What parts of a shape are discriminative?

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Outline

- Introduction to shape matching
- Motivation
- Identifying Discriminative Parts
- Experiments
- Summary

Introduction to Shape Matching

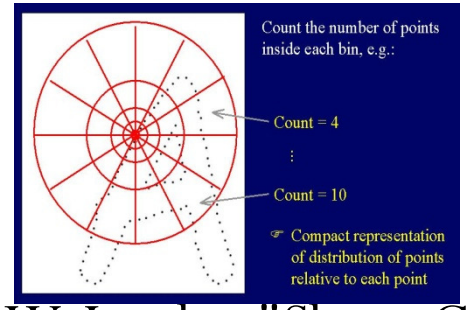
- No color, no texture.
- Enables class-level recognition
- Applications: Content-Based Image Retrieval

Introduction – Standard Pipeline

- Extract shape boundaries
- Uniformly sample boundary
- Compute features at these boundary points
- Solve correspondence problem to match features

Introduction – Shape features

- Belongie, S.; Malik, J.; Puzicha, J.; , "Shape matching and object recognition using shape contexts," *PAMI 2002*.



- Haibin Ling, David W. Jacobs, "Shape Classification Using the Inner-Distance", *PAMI, 2007*. (IDSC)

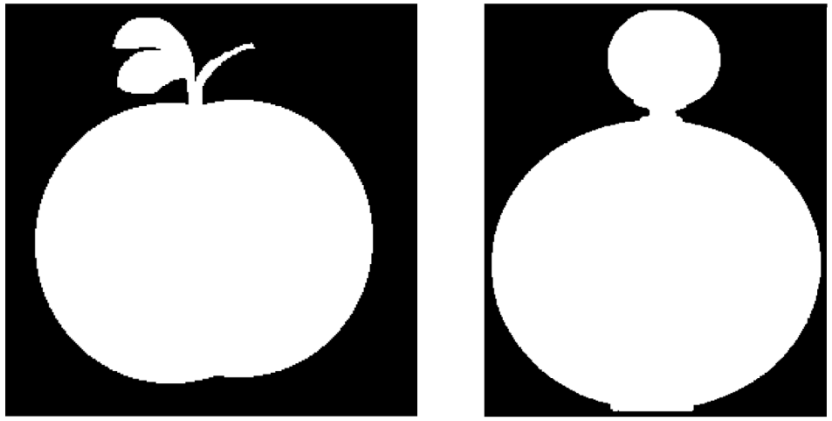
A Look-Back At The “Standard Pipeline”

- Extract shape boundaries
- ***Uniformly(!)*** sample boundary
- Compute features at these boundary points
- Solve correspondence problem to match features

Are all parts of the shape uniformly discriminative?

Motivation

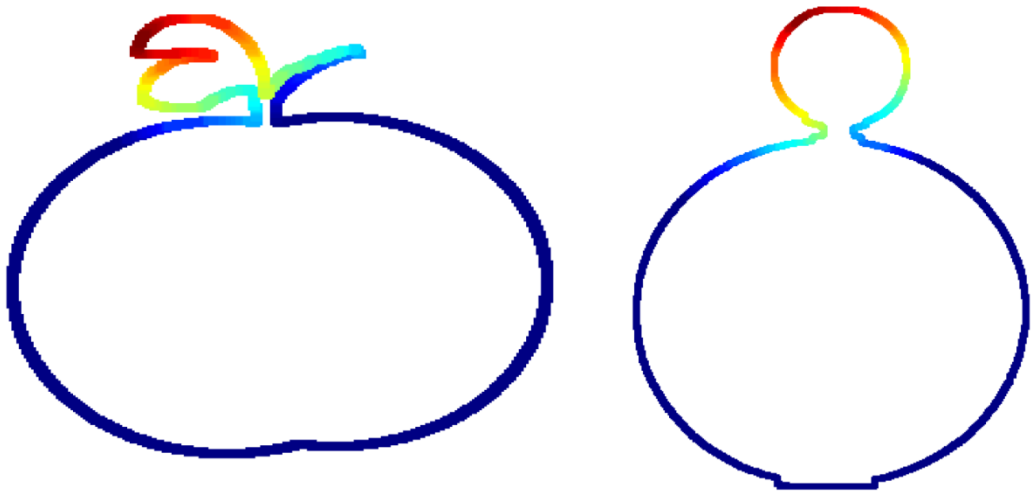
- Look at the example below



- Globally, looks similar
- But, has strong local discriminative parts
- Clearly, certain parts are more important than others.

