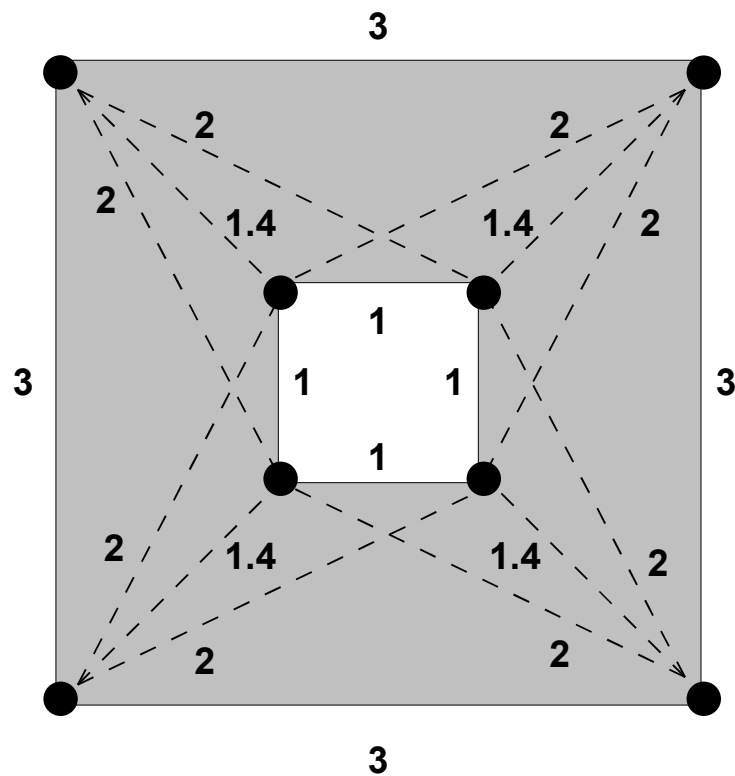
Inner Distance

Example: Inner Distance



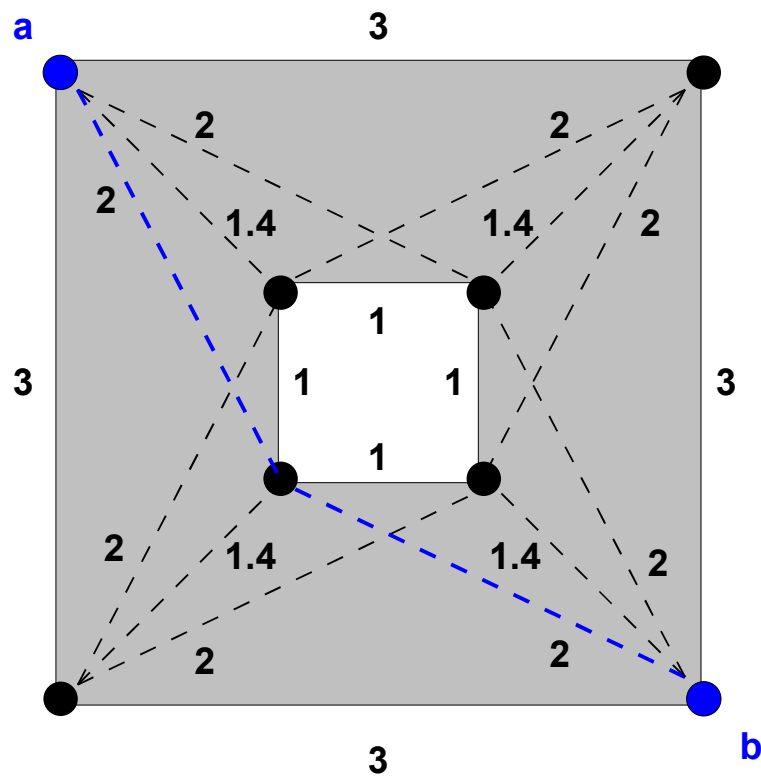
Inner Distance

Example: Inner Distance



Inner Distance

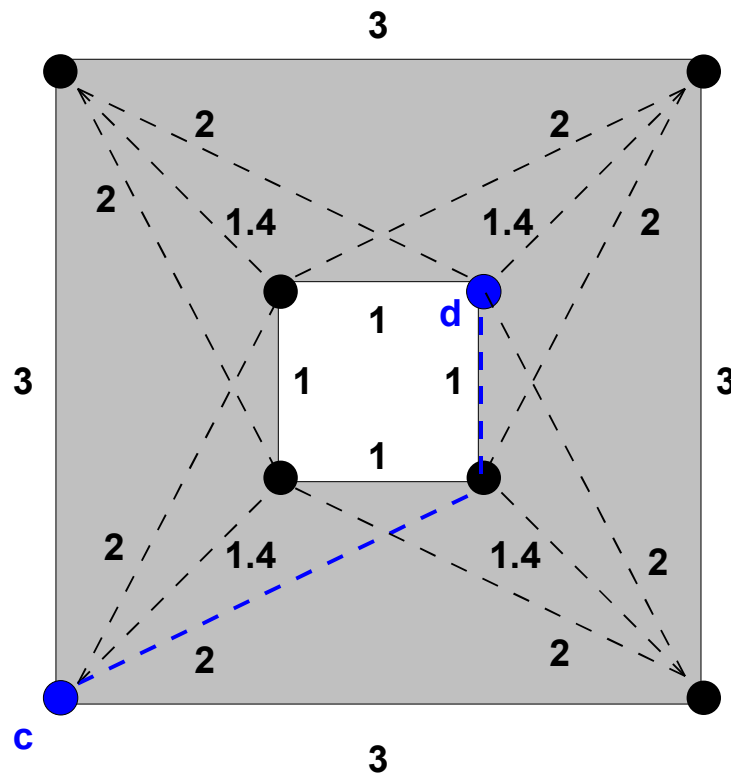
Example: Inner Distance



$$d(a, b) = 4$$

Inner Distance

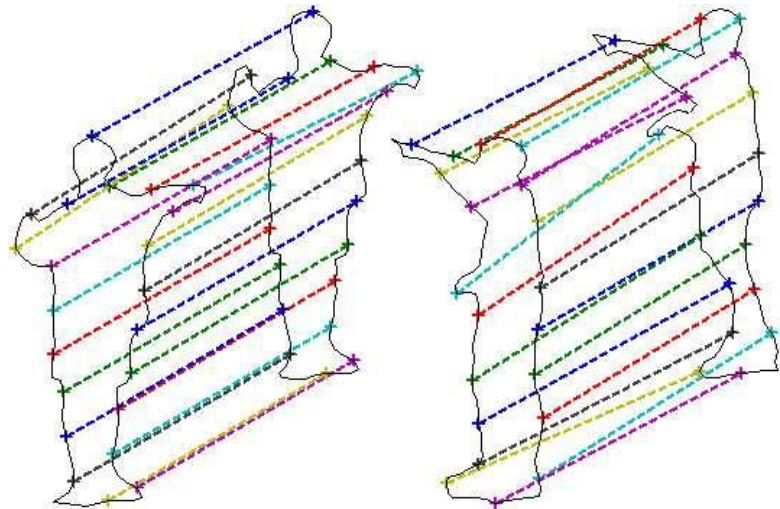
Example: Inner Distance



$$d(c, d) = 3$$

An Extension to Shape Contexts

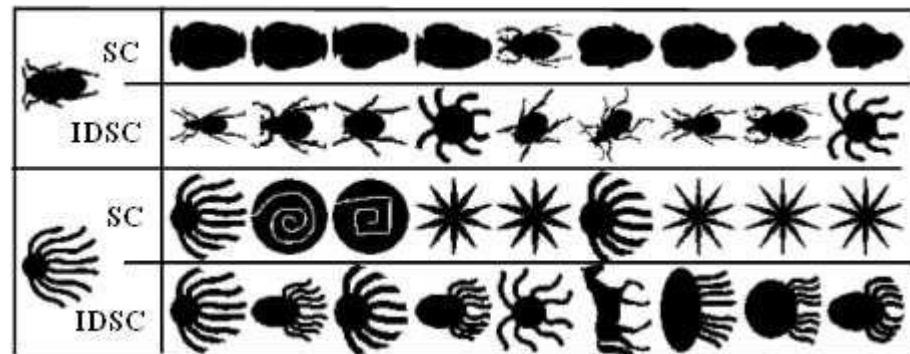
- Redefine the bins with inner-distance
 - Euclidean distance is replaced directly with the inner-distance



Results (MPEG7 dataset)

Algorithm	CSS	Visual Parts	SC
Score	75.44%	76.45%	76.51%

