

# A Hierarchical Representation for Matching Deformable Shapes

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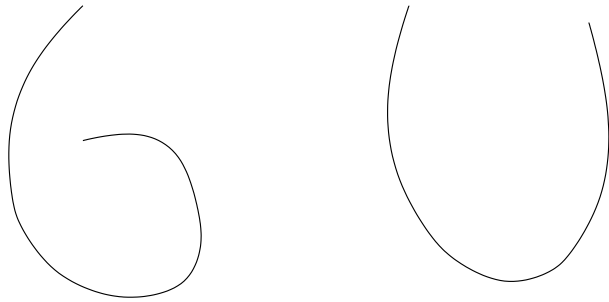
# Shape-based recognition



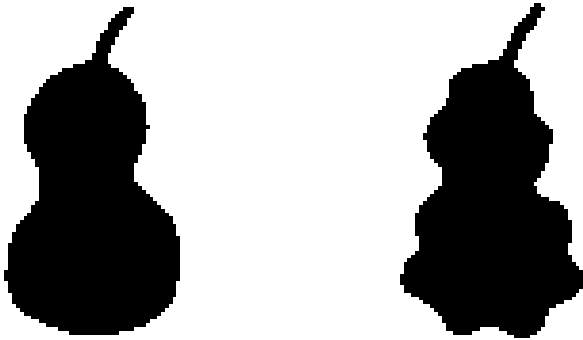
- Humans can easily recognize objects using shape information
- Classical approach for recognizing rigid object
- Important for many object categories
  - Fairly abstract representation

# Local deformation models

- Measure amount of bending and stretching necessary to turn one curve into another --- only captures local information [Basri, et al 95], [Younes, 98]



can turn these into each other without much bending at any point



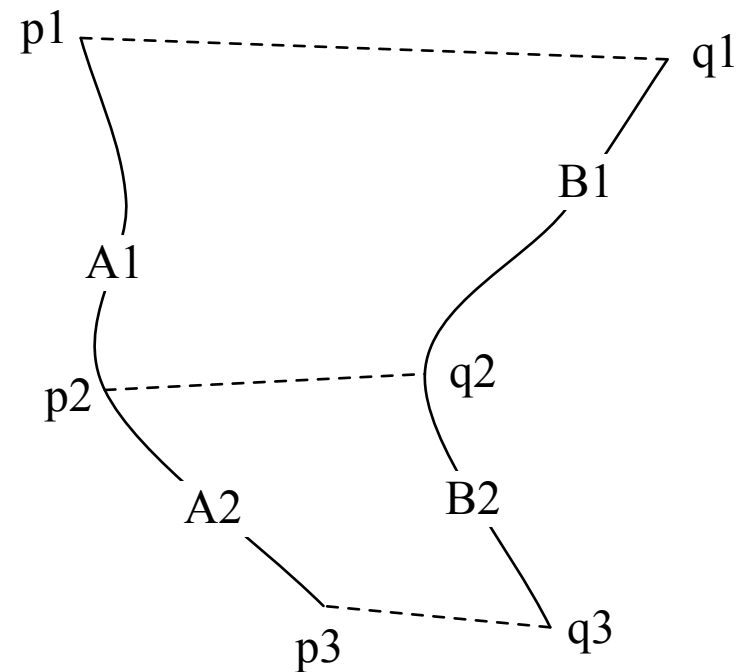
Similar objects with completely different local boundary properties

# Compositional model

- Consider arrangement of points far from each other
- Combine matchings between subcurves to form longer matchings