Motivation

- Can we learn what the discriminative parts are (as below)?



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Discriminative Parts

- Definition: Parts of an object that are most different from parts of other objects belonging to similar-looking classes.

- Identifying discriminative parts:
  - Divide the shape into multiple parts
  - Find how unique each part is, compared to the negative examples
  - Assign an importance score to the part, which is directly proportional to its uniqueness

Extract parts of the shape - 1

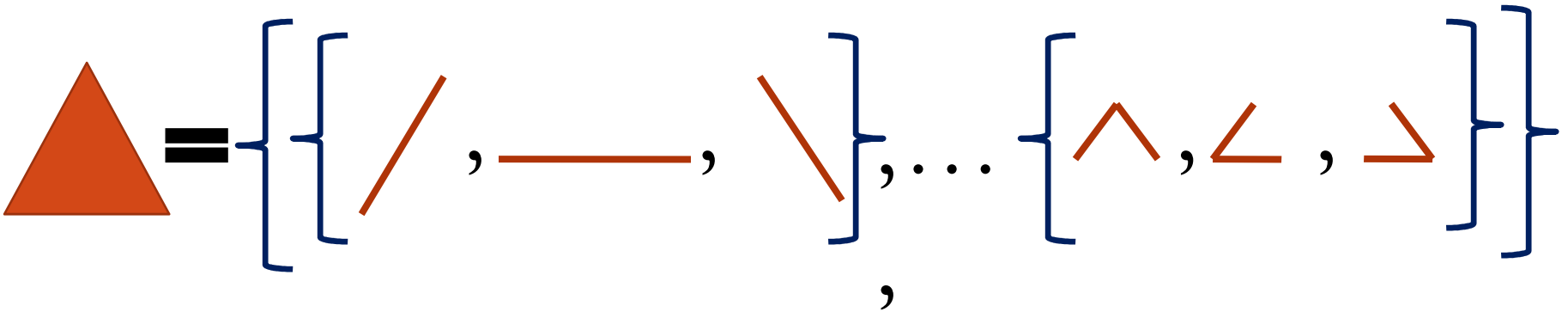
- To identify discriminative parts, we need parts!
- How do we get parts from a shape?
- One way: Make cuts at points of extremum on the contour
- But, identifying extrema points is difficult and subjective.
- Therefore, we *randomly* split the contour into parts

Extract parts of the shape - 2

- Given a shape, S_i extract its contour C_i
- Randomly split the contour into p contour segments

$$C_i^{seg} = \{C_i^{seg_1}, C_i^{seg_2}, ..., C_i^{seg_p}\}$$

- Repeat the procedure T times to get T sets of p random parts.



Compare Parts to Negative Shapes

- Compare parts from a positive shape S_i^+ to the parts from negative shapes $S^- = \{S_1^-, S_2^-, ..., S_{|S^-|}^-\}$

- However, $|S^-|$ can be very large!

- Therefore, we compare the parts from S_i^+ to the parts from just the ***k*** "hardest" negatives.