Algorithm	Curve Edit	Gen. Model	IDSC
Score	78.17%	80.03%	85.40%



Outline

- Shape Distance and Correspondence
 - Hausdorff Distance
 - Shape Context
 - Inner Distance
- Hierarchical Approach
 - *Hierarchical Matching*
- Machine Learning Approach
 - Boundary Fragment Model

Hierarchical Matching of Deformable Shapes

2007

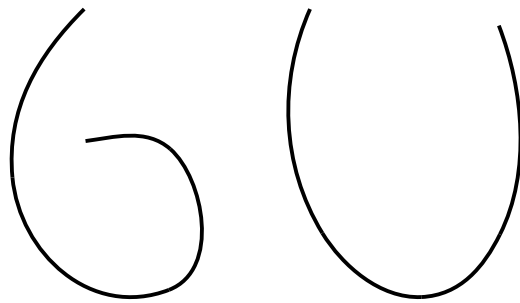
P. Felzenszwalb and J. Schwartz



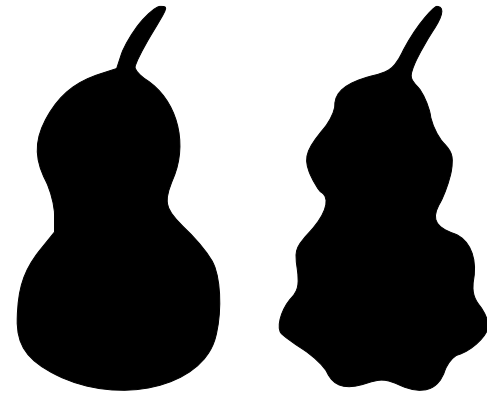
Overview

- Use hierarchical representation to capture shape information at multiple levels of resolution
- Capture global properties by compositing adjacent curve matches

