



INSTITUTE OF INFORMATION AND
COMMUNICATION TECHNOLOGIES
BULGARIAN ACADEMY OF SCIENCE



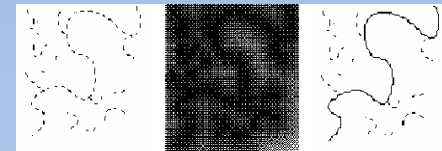
Shape context

Centro de Visión por Computador,
Departament de Matemàtica Aplicada i Anàlisi,
Universitat de Barcelona

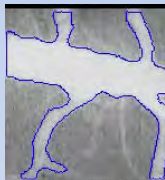
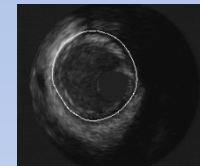


Deformable models

$$U(p) = \inf_{Q \in \mathcal{L}_p} \left\{ \int_Q P(Q) + \alpha \left| \frac{\delta Q}{\delta s} \right|^2 ds \right\}$$



$$E_{snake} = \int_0^1 E_{int}(u(s)) + E_{ext}(u(s)) ds.$$



$$Q_t = g(I)(c + k)\vec{n} - (\nabla g, \vec{n})\vec{n}$$

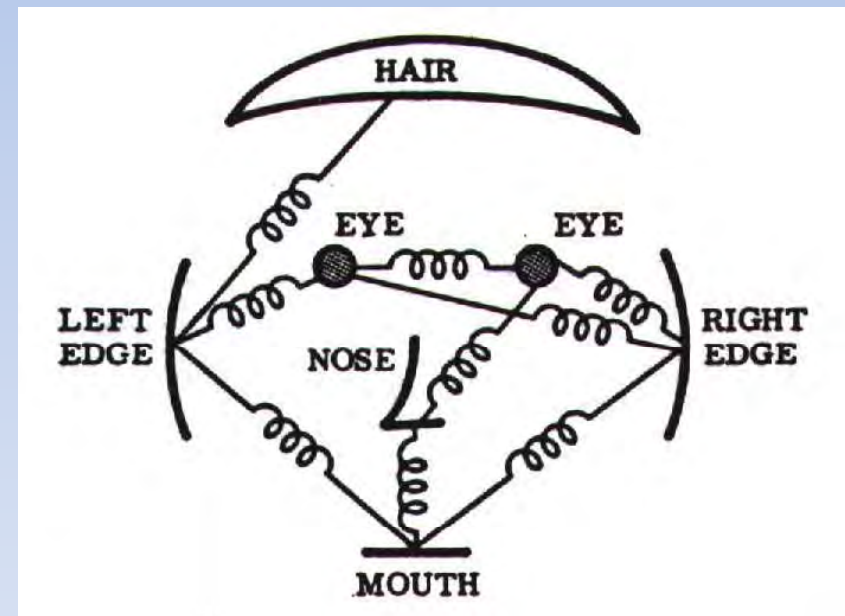


$$E(L) = \sum_{p \in \mathcal{P}} D_p(L_p) + \sum_{(p,q) \in \mathcal{N}} V_{p,q}(L_p, L_q),$$

All four models are based only on local control on the geometric shape.

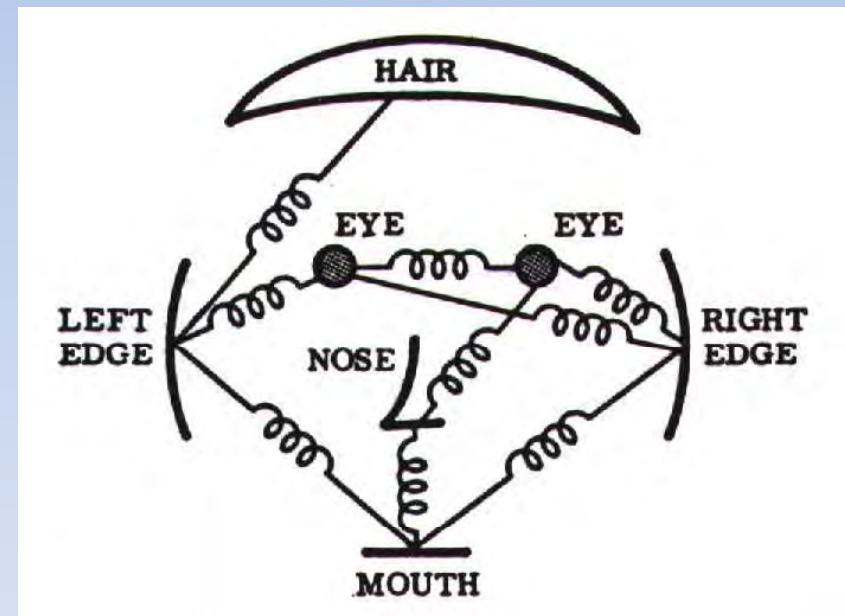
Representation

- Object as set of parts
 - Generative representation
- Model:
 - Appearance of parts
 - Relative locations between parts
- Issues:
 - How to model location and mutual relations
 - How to represent appearance
 - Sparse or dense (pixels or regions)
 - How to handle occlusion/clutter



Representation

- Object as set of parts
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- Issues:
 - How to model location and mutual relations
 - How to represent appearance
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Sparse representation

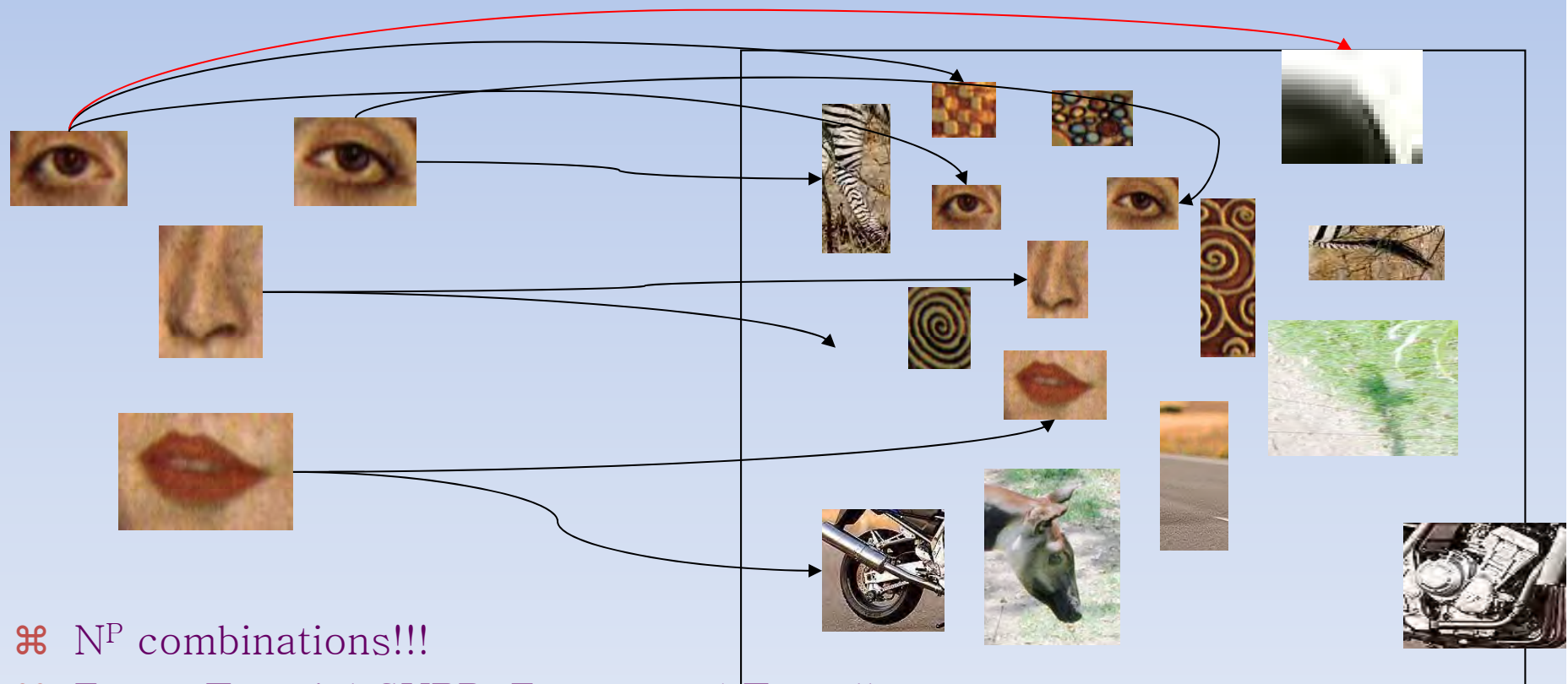
- + Computationally tractable (10^5 pixels \rightarrow 10^1 -- 10^2 parts)
- + Avoid modeling global variability
- + Success in specific object recognition



- Throw away most image information
- Parts need to be distinctive to separate from other classes

The correspondence problem

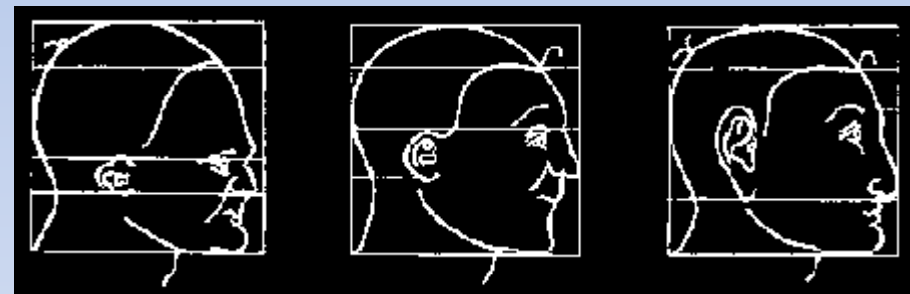
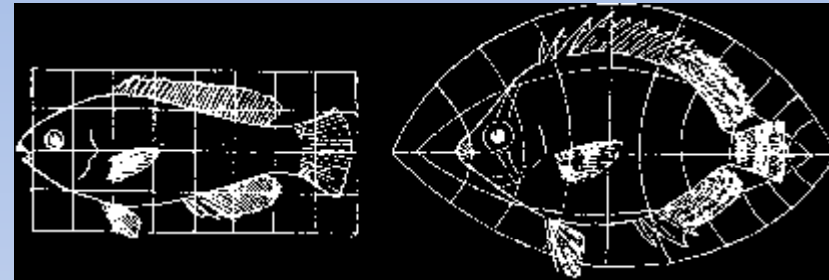
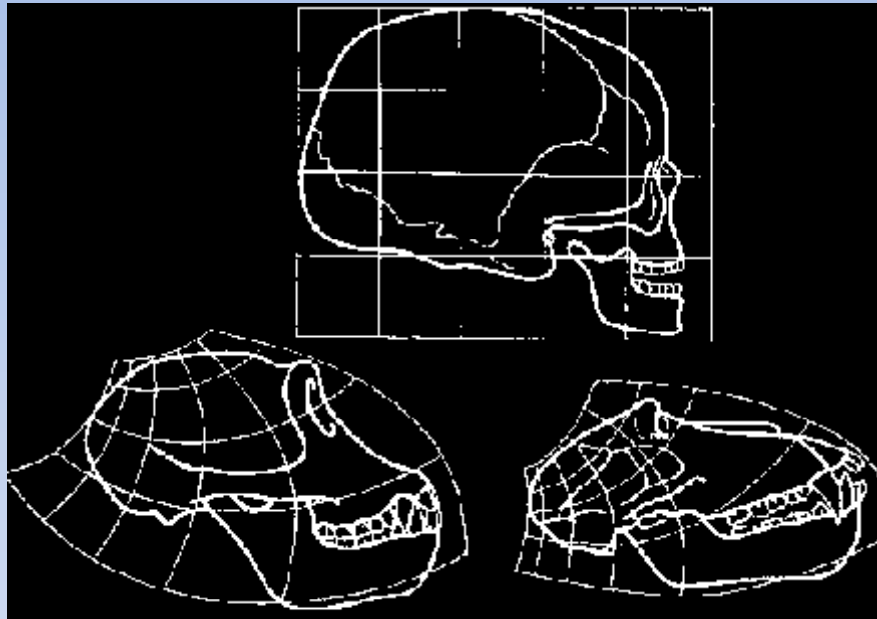
- Model with P parts
- Image with N possible locations for each part



⌘ N^P combinations!!!