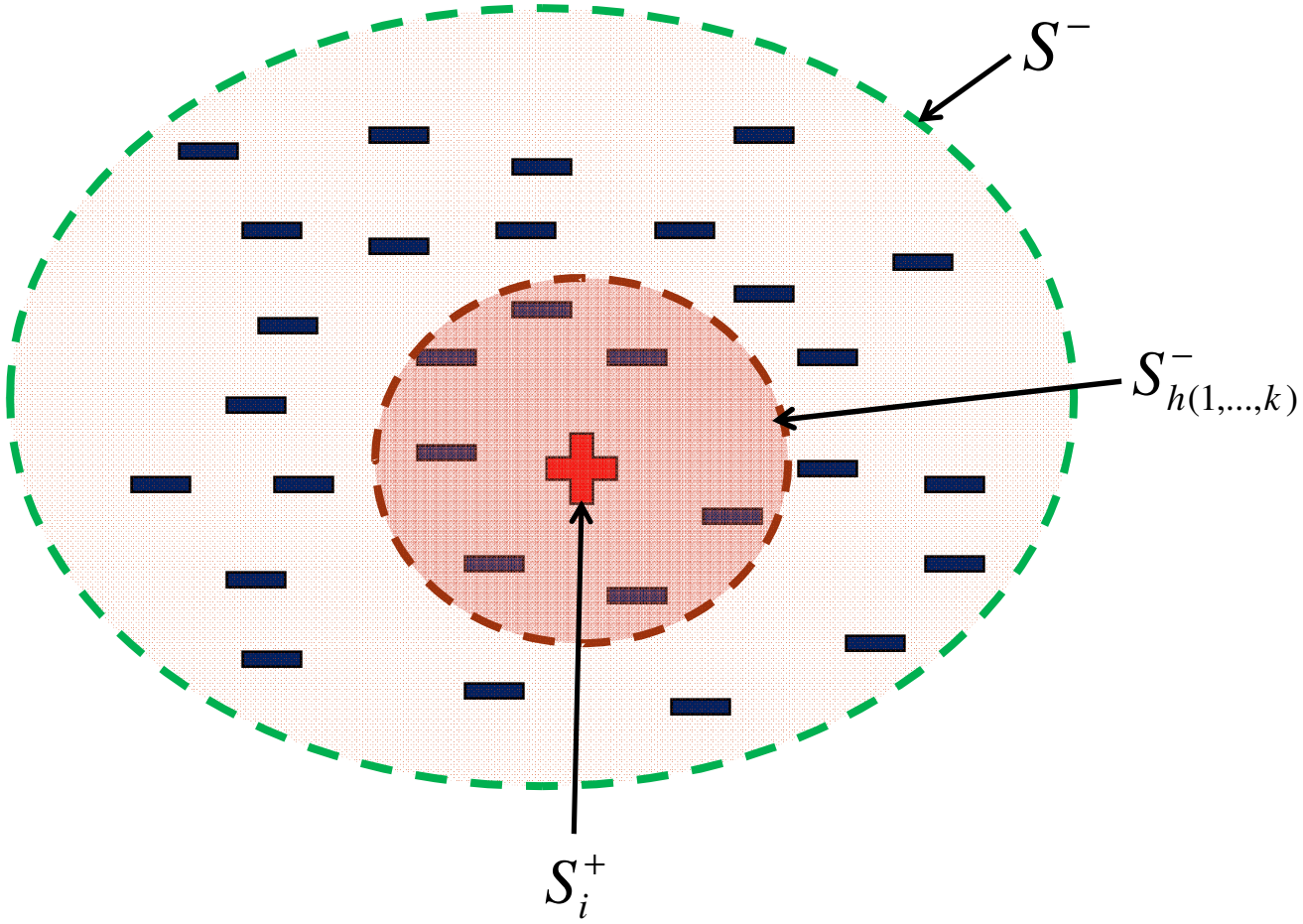
Identifying "Hard" Negatives

- A "hard" negative is one which looks similar to the positive shape, S_i^+ but from a different class.
- Therefore, the "hardest" negative is can be found by,

$$S_h^- = \min_{S_j^- \in S^-} \Psi_{IDSC}(S_i^+, S_j^-)$$

- Ψ is the cost of matching two shapes using some shape matching technique.
- We use IDSC to compute the "distance" between shapes

Illustration

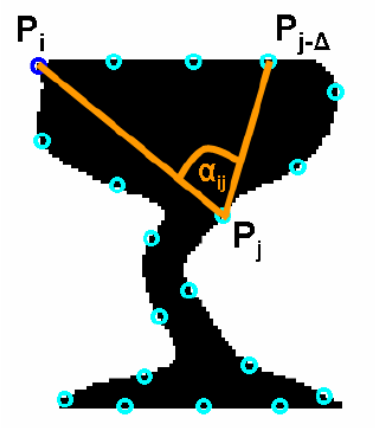


Shape Descriptor - 1

- To compare, describe each part using a shape descriptor.
- Requirements:
  - Invariant to translations
  - Invariant to rotation
  - Invariant to scale
  - Should be a ***partial*** shape descriptor! (Most important requirement)

Shape Descriptor - 2

- Donoser et al. "Efficient partial shape matching of outer contours", ACCV 2009.



$$\alpha_{ij} = \angle\left(\overline{P_i P_j}, \overline{P_j P_{j-\Delta}}\right)$$

$$A = \begin{pmatrix} \alpha_{11} & . & . & . & \alpha_{1N} \\ . & . & & & . \\ . & & . & & . \\ . & & & . & . \\ \alpha_{N1} & . & . & . & \alpha_{NN} \end{pmatrix}$$

- Any sub matrix of the above matrix, is a partial shape descriptor.