Local vs. Coarse Features

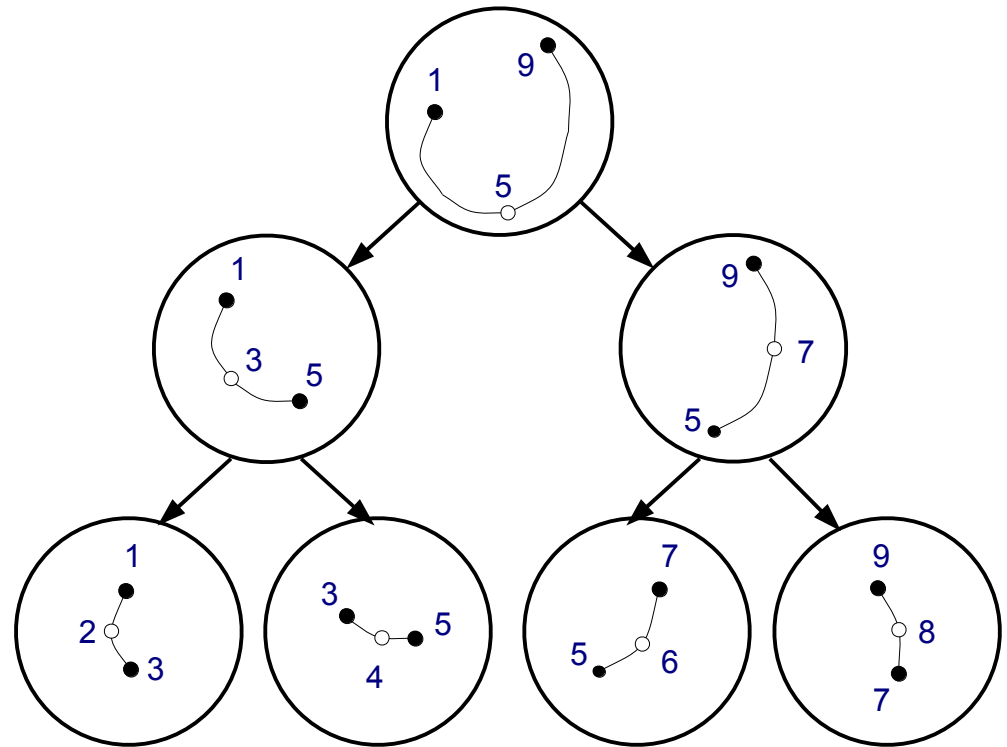


a)




b)

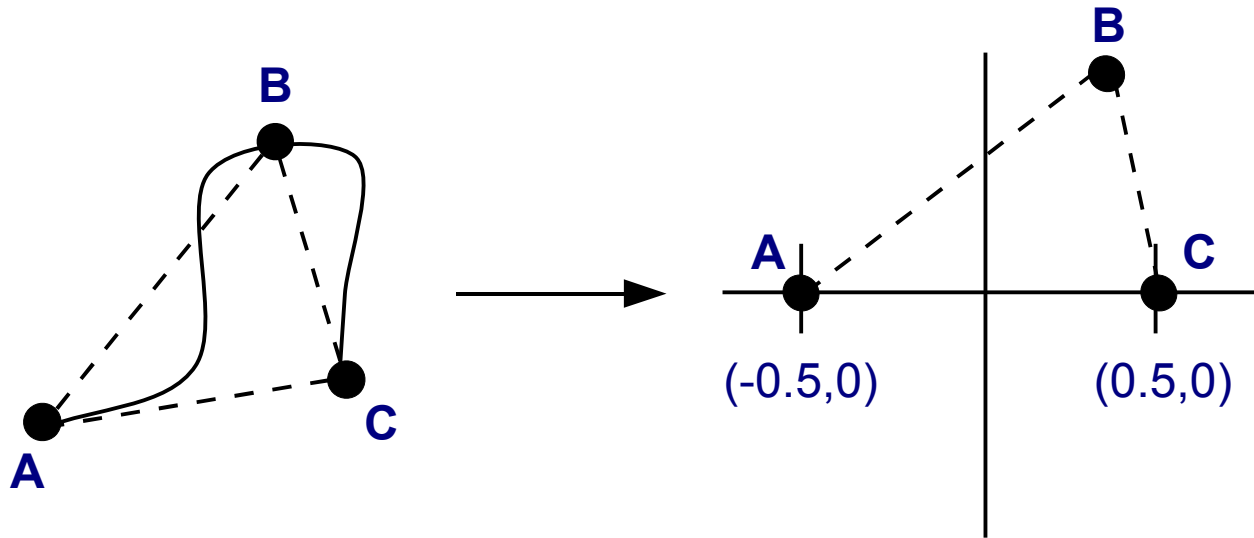
The Shape-Tree



Bookstein Coordinates

- Encode the relative positions of 3 points as a point in the plane
 - A simple way to represent the relative location of a midpoint in the shape tree
 - Given 3 points there exists a unique similarity transformation which maps:
 - P_1 to $(-0.5, 0)$
 - P_2 to $(0.5, 0)$
 - P_3 to the Bookstein coordinate
- 

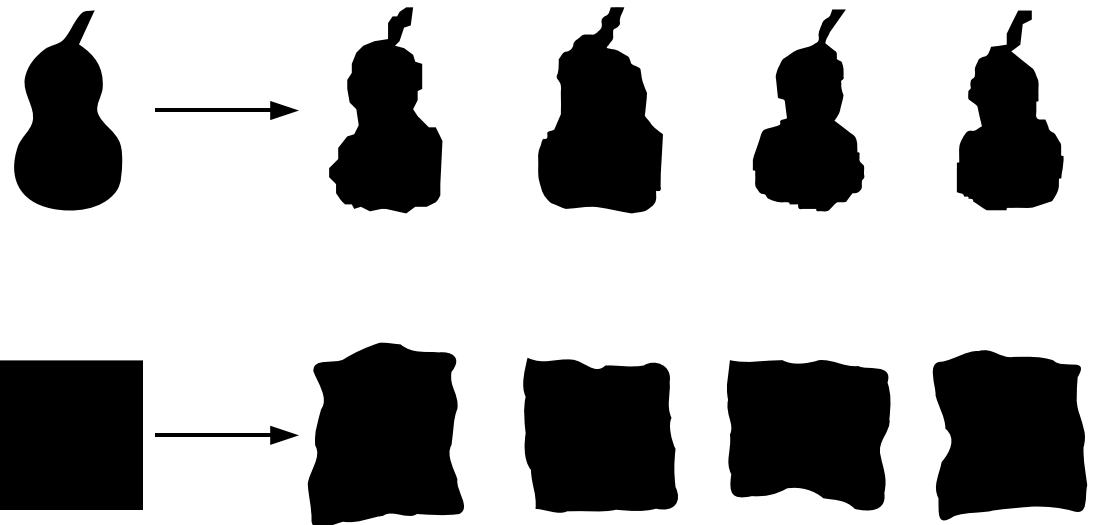
Relative Locations



- Bookstein coordinates for representing $B \mid A, C$
- There exists a unique similarity transformation T taking:
 - A to $(-0.5, 0)$
 - C to $(0.5, 0)$
- We are interested in $T(B)$