⌘ From: Tutorial CVPR, Fergus and Torralba.

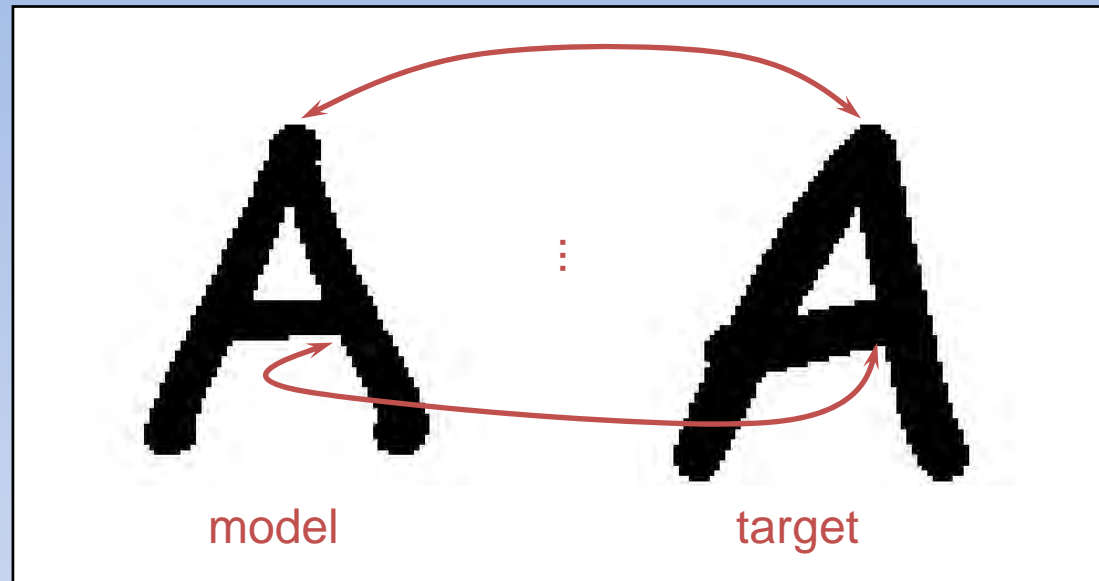
Biological Shape



⌘ D'Arcy Thompson: On Growth and Form, 1917

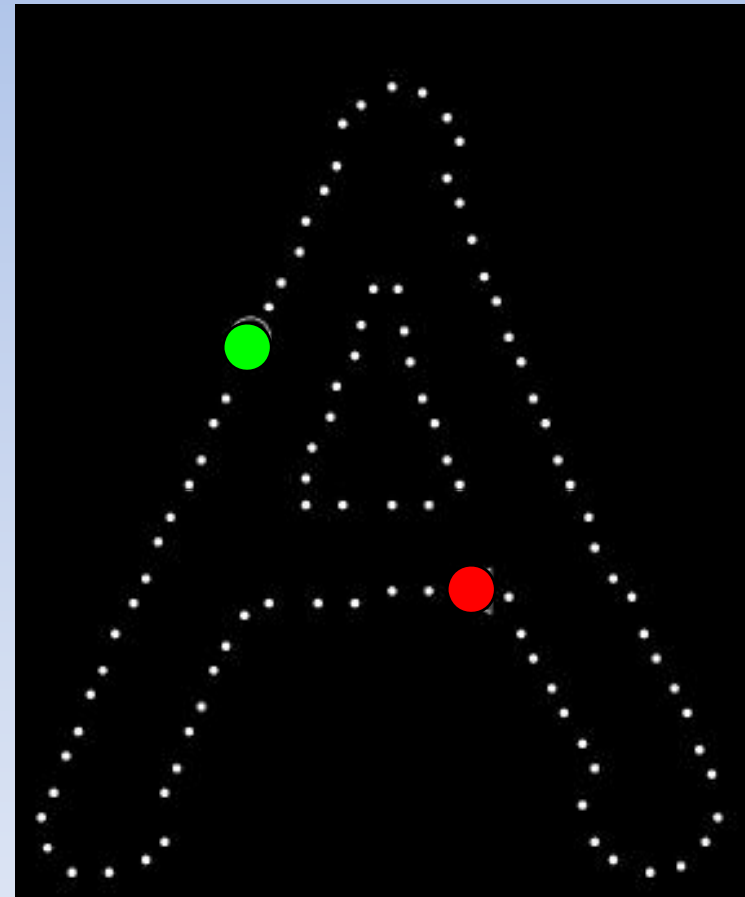
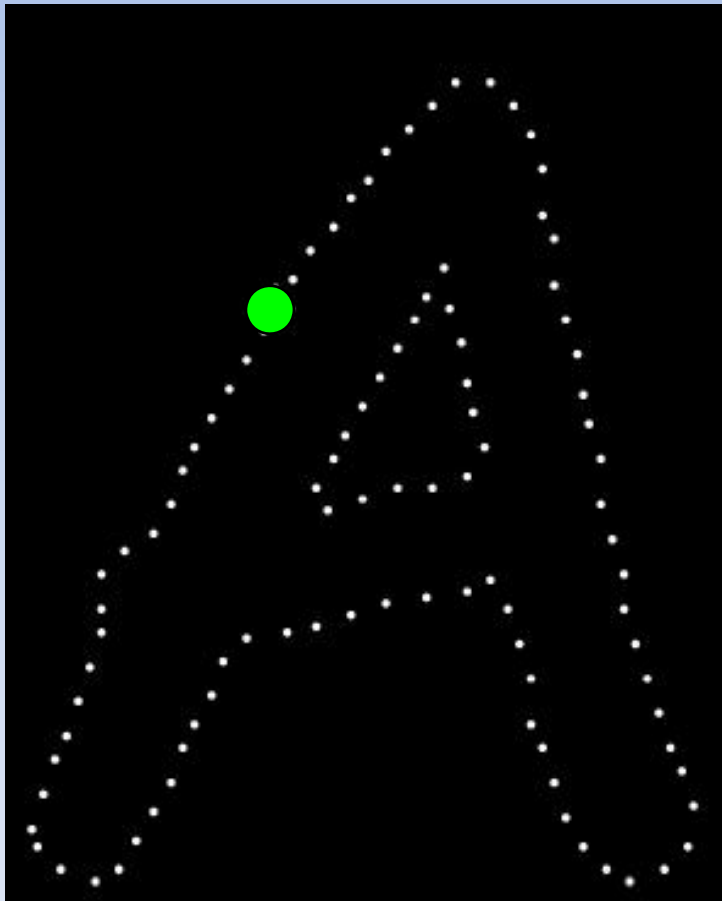
☒ studied transformations between shapes of organisms

Matching Framework

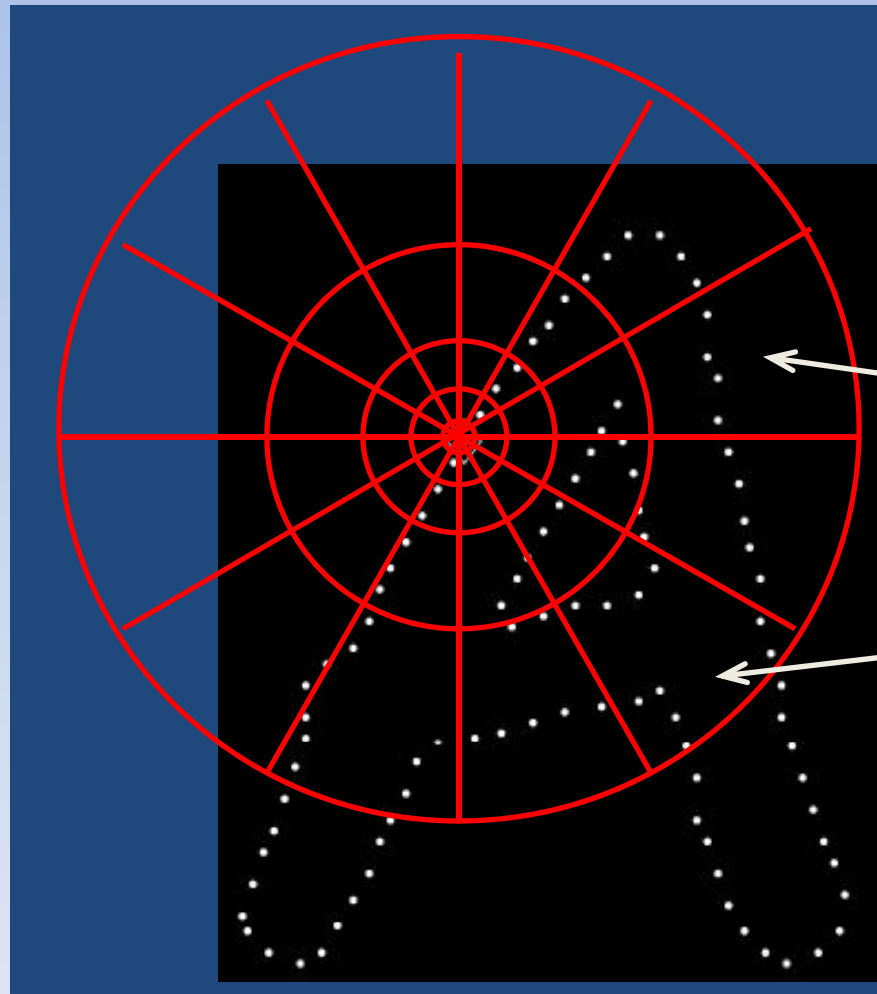


- ⌘ Find correspondences between points on shape
- ⌘ Estimate transformation & measure similarity
- ⌘ From: Greg Mori, Jitendra Malik: Recovering 3D Human Body Configurations Using Shape Contexts. IEEE Trans. Pattern Anal. Mach. Intell. 28(7): 1052–1062 (2006)