- Figure from Donoser et al. ACCV '09

Segment Distinctiveness

- Probability of distinctiveness of a part is proportional to the cost of matching the part to the hard negatives.

$$P\left(seg_s^+\right) = \frac{1}{Z}\exp\left(L(seg_s^+)\right)$$

- Z is the normalization constant, and

$$L(seg_s^+) = \frac{1}{|C_{h_{(1,\ldots,k)}}^{seg^-}|}\sum_j d(seg_s^+, seg_j^-)$$

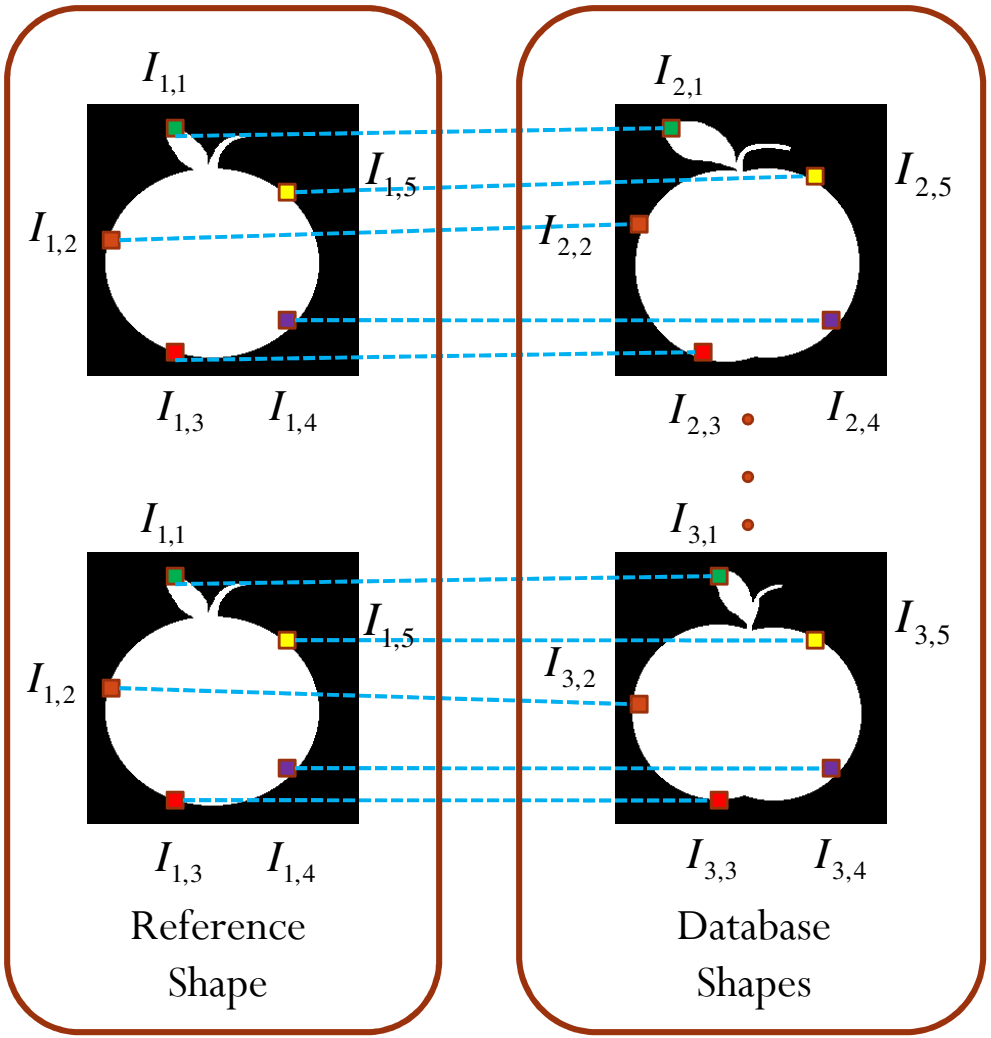
  Average distance between the part and the hard negatives.

- Repeat for all T cuts; average probability over T repetitions gives the part distinctiveness.