Deformation model

- Independently perturb relative locations stored in a shape-tree
 - Reconstructed curve is perceptually similar to original
 - Local and global properties are preserved



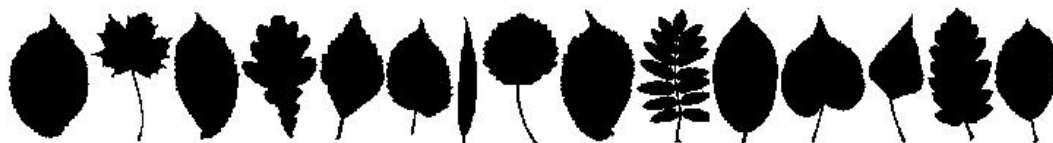
Distance Between Curves

- Given curves A and B
- Can't compare shape-trees for A and B built separately
- Fix shape-tree for A and look for map from points in A to points in B that doesn't deform the shape-tree much
- Efficient $\mathcal{O}(nm^3)$ DP algorithm, where
 $(n = |A|, m = |B|)$

Recognition Results

Swedish Leaf Dataset (15 species with 75 examples each)

Nearest Neighbor Classification			
Algorithm	Shape-Tree	Inner-Distance	Shape Context
Score	96.28%	94.13%	88.12%



MPEG7 Dataset

Bullseye Score		
Algorithm	Shape-Tree	Inner-Distance
Score	87.70%	85.40%

Algorithm	Curve Edit	Shape Context
Score	78.14%	76.51%

Matching in Cluttered Images

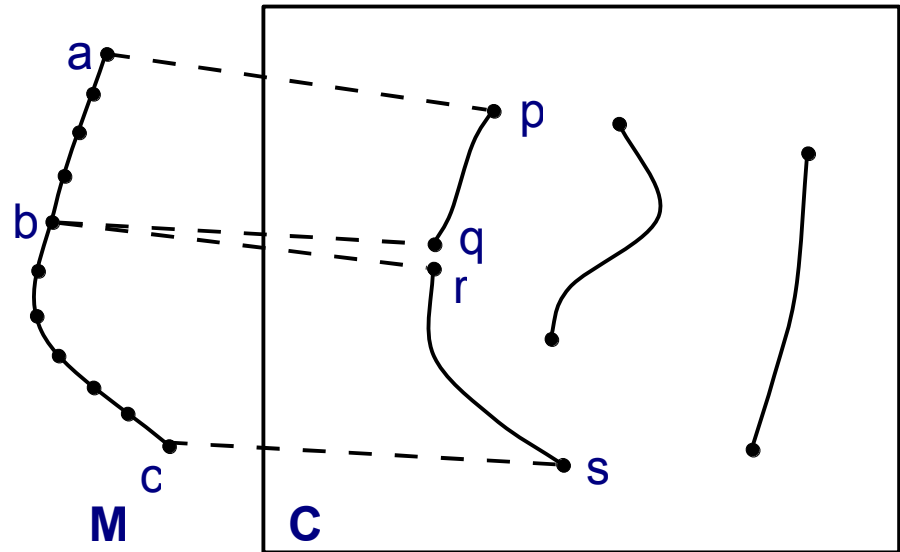
- Given M the model curve and C the set of curves in the image
- Use DP to match each curve in C to every subcurve of M
 - Running time is linear on total length of image contours and cubic in the length of the model
- Stitch partial matchings together to form longer matchings
 - Use compositional rule

Compositional Rule

If $\|q - r\| < \tau$ compose $\text{Match}([a,b], [p,q])$ and $\text{Match}([b,c], [r,s])$