Comparing Pointsets



Shape Context



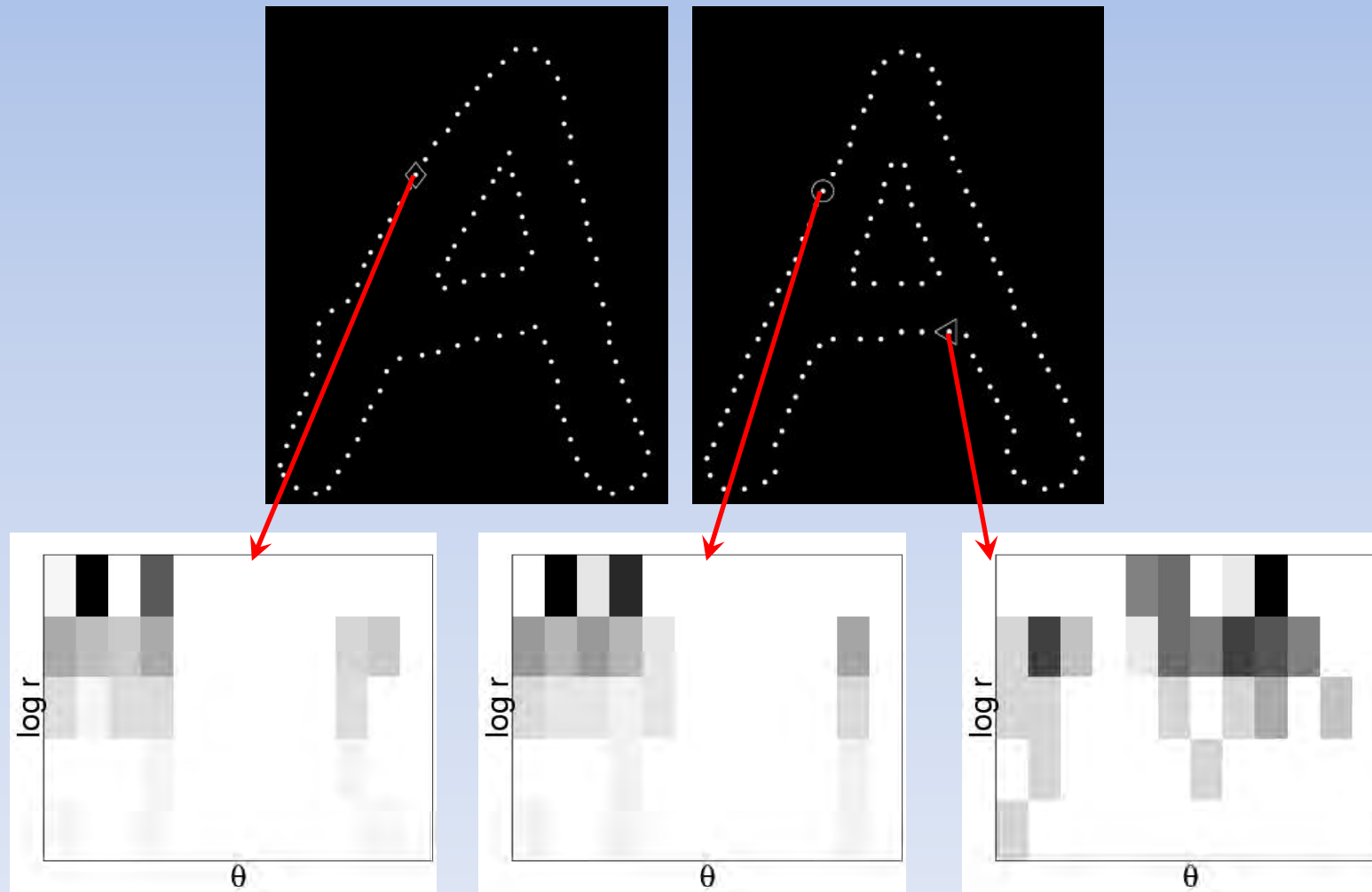
Count the number of points inside each bin, e.g.:

Count = 4

Count = 10

→ Compact representation of distribution of points relative to each point

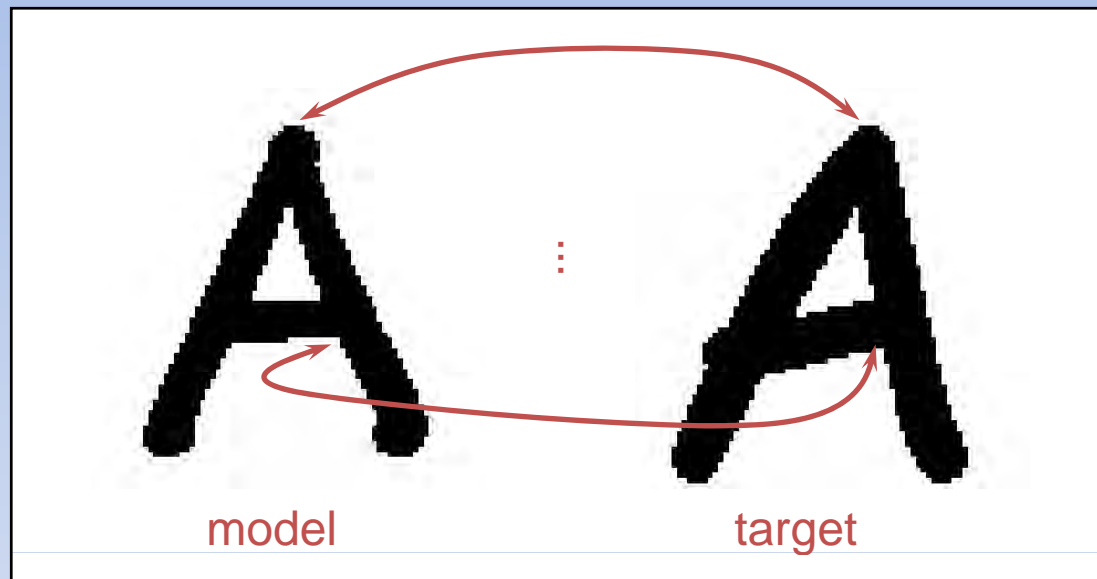
Shape Context



Shape Contexts

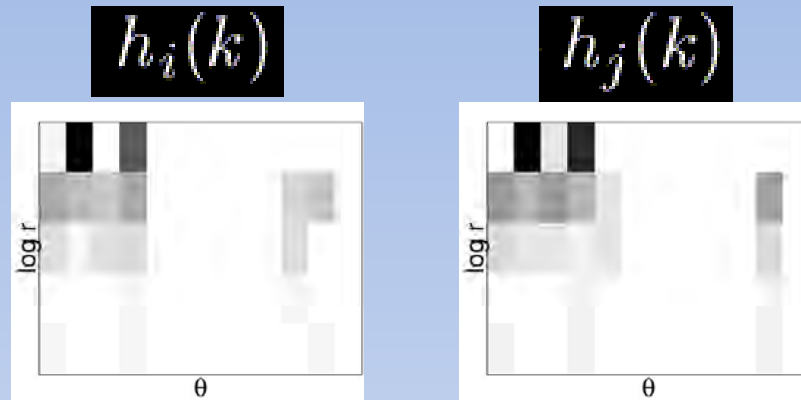
- Invariant under translation and scale
- Can be made invariant to rotation by using local tangent orientation frame
- Tolerant to small affine distortion
 - Log-polar bins make spatial blur proportional to r

Matching Framework



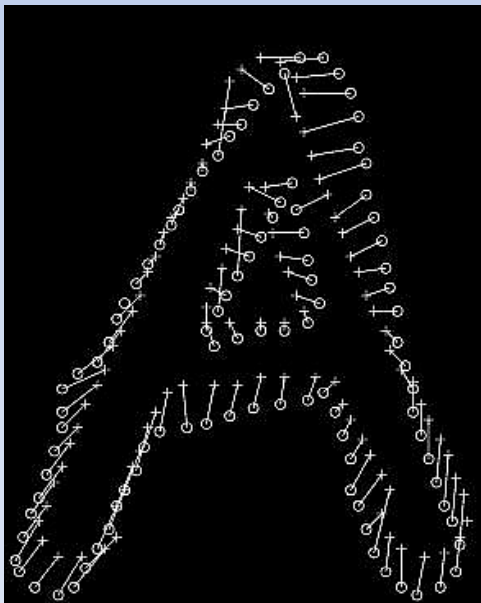
- ⌘ Find correspondences between points on shape
- ⌘ Estimate transformation & measure similarity

Comparing Shape Contexts



Compute matching costs using Chi Squared distance:

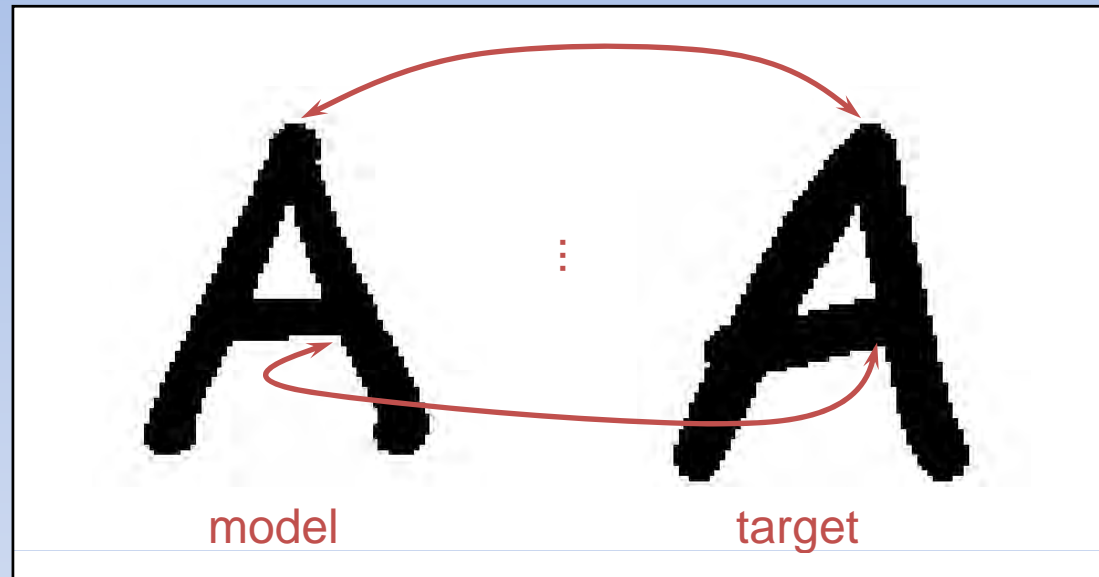
$$C_{ij} = \frac{1}{2} \sum_{k=1}^K \frac{[h_i(k) - h_j(k)]^2}{h_i(k) + h_j(k)}$$



Recover correspondences by solving linear assignment problem with costs C_{ij}

[Jonker & Volgenant 1987]

Matching Framework



⌘ Find correspondences between points on shape

⌘ Estimate transformation & measure similarity

Thin Plate Spline Model

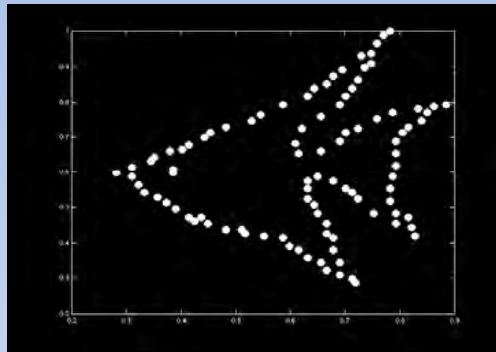
⌘ Minimizes bending energy:

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

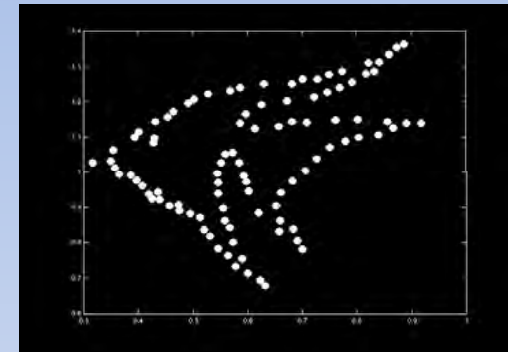
⌘ Solve by inverting linear system

⌘ Can be regularized when data is inexact

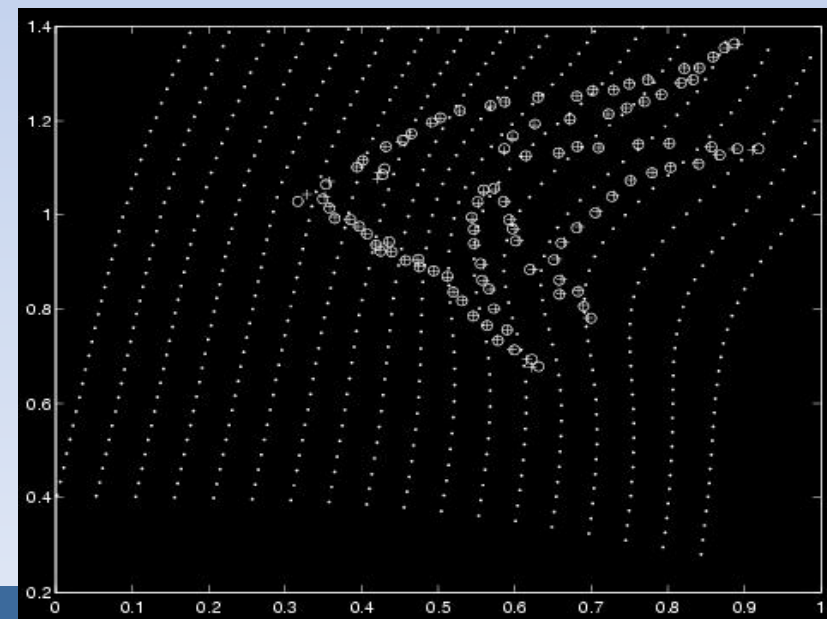
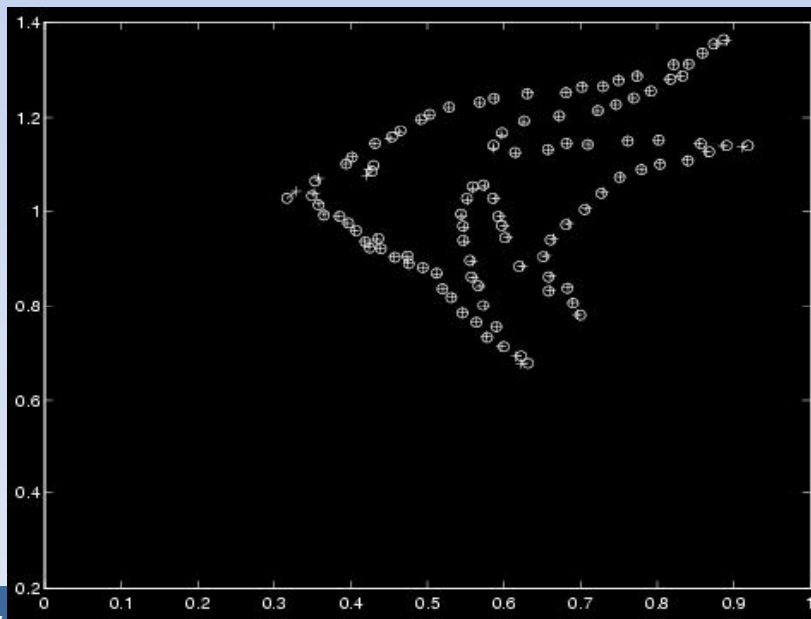
Matching Example



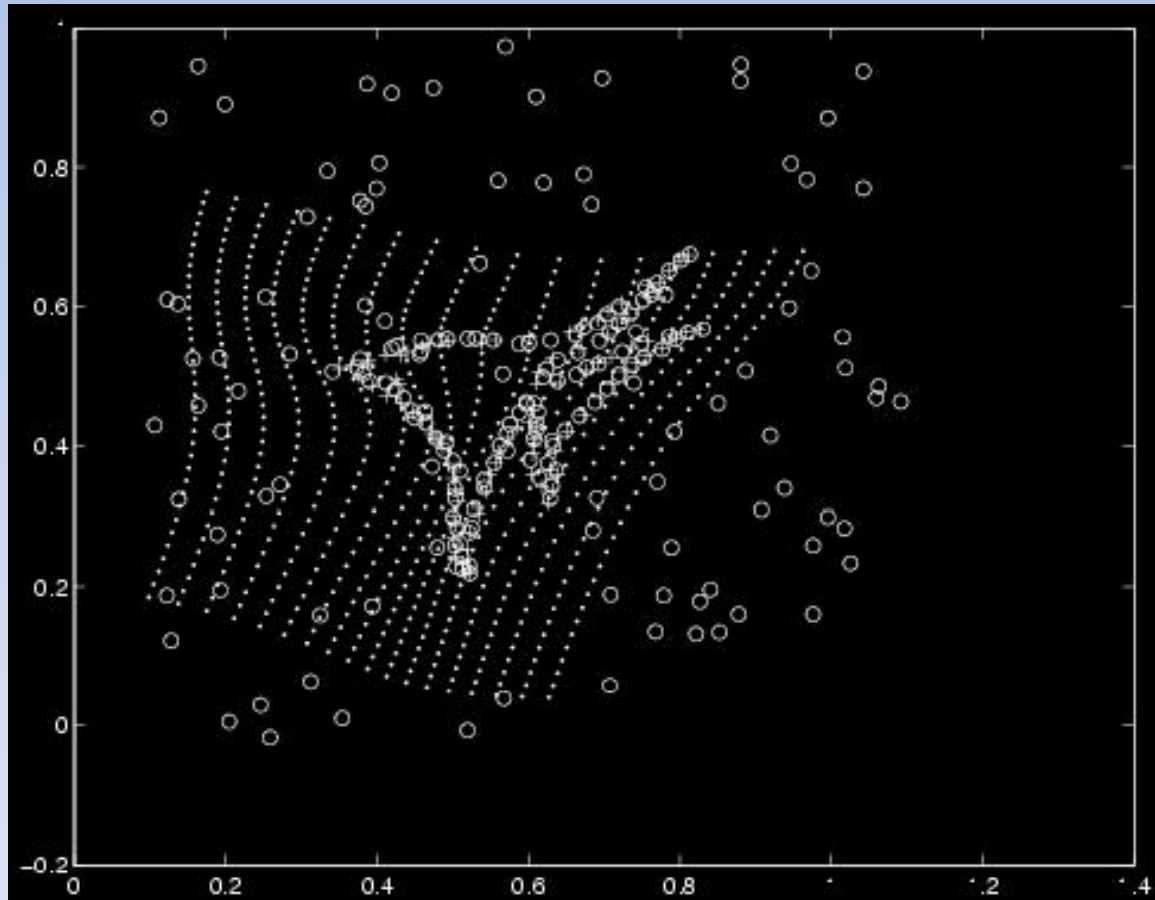
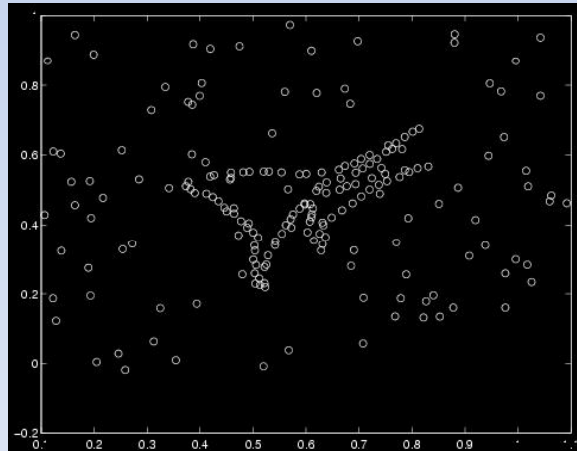
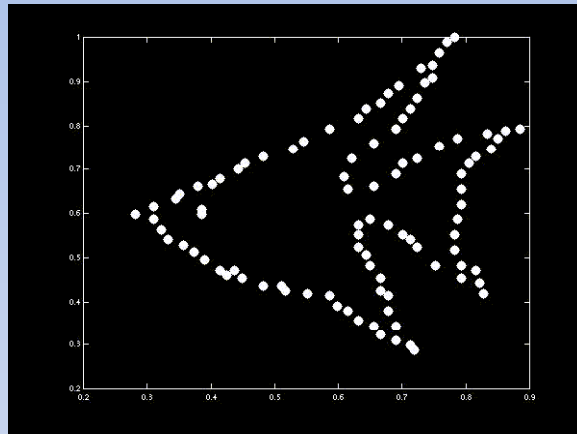
model



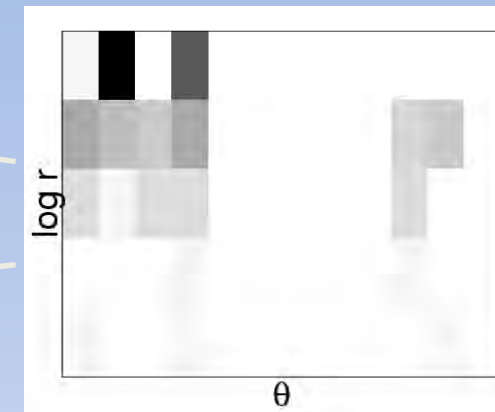
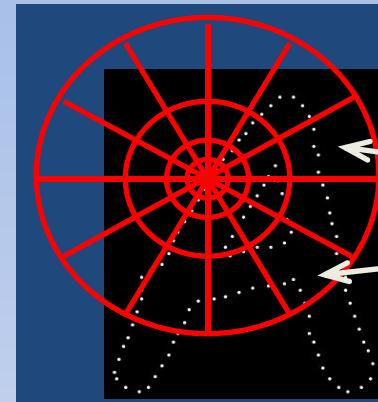
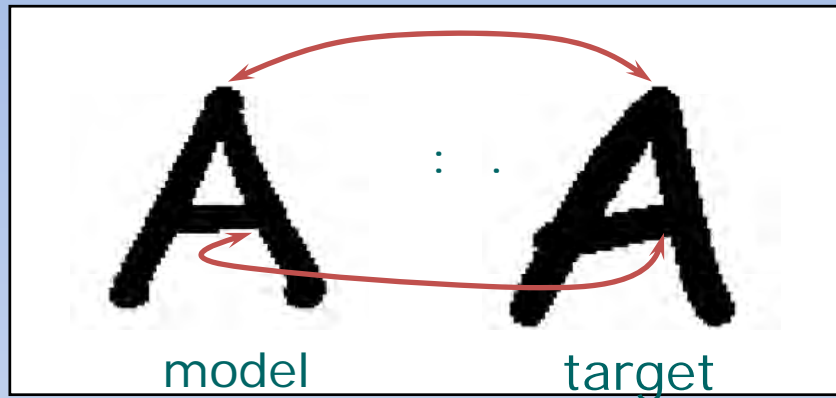
target