Part Consistency

- How consistent are the distinctiveness across different shapes of the same class?
- Match shapes using IDSC and find correspondences
- Store corresponding distinctiveness values in a matrix, Q.
- Agreement in part distinctiveness implies a steep drop in the singular values of Q.
- Can be quantified using the AUC of the top M singular values of Q.

Part Consistency Matrix



$$Q = \begin{bmatrix} I_{1,1} & I_{2,1} & I_{3,1} \\ I_{1,2} & I_{2,2} & I_{3,2} \\ I_{1,3} & I_{2,3} & I_{3,3} \\ I_{1,4} & I_{2,4} & I_{3,4} \\ I_{1,5} & I_{2,5} & I_{3,5} \end{bmatrix}$$

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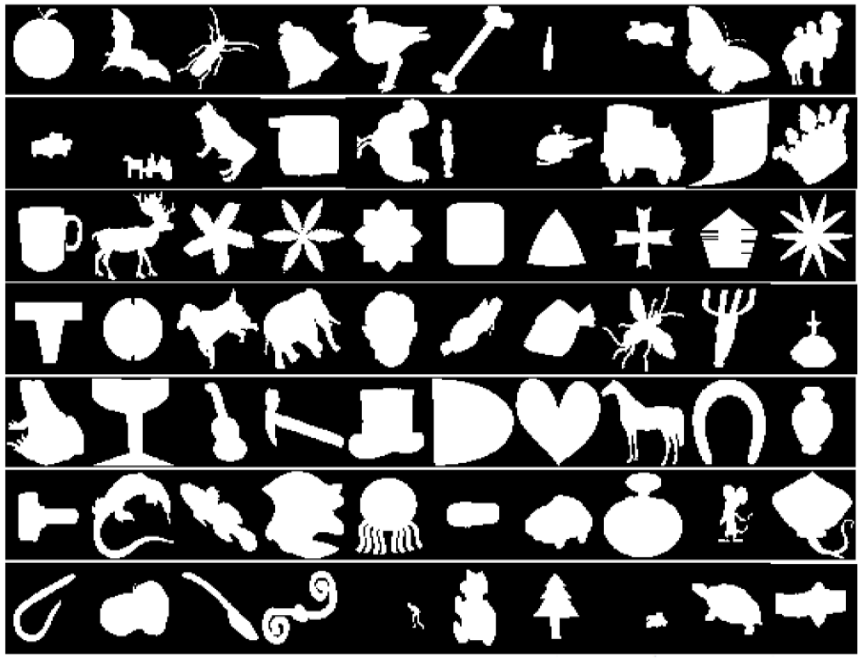
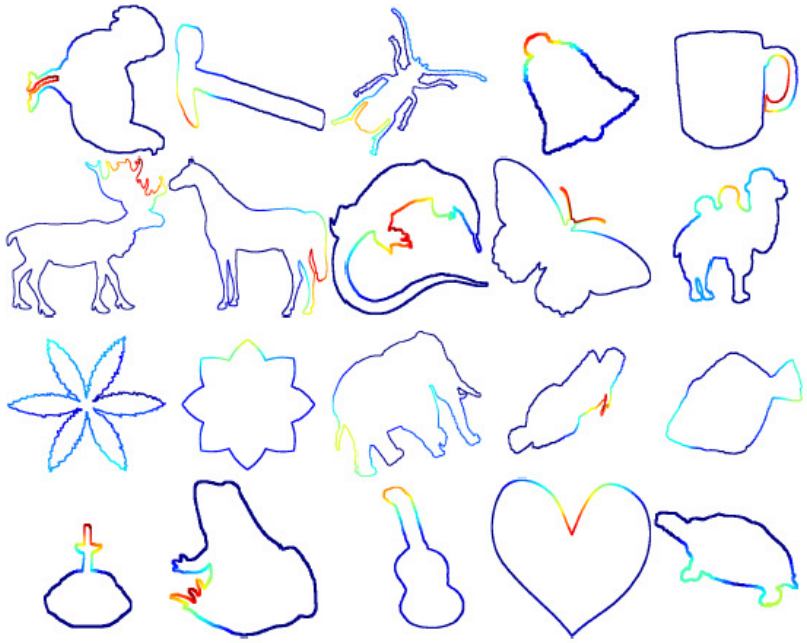
Experiments

- We perform the experiments on the MPEG-7 Shape database.
- 1400 images; 70 classes, 20 objects per class.



Experiments

- Example heat maps from various classes.
- Semantically meaningful parts are identified as being distinctive.