$$\text{Match}([a,b],[p,q]) = w_1$$

$$\text{Match}([b,c],[r,s]) = w_2$$



$$m = \frac{q + r}{2}$$

$$\text{Match}([a,c],[p,s]) =$$

$$w_1 + w_2 + \text{dif}((b|a, c), (m|p, s))$$

Example: Detection



Input Image



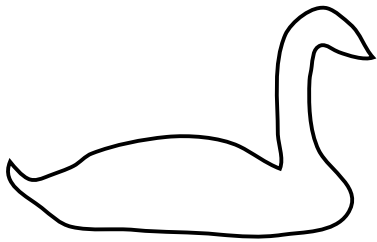
Edge Map



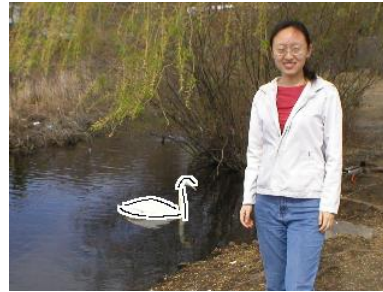
Contours



Detection



Model



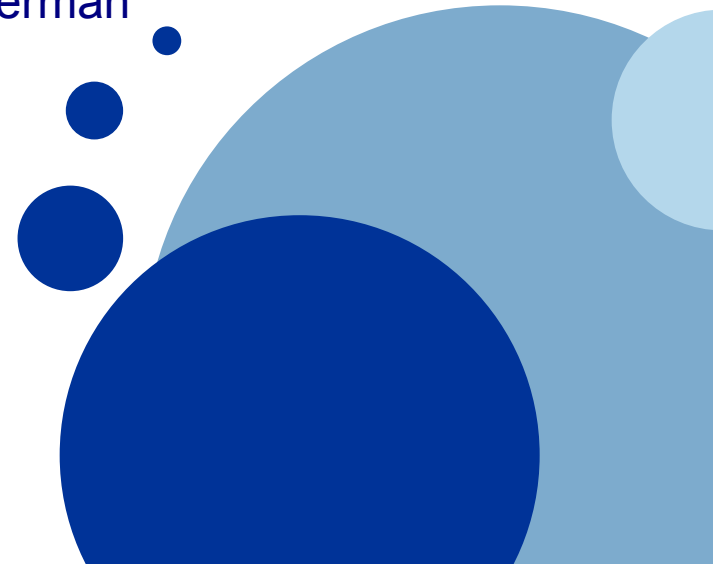
Outline

- Shape Distance and Correspondence
 - Hausdorff Distance
 - Shape Context
 - Inner Distance
- Hierarchical Approach
 - Hierarchical Matching
- Machine Learning Approach
 - *Boundary Fragment Model*

A Boundary-Fragment-Model for Object Detection

2006

A. Opelt, A. Pinz, and A. Zisserman

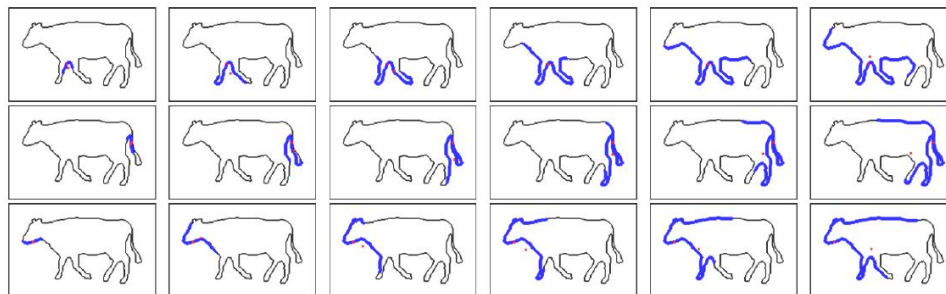


Overview

- Object class detection using object boundaries instead of salient image features
- A learning technique to extract discriminating boundary fragments
- Use boosting to select discriminative combinations of boundary fragments (weak detectors) to form a strong detector

Learning Boundary Fragments

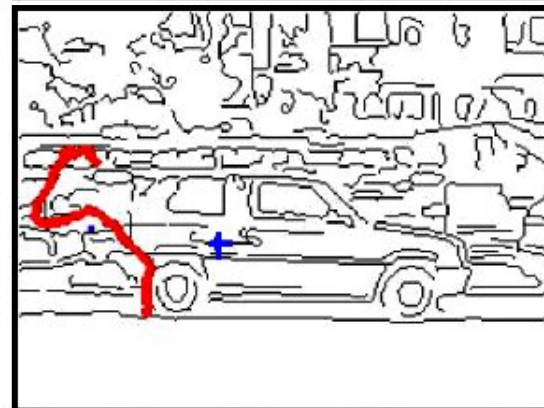
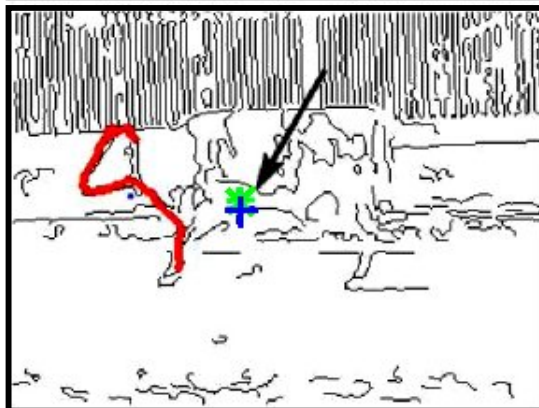
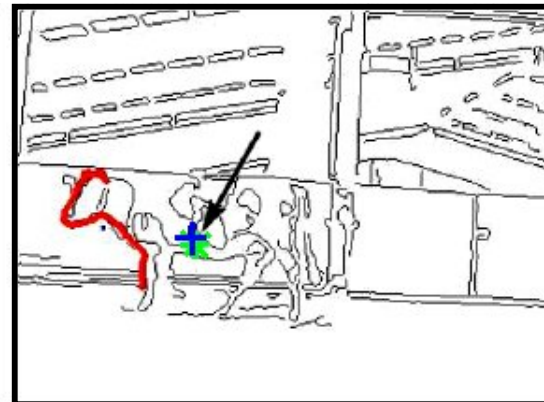
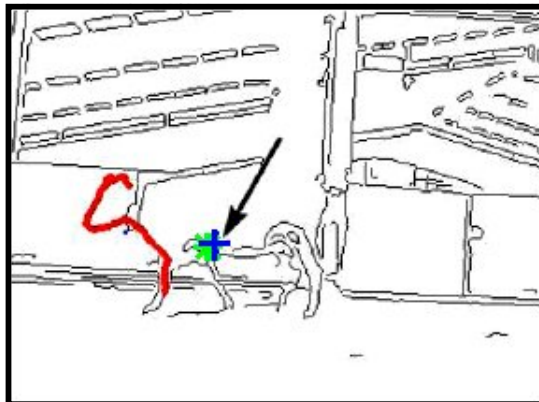
- Given
 - A training image set with the object delineated by a bounding box
 - A validation image set labeled with whether the object is absent or present, and the object's centroid
- From the edges of the training images identify fragments that:
 - Discriminate objects from the target category from other objects
 - Give a precise estimate of the object centroid