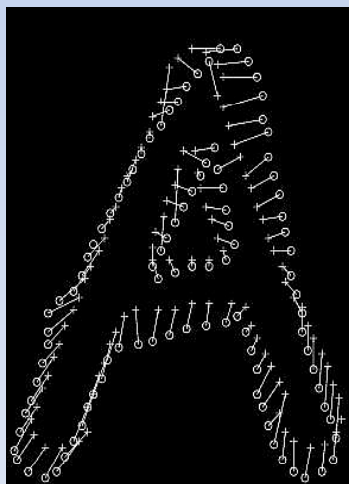
Outlier Test Example



Extending features to contexts



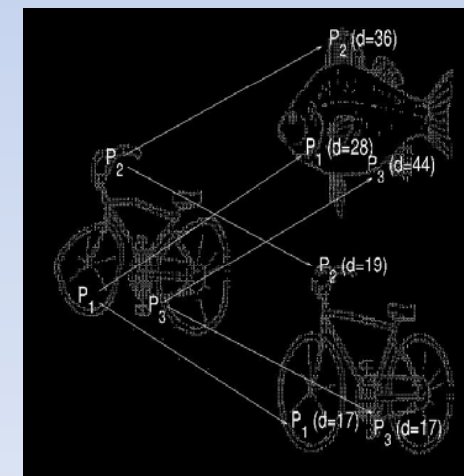
$$O_j \rightarrow \{ \{c_{11}, c_{12}, \dots, c_{1m_1}\}, \{c_{21}, c_{22}, \dots\}, \dots, \{c_{n1}, \dots, c_{nm_n}\} \} = \{C_{1j}, C_{2j}, \dots, C_{nj}\}$$



1. Landmarks correspondences based on correlograms

2. Non-rigid correspondence based on Thin-Plate Splines

3. Retrieval based on the object descriptors difference

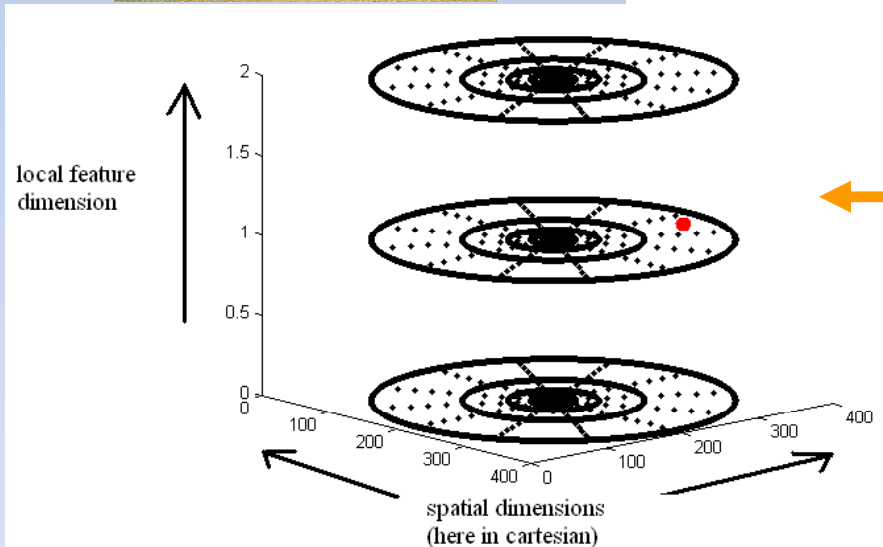
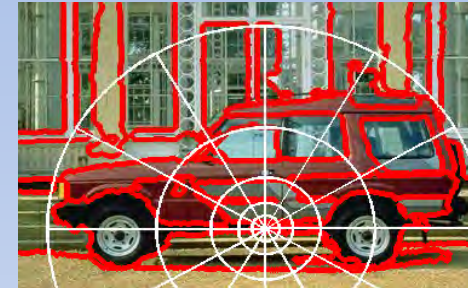
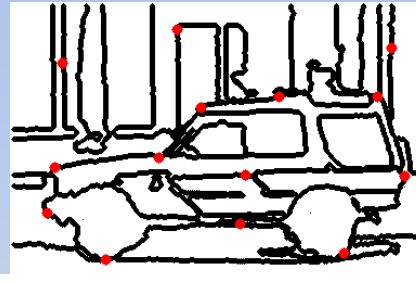


Non-rigid matching based on context

- **How to choose landmarks?**
- **How to extend the method to real images?**
- **How to choose adequate local descriptors?**
- **How to construct compact and efficient contexts for object retrieval?**
- **Robust classification can help to:**
 - **Select the most relevant local descriptors**
 - **Construct compact object contexts**
 - **Achieve object retrieval invariant to transformations, different appearance and views of the object**

The feature space

Let us consider a context consisting of local descriptors and mutual spatial relations



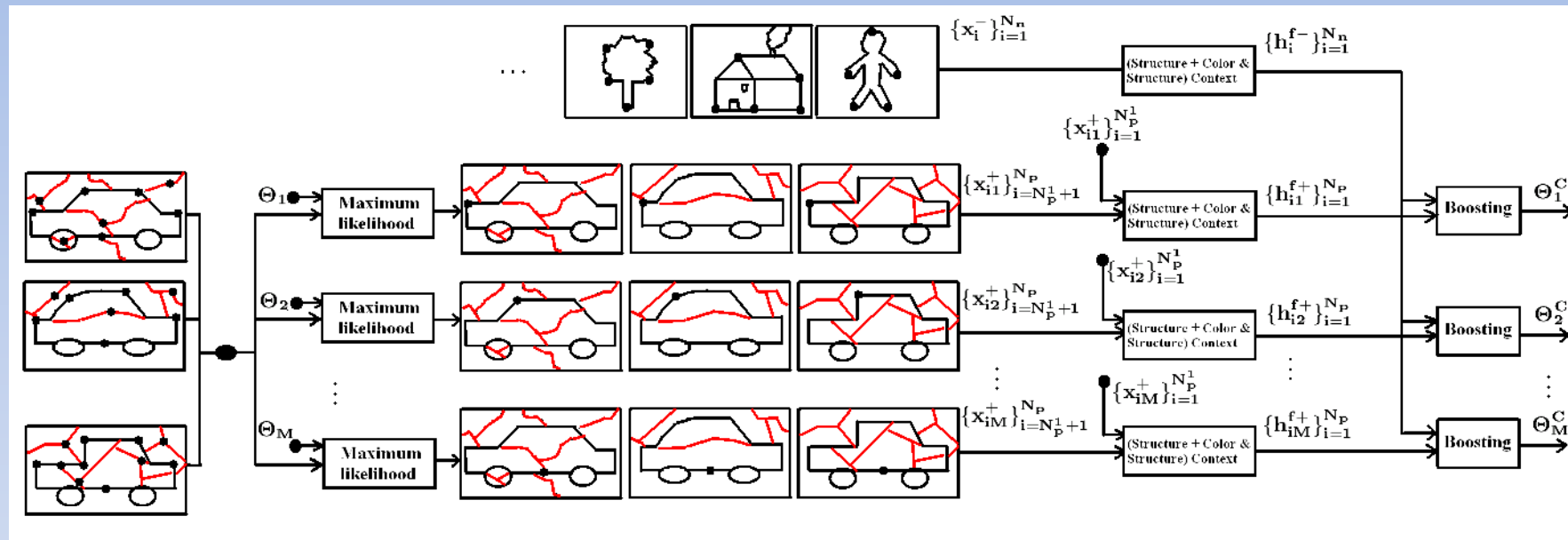
$$X = \{x_j\}_{j=1}^M$$

$$(p_i - x_j) \rightarrow (\alpha_{ij}, r_{ij})$$

$$v_{ij} = (\alpha_{ij}, r_{ij}, l_{i1}, l_{i2}, \dots, l_{id})$$

From: Jaume Amores, Nicu Sebe, Petia Radeva: Fast Spatial Pattern Discovery Integrating Boosting with Constellations of Contextual Descriptors. CVPR (2) 2005: 769-774

Object descriptors



- Apply the classifiers to detect the landmarks in the non-segmented images
- Form the complete context

Terms in Similarity Score

- Shape Context difference
- Local Image appearance difference
 - orientation
 - gray-level correlation in Gaussian window
 - ... (many more possible)
- Bending energy

Object Recognition Experiments

- Handwritten digits
- COIL 3D objects (Nayar-Murase)
- Human body configurations
- Trademarks

Handwritten Digit Recognition

- MNIST 60 000:
 - linear: 12.0%
 - 40 PCA+ quad: 3.3%
 - 1000 RBF +linear: 3.6%
 - K-NN: 5%
 - K-NN (deskewed): 2.4%
 - K-NN (tangent dist.): 1.1%
 - SVM: 1.1%
 - LeNet 5: 0.95%

⌘ MNIST 600 000 (distortions):

- ⊠ LeNet 5: 0.8%
- ⊠ SVM: 0.8%
- ⊠ Boosted LeNet 4: 0.7%

⌘ MNIST 20 000:

- ⊠ K-NN, Shape Context matching: 0.63%

Introduction

Descriptors

Matching

Results

IVUS retrieval

210: 9 → 7



448: 4 → 9



583: 8 → 3



692: 8 → 9



717: 1 → 7



948: 8 → 9



1034: 8 → 0



1113: 4 → 6



1227: 7 → 2



1248: 9 → 5



1300: 5 → 7



1320: 8 → 3



1531: 8 → 7



1682: 3 → 7



1710: 9 → 5



1791: 2 → 7



1879: 8 → 3



1902: 9 → 4



2041: 5 → 6



2074: 5 → 6



2099: 2 → 0



2131: 4 → 9



2183: 1 → 2



2238: 5 → 6



2448: 4 → 9



2463: 2 → 0



2583: 9 → 7



2598: 5 → 3



2655: 6 → 1



2772: 4 → 9



2940: 9 → 7



3063: 8 → 6



3074: 1 → 2



3251: 2 → 6



3423: 6 → 0



3476: 3 → 7



3559: 5 → 0



3822: 9 → 4



3851: 9 → 4



4094: 9 → 7



4164: 9 → 7



4202: 1 → 7



4370: 9 → 4



4498: 8 → 7



4506: 9 → 7



4663: 9 → 7



4732: 8 → 9



4762: 9 → 4



5736: 5 → 3



5938: 5 → 3



6555: 2 → 7



6572: 9 → 7



6577: 7 → 1



6598: 0 → 7