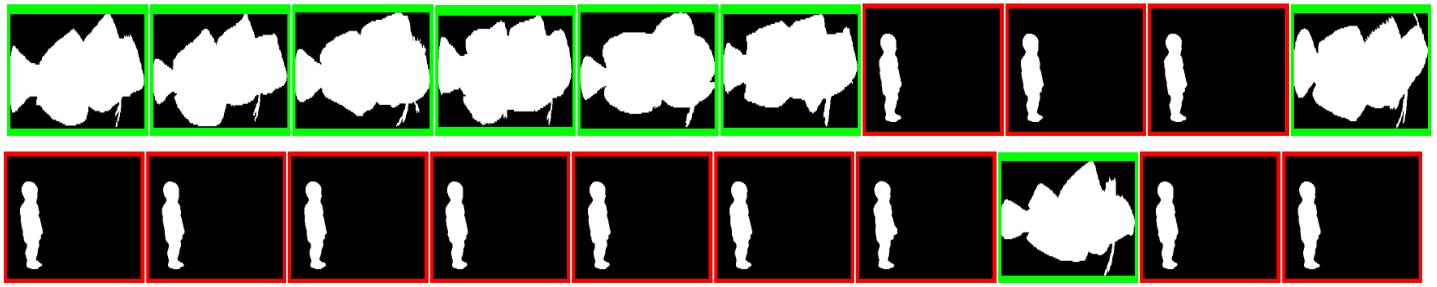


Experiments

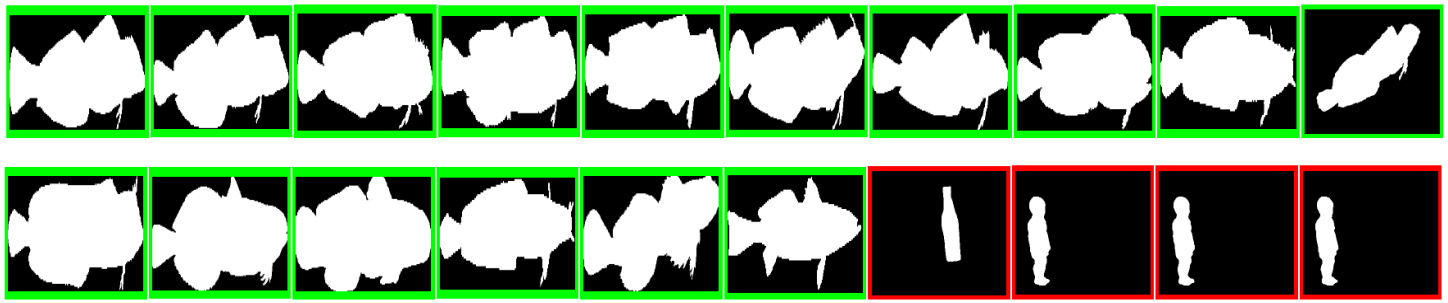
- Retrieval experiment performed by modifying the sampling scheme on the contours.
- IDSC uses uniform sampling and then computes its descriptor.
- We used importance sampling and then computed the same descriptor.
  - More points were sampled at regions of high distinctiveness.