Example: Good Boundary Fragment

+ = Estimated Centroid

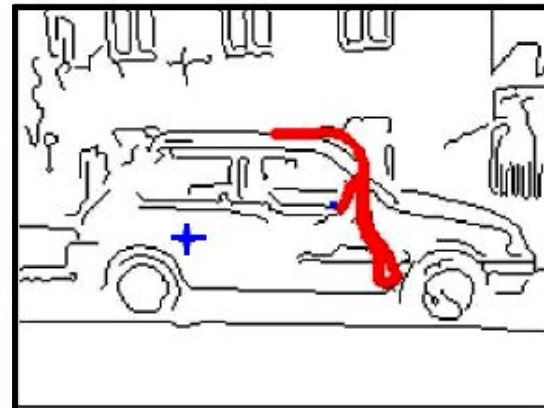
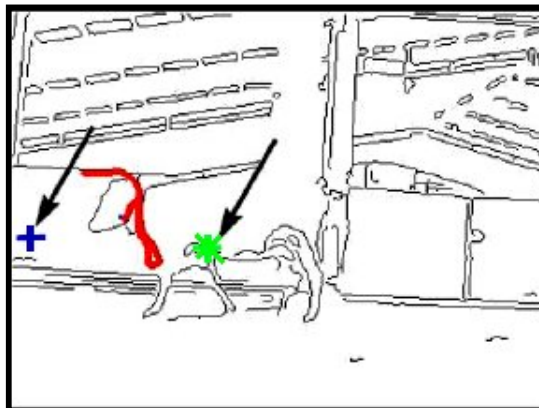
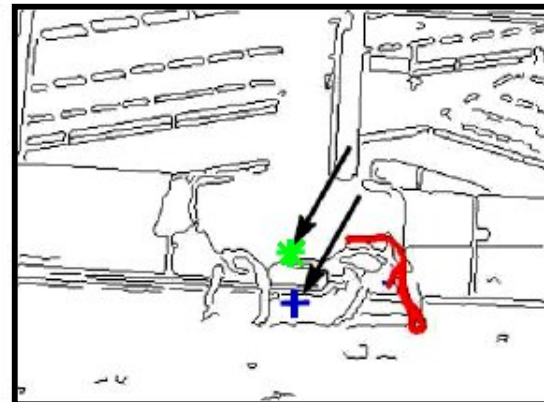
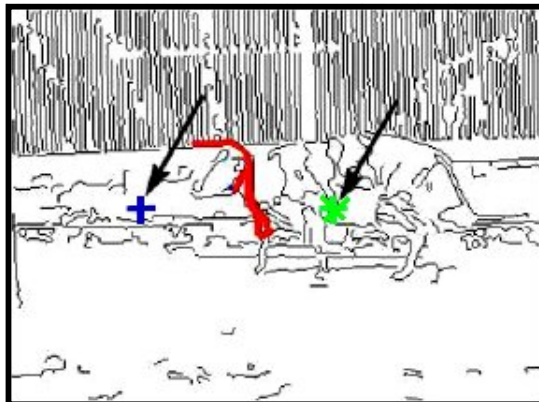
* = Correct Centroid



Example: Poor Boundary Fragment

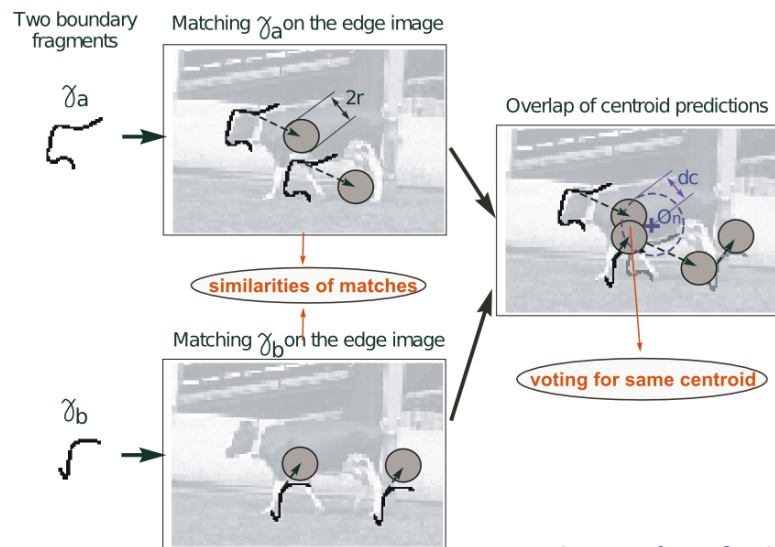
+ = Estimated Centroid

* = Correct Centroid



Weak Detectors

- A weak detector is composed of k (typically 2 or 3) boundary fragments
- Detection should occur when
 - The k fragments match the image edges
 - The centroids concur
 - For positive images the centroid estimate agrees with the true object centroid



Strong Detector

- Given weak detectors h_i
- Using AdaBoost
 - In each round find the weak detector that obtains the best detection results on the current weighting

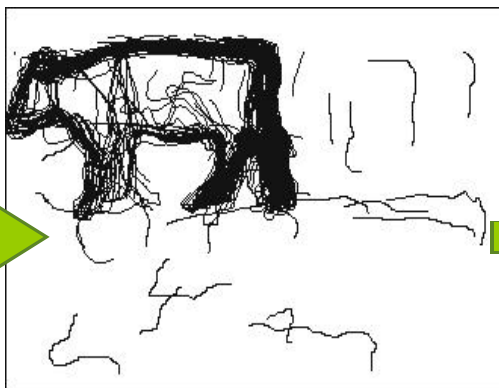
$$H(I) = \text{sign} \left(\sum_{i=1}^T h_i(I) w_{h_i} \right)$$