6884: 1 → 2



8066: 8 → 0



8280: 8 → 4



8317: 7 → 2



8528: 4 → 9



9506: 7 → 2



9643: 9 → 7



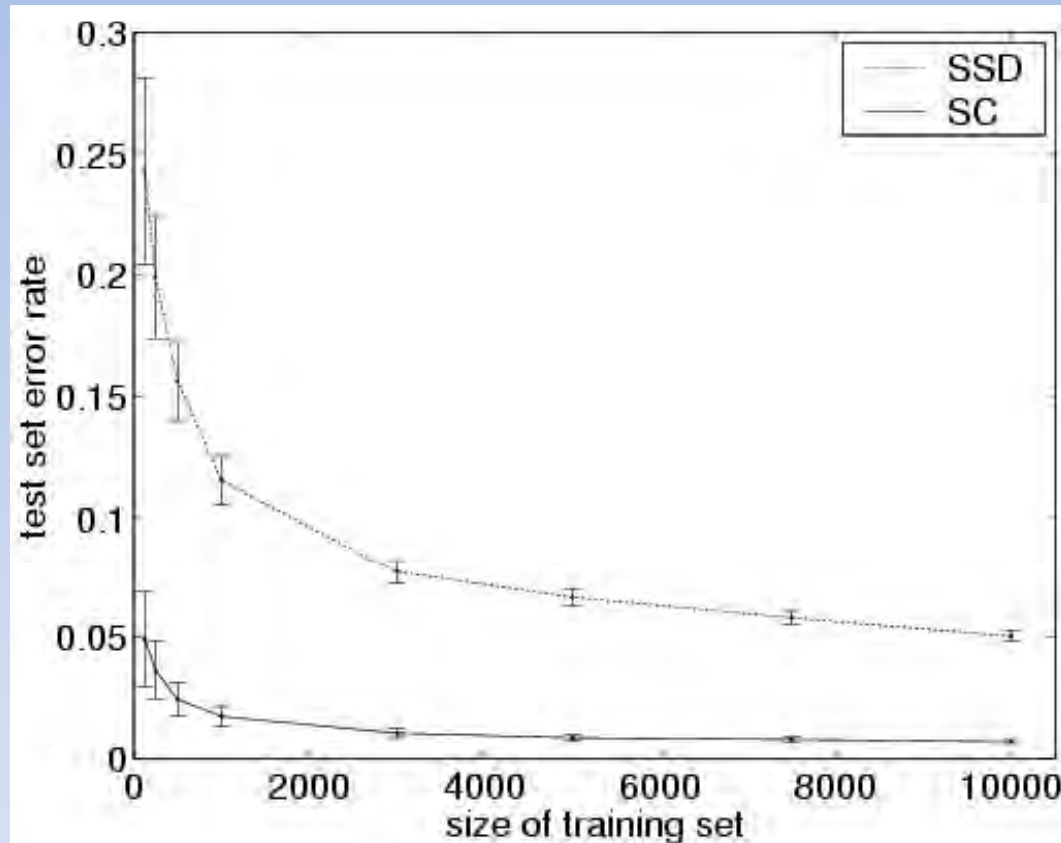
9730: 5 → 6



9851: 0 → 6

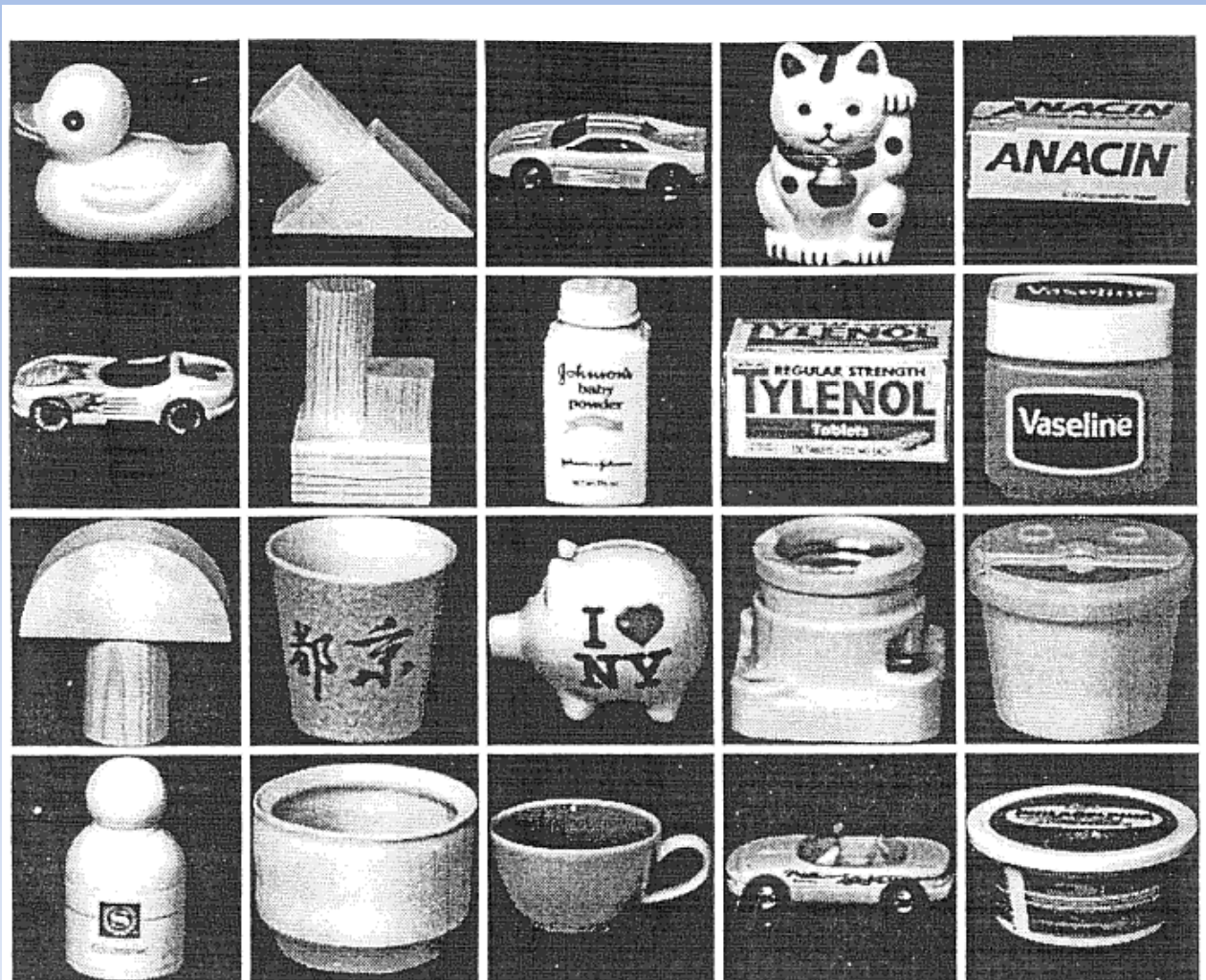


Results: Digit Recognition

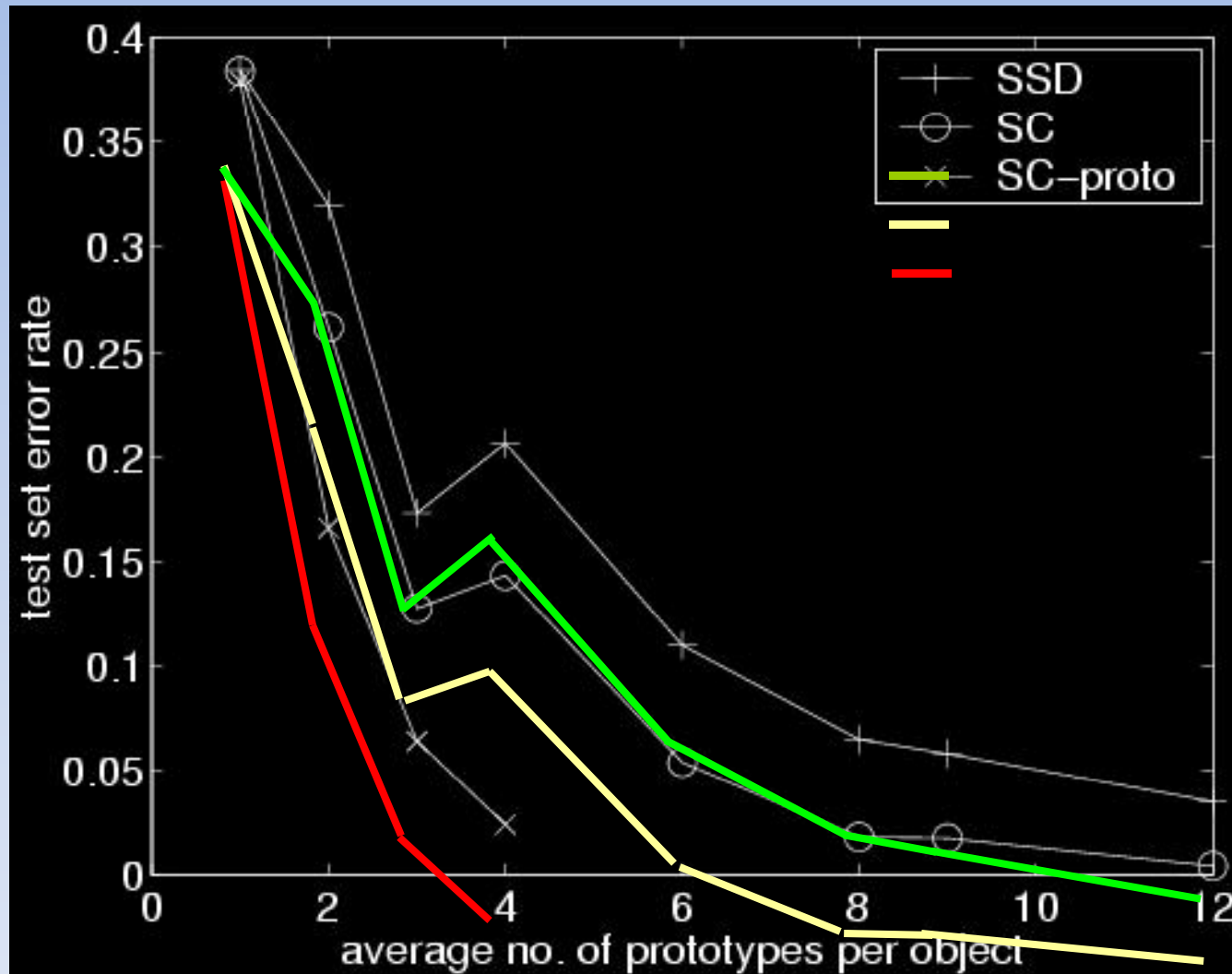


1-NN classifier using:
Shape context + 0.3 * bending + 1.6 * image appearance

COIL Object Database



Error vs. Number of Views

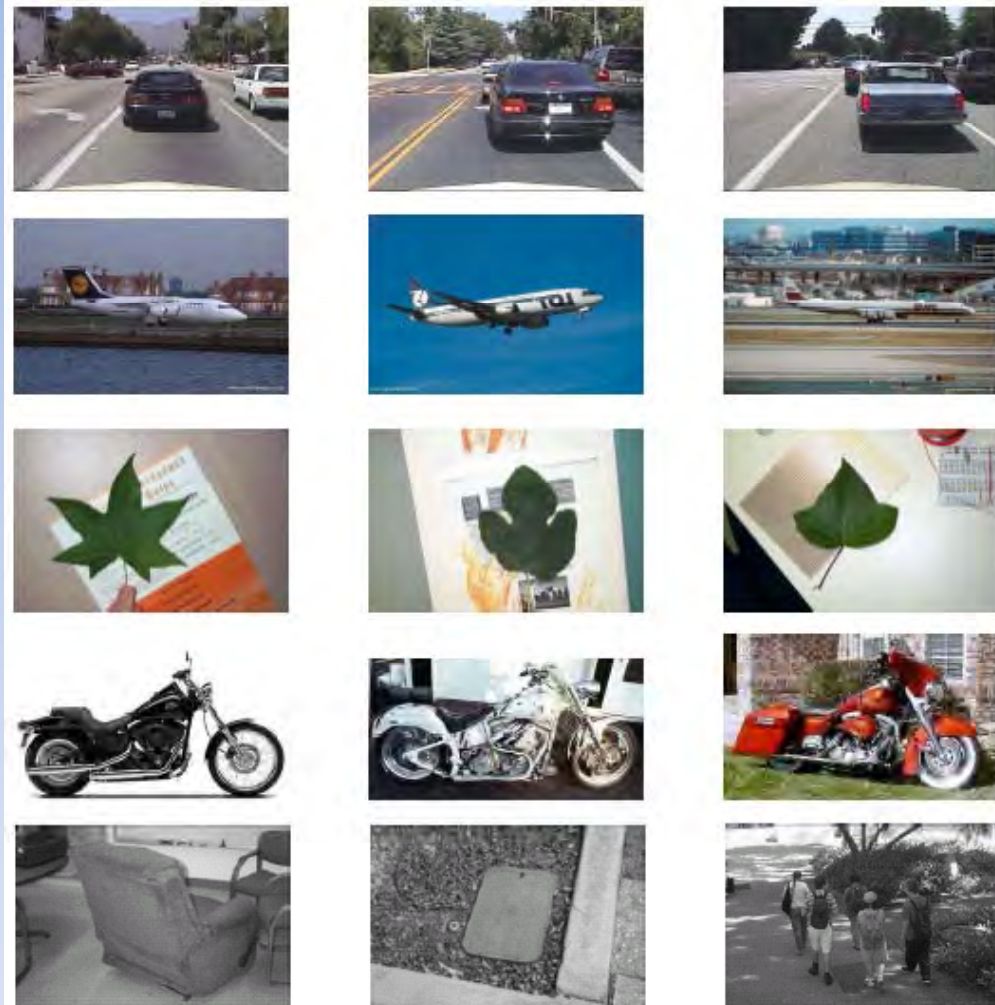


Prototypes Selected for 2 Categories

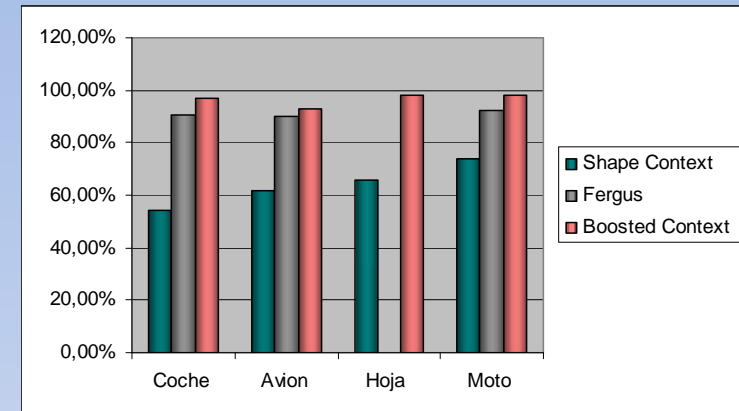


Details in Belongie, Malik & Puzicha (NIPS2000)

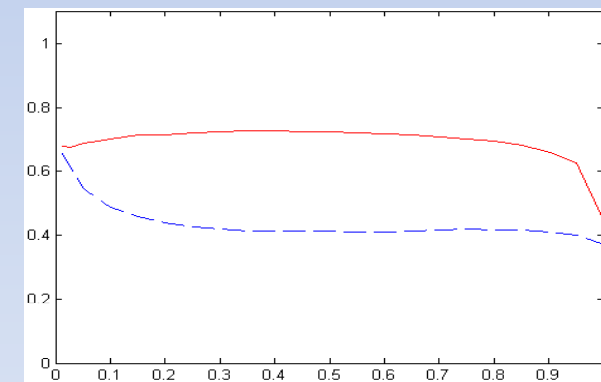
Retrieval validation



- 3512 images,
- 4 categories



Error rate estimated by the ROC curve

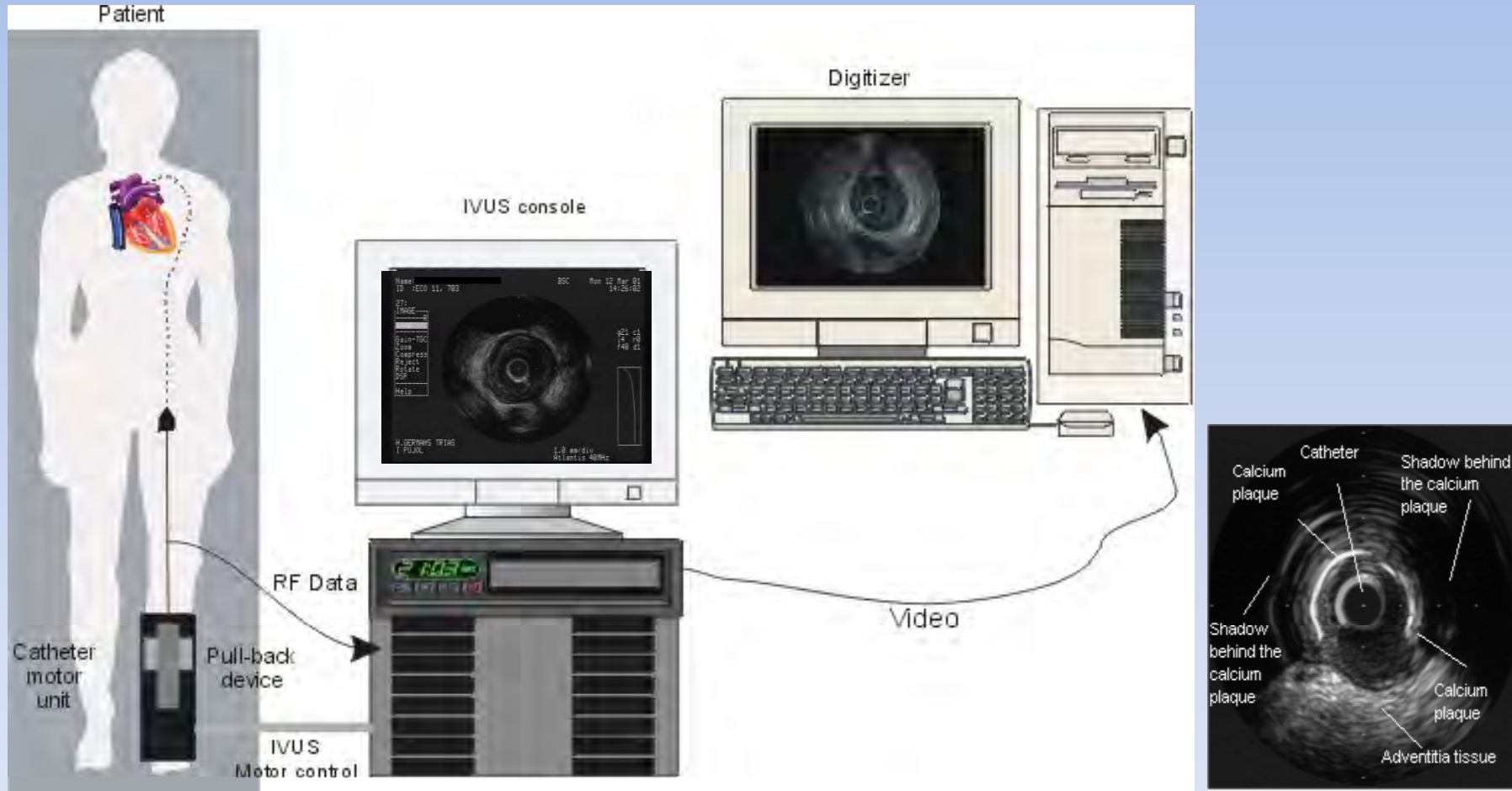


The "Precision-Recall" curve for car category

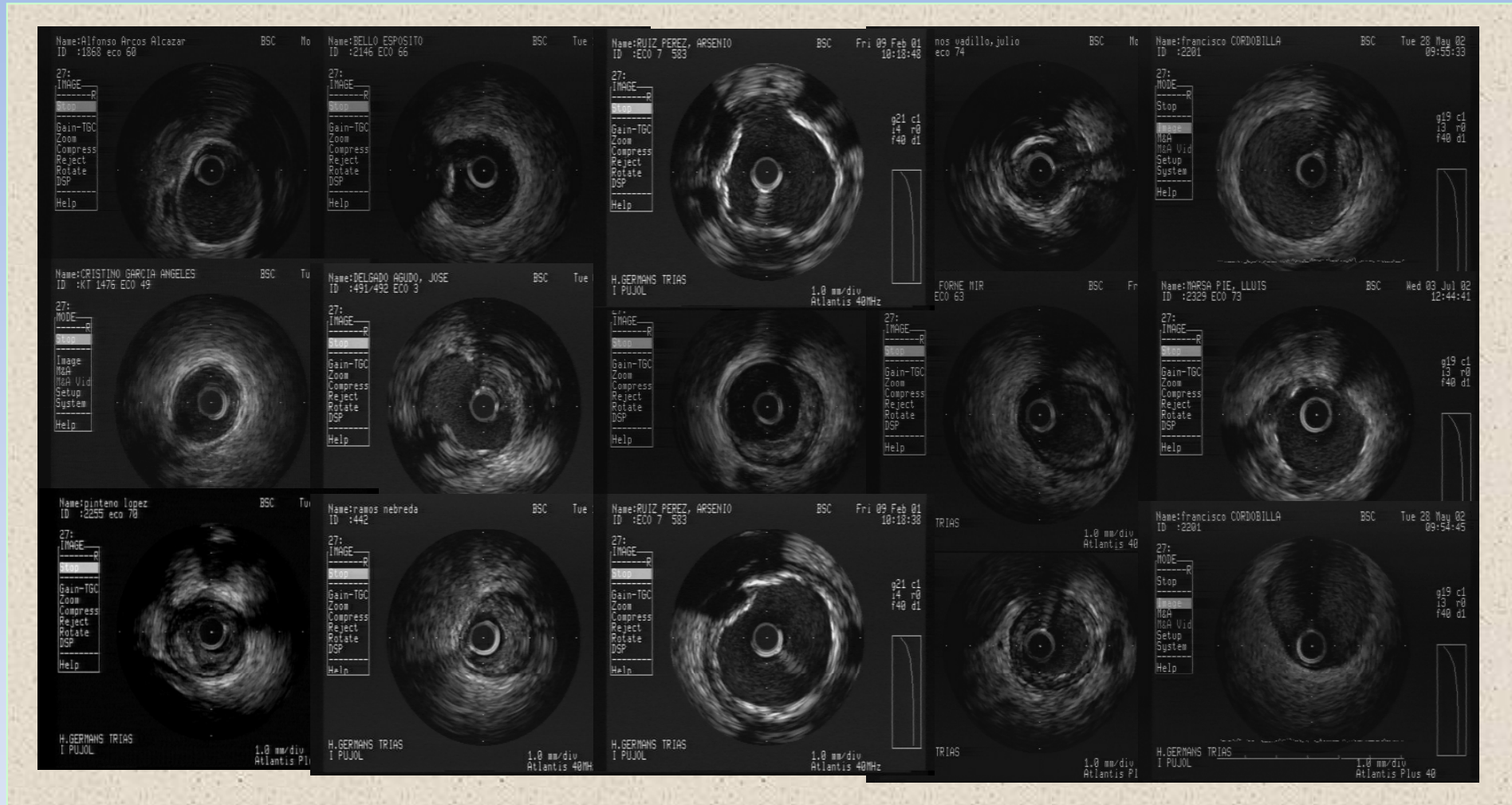
$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