Experiments

- Uniform Sampling



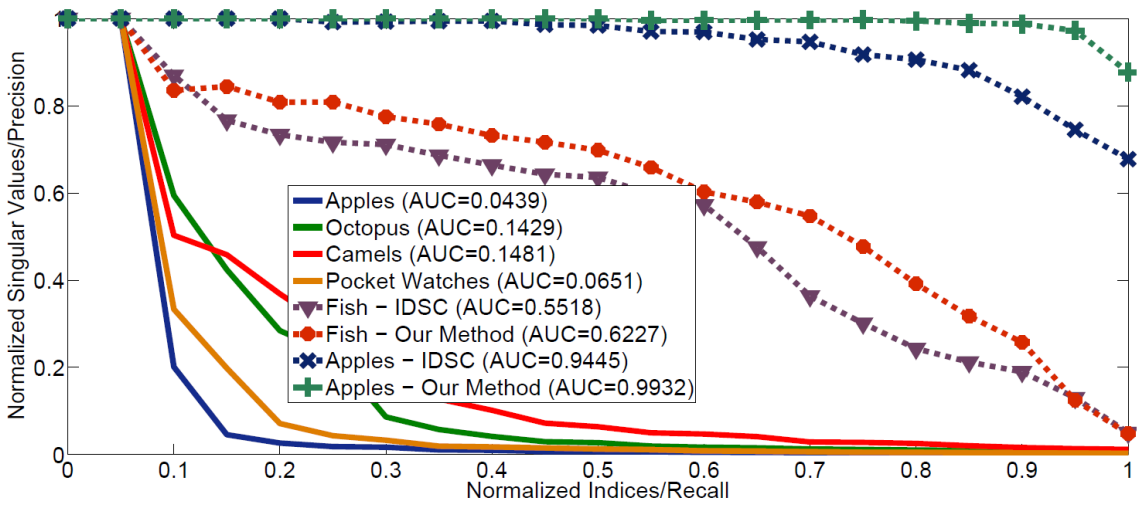
- Importance Sampling



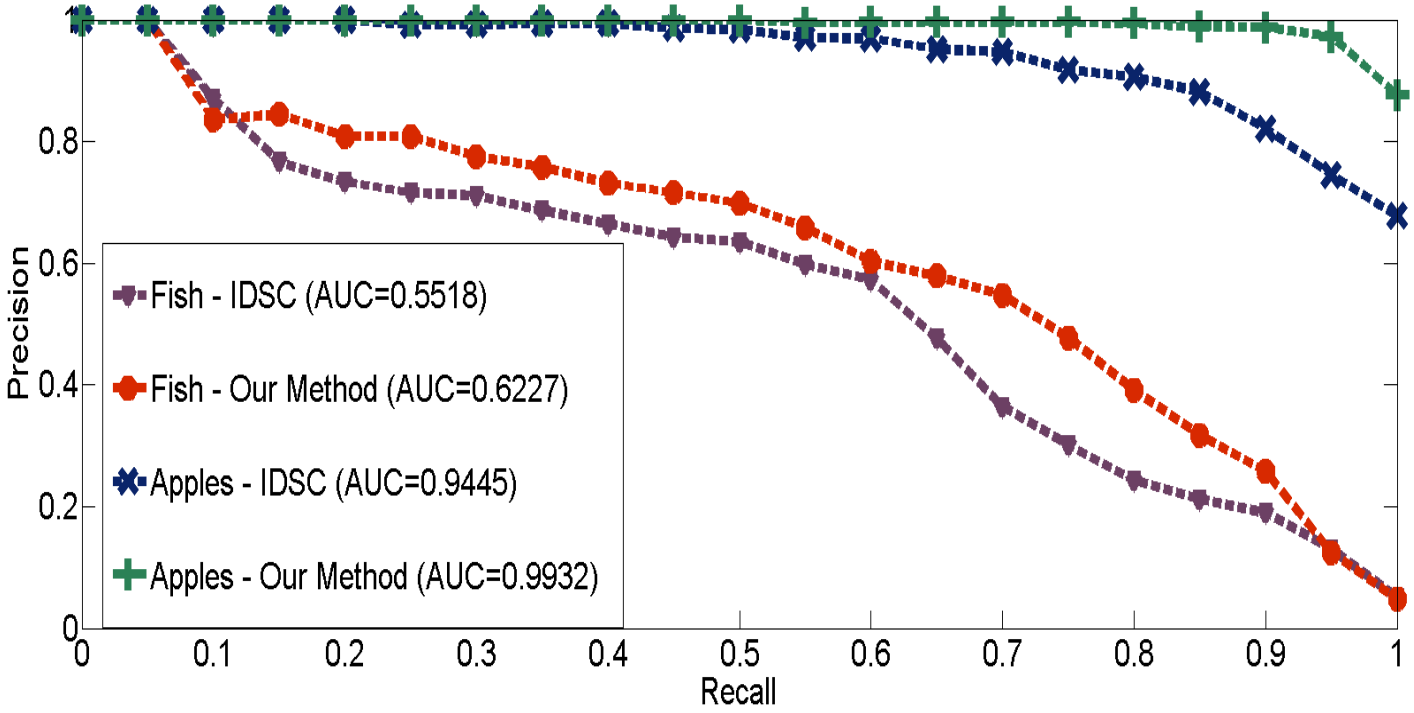
Experiments

- Part consistency example

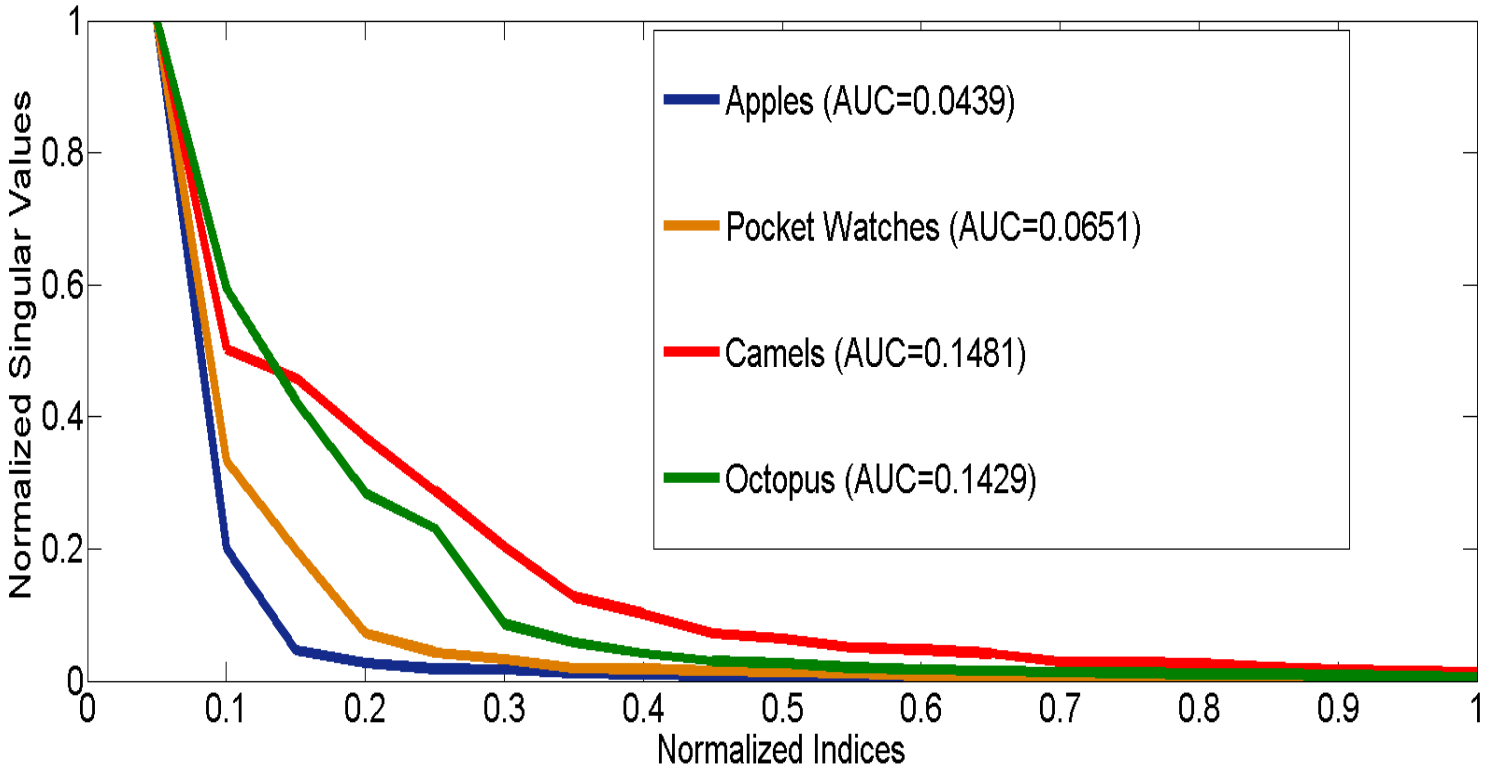
- P/R plots (importance sampling does better) and the AUC plots (steep drop in singular values).



P/R Curves


Precision
Recall
0
0.2
0.4
0.6
0.8
1
0.1
0.3
0.5
0.7
0.9
Fish - IDSC (AUC=0.5518)
Fish - Our Method (AUC=0.6227)
Apples - IDSC (AUC=0.9445)
Apples - Our Method (AUC=0.9932)

Singular Value Curves



Summary

- Introduced the concept of distinctiveness with a strong motivating example.
- Provided a simple way to extract distinctive parts.
- Showed that the method produces semantically meaningful parts as distinctive.
- Consistently identifies the same semantic parts as meaningful.
- Future work: Investigate shape descriptors that make use of importance maps.

Thank you!