Example: Detection and Segmentation

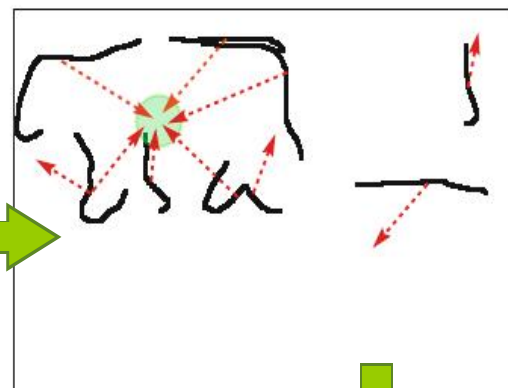
Original Image



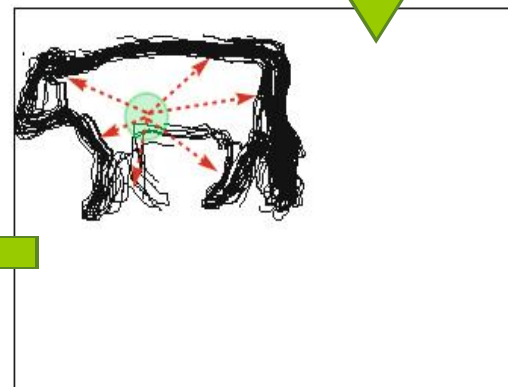
All Matched
Boundary Fragments



Centroid Voting on
Subset of Fragments

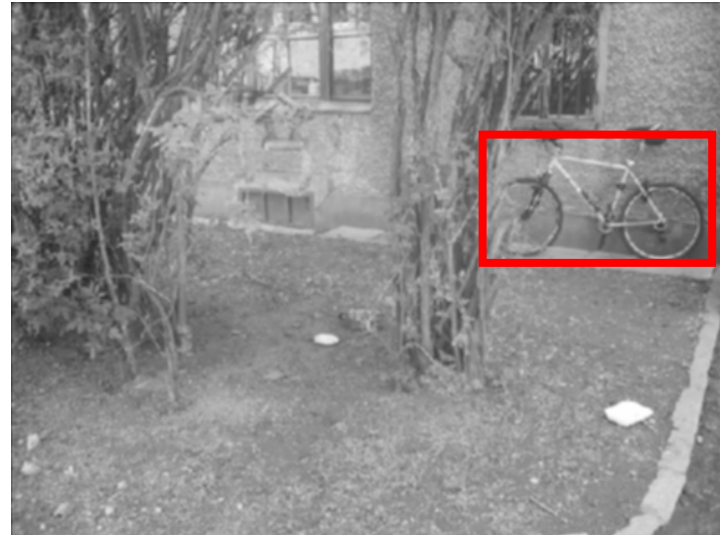


Detection and
Segmentation



Backprojected
Maximum

Example: Detection and Localization



Results

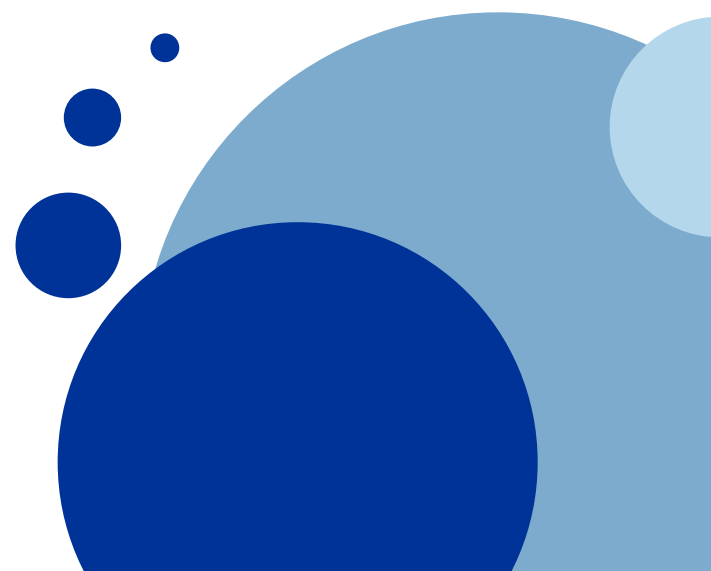
ROC Error Rate									
Algorithm	BFM	[12]	[22]	[25]	[2]	[3]	[14]	[26]	[28]
cars-rear	0.50%	8.80%	8.90%	21.40%	3.10%	2.30%	1.80%	9.80%	-
airplanes	2.60%	6.30%	11.10%	3.40%	4.50%	10.30%	-	17.10%	5.60%

Detection Error		
Algorithm	BFM	[18]
cars-rear	2.25%	6.10%

Recognizing Objects in Adversarial Clutter: Breaking a Visual CAPTCHA

2003

G. Mori and J. Malik



What is a CAPTCHA?

- **Definition:** Completely Automated Public Turing test to tell Computers and Humans Apart.
- Used to prevent automated SPAM.
- Also to read books!

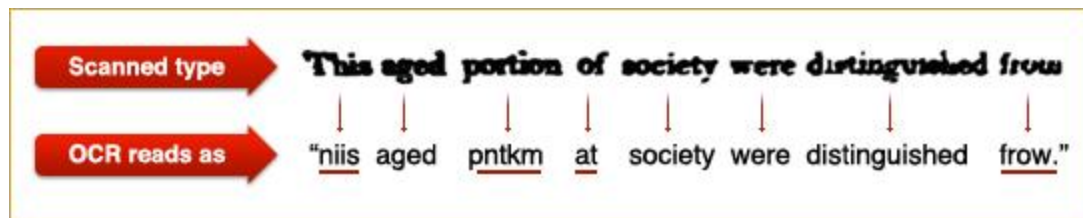


Applications of CAPTCHAs

- Preventing blog SPAM
 - Protecting web site registration
 - Protecting email addresses from scrapers
 - Preventing dictionary attacks
 - Online polling
 - Blocking search engines
 - Blocking email SPAM
- 

Human Assisted OCR

- Roughly 60 million CAPTCHAs are solved by humans every day.
- Equivalent to about 150,000 hours of work.
- Why not use these CAPTCHAs for hard OCR tasks?