IVUS retrieval by shape context



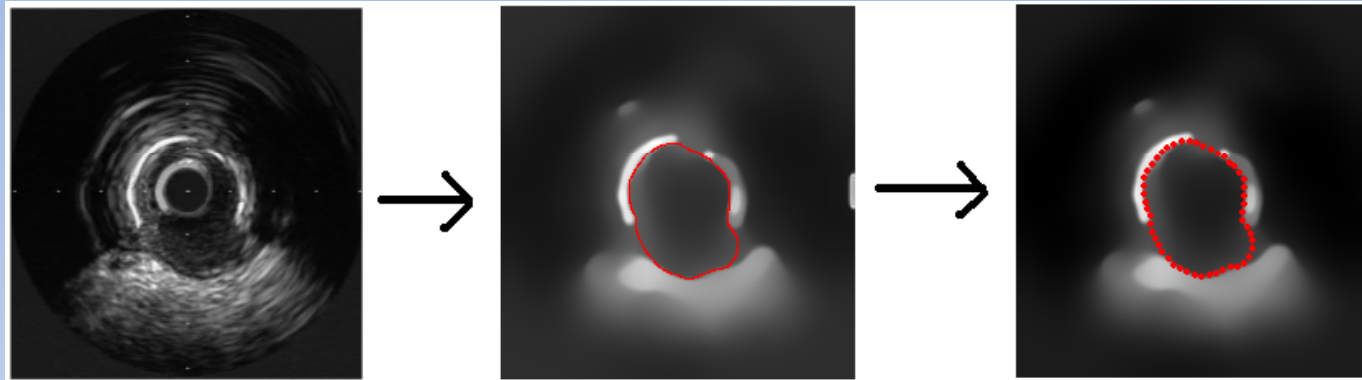
Tissue characterization and retrieval



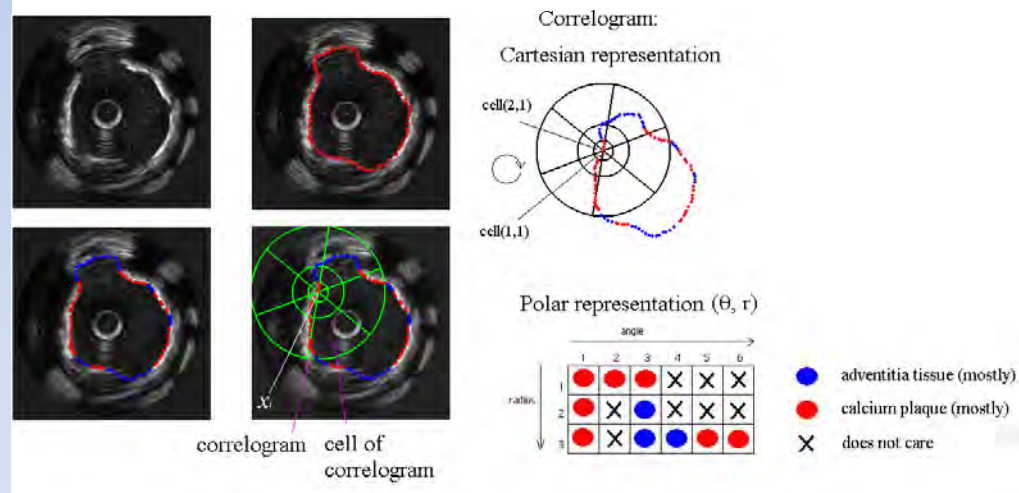
Context shape for IVUS retrieval

- What should be our features?
 - Generate context on different and customized feature set
- What should be our classifiers?
 - Generate (multiple) classifiers
 - Determine the decision rule

Boosted Context Retrieval of IVUS

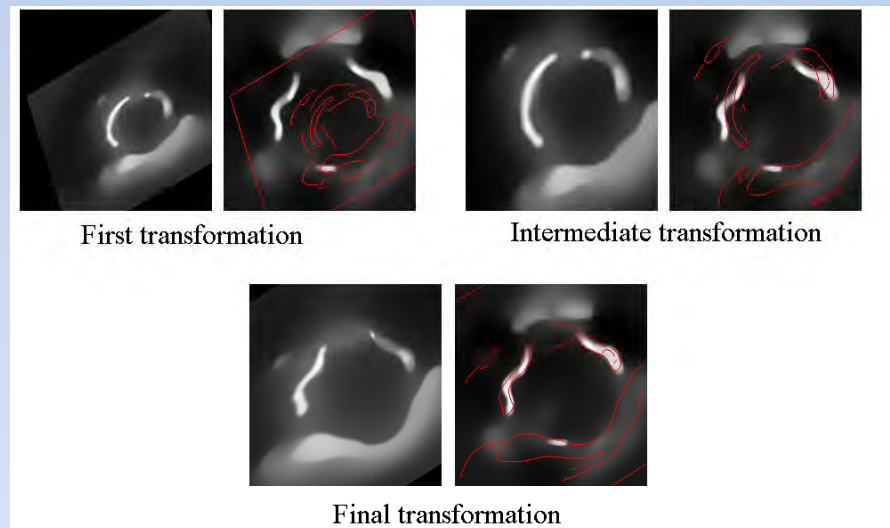
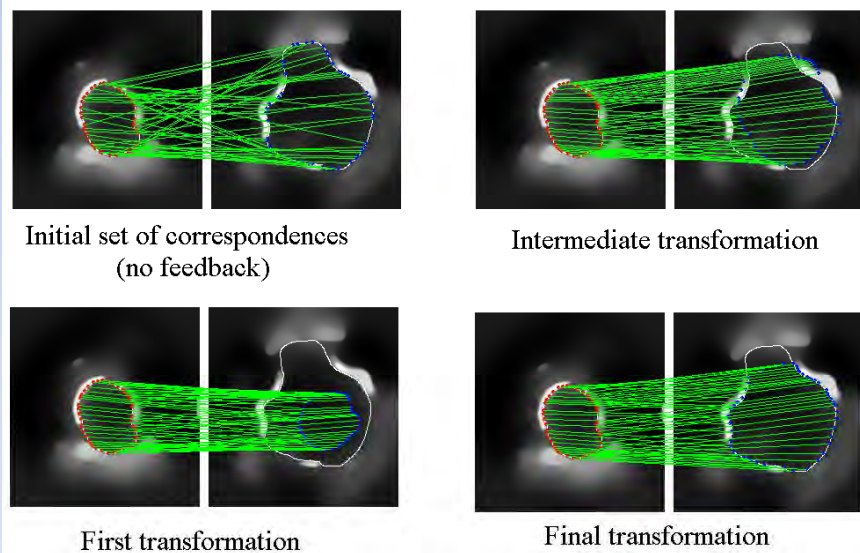
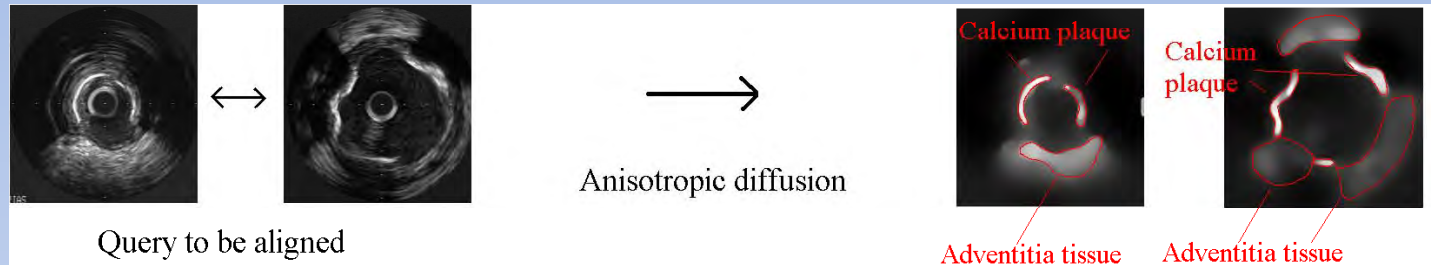


Correlogram 2-D

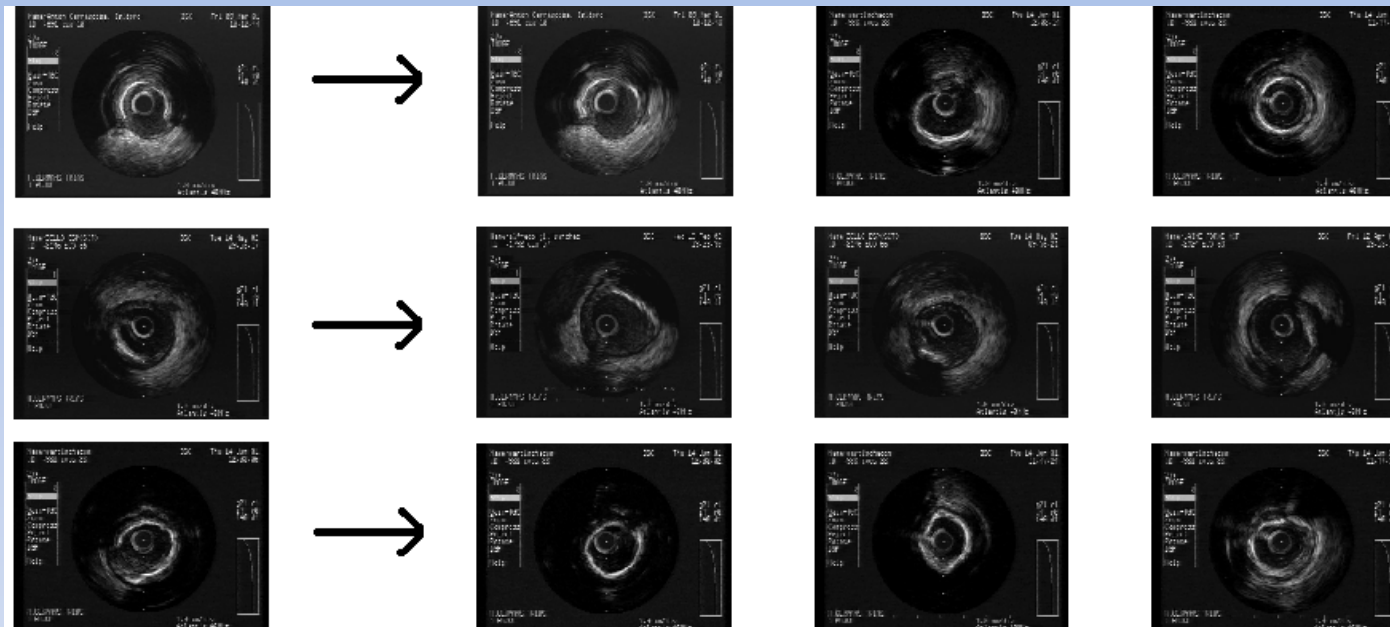


From: Jaume Amores, Petia Radeva: Retrieval of IVUS images using contextual information and elastic matching. *Int. J. Intell. Syst.* 20(5): 541-559 (2005)

Context Matching of IVUS



Context Retrieval



Test: the probability to appear the most similar case in the first 3 automatically retrieved is 85%.

Conclusions

- Elegant way to integrate relation between parts of the object into the registration process
- Not necessarily connected object boundaries
- Allows to extend to 3D and 4D
- Allows to integrate different feature descriptors
- Validated in extensive public domain databases and medical problems