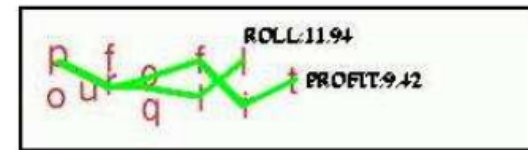
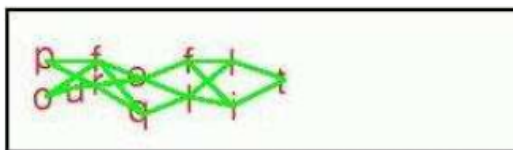
Why Break a CAPTCHA?

- CAPTCHAs help prevent SPAM
- They also offer challenges to the AI community
- A win-win situation:
 - If the CAPTCHA is not broken then SPAM is blocked
 - If it is broken then an AI problem has been solved

Approach 1

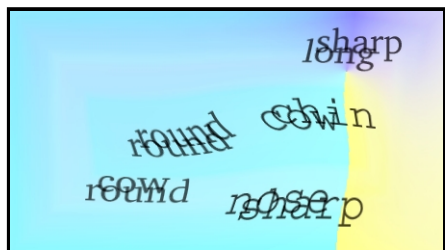


- Detect letters using the Shape Context approach
 - Extended so that the SC includes the dominant tangential direction of the edges in each bin
- Form a directed acyclic graph of the letters to find candidate words
- Choose the most likely word based on the average deformable match cost of the individual letters

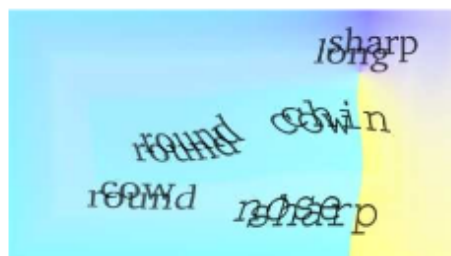


Approach 2

- For harder CAPTCHAs matching on letter sized regions is too difficult



- Match on groups of letters instead



Example: EZ-Gimpy

polish



store



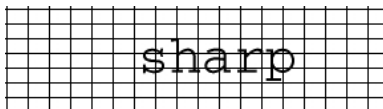
sound



rice



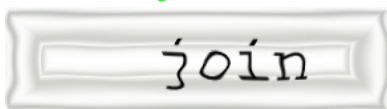
east



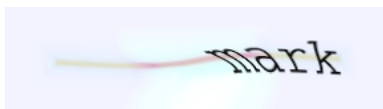
weight



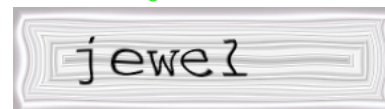
join



sock



jewel



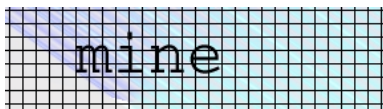
horse



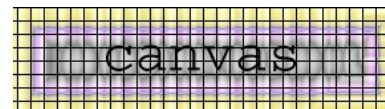
space



mine

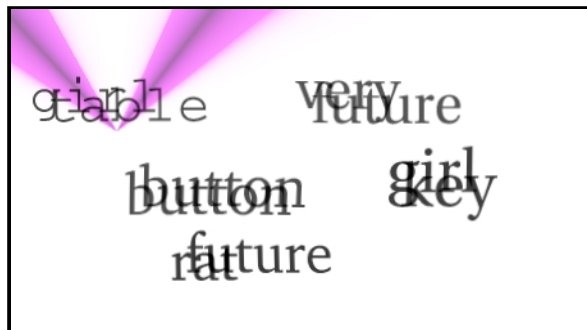


canvas

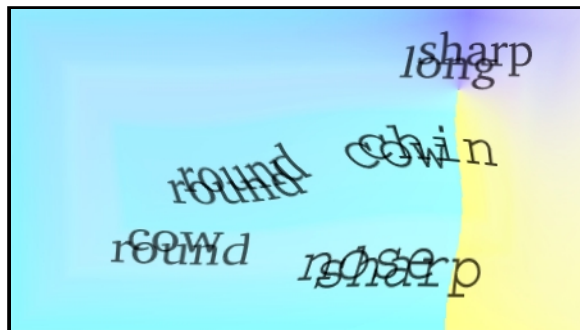


Breaking CAPTCHA

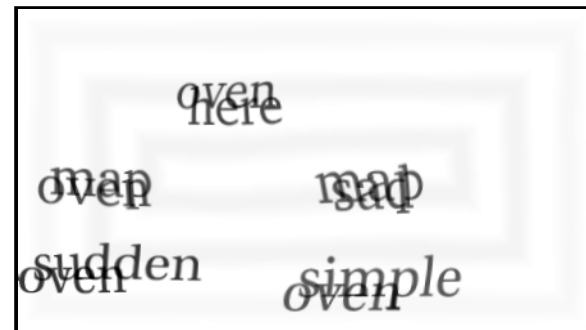
Example: 3 Word CAPTCHA



future key have



sharp round long



sudden apple over



with true sponge

Discussion Points

- How can shape matching be made more robust to clutter?
 - What applications are not suitable for shape matching? Which are?
 - How can methods like Shape Context take advantage of available training data?
 - How can appearance and shape features be best combined?
 - What other hard AI problems can be used as CAPTCHAs?
- 