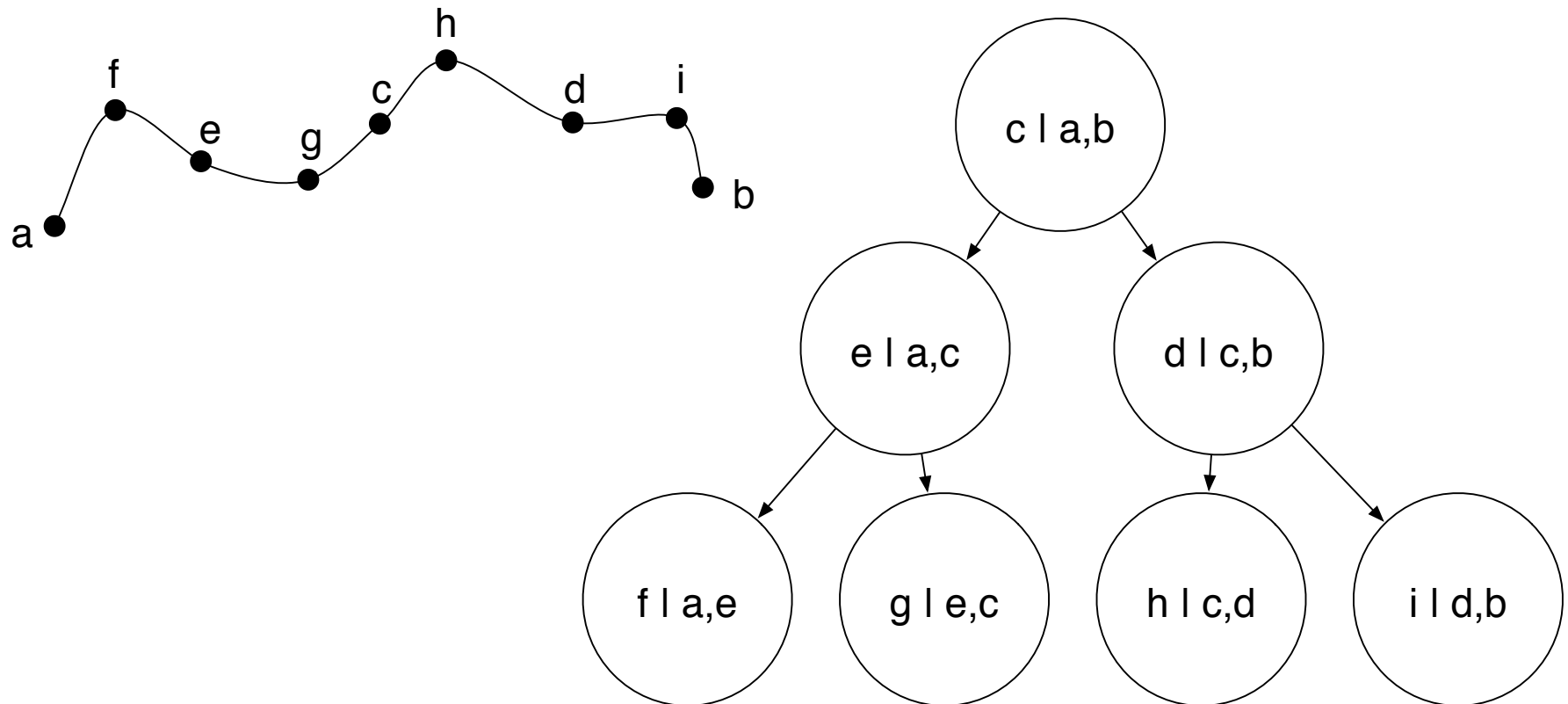
Combine matching from  $A_1$  to  $B_1$   
with matching from  $A_2$  to  $B_2$

quality depends on quality of  
matchings being combined and  
arrangement of  $(p_1, p_2, p_3)$ ,  $(q_1, q_2, q_3)$



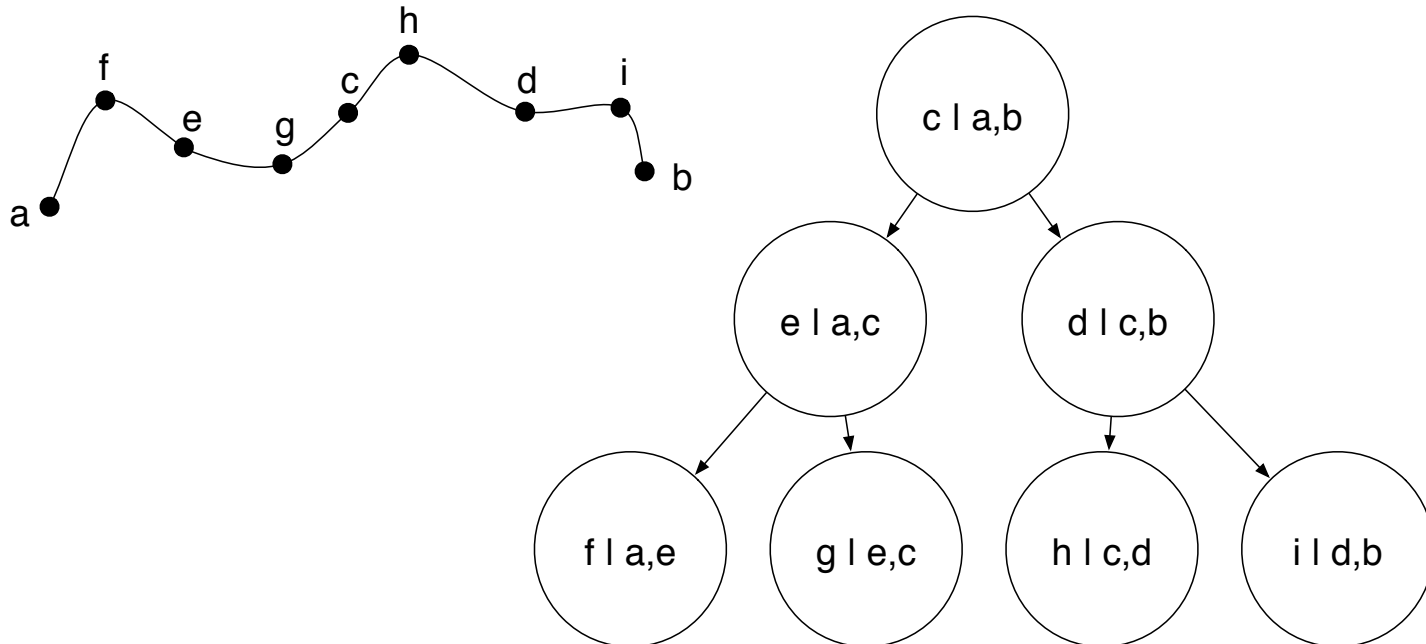
# Shape-tree

- Shape-tree of curve from a to b:
  - Select midpoint c, store location w.r.t. a,b frame
  - Left child is a shape-tree of sub-curve from a to c
  - Right child is a shape-tree of sub-curve from c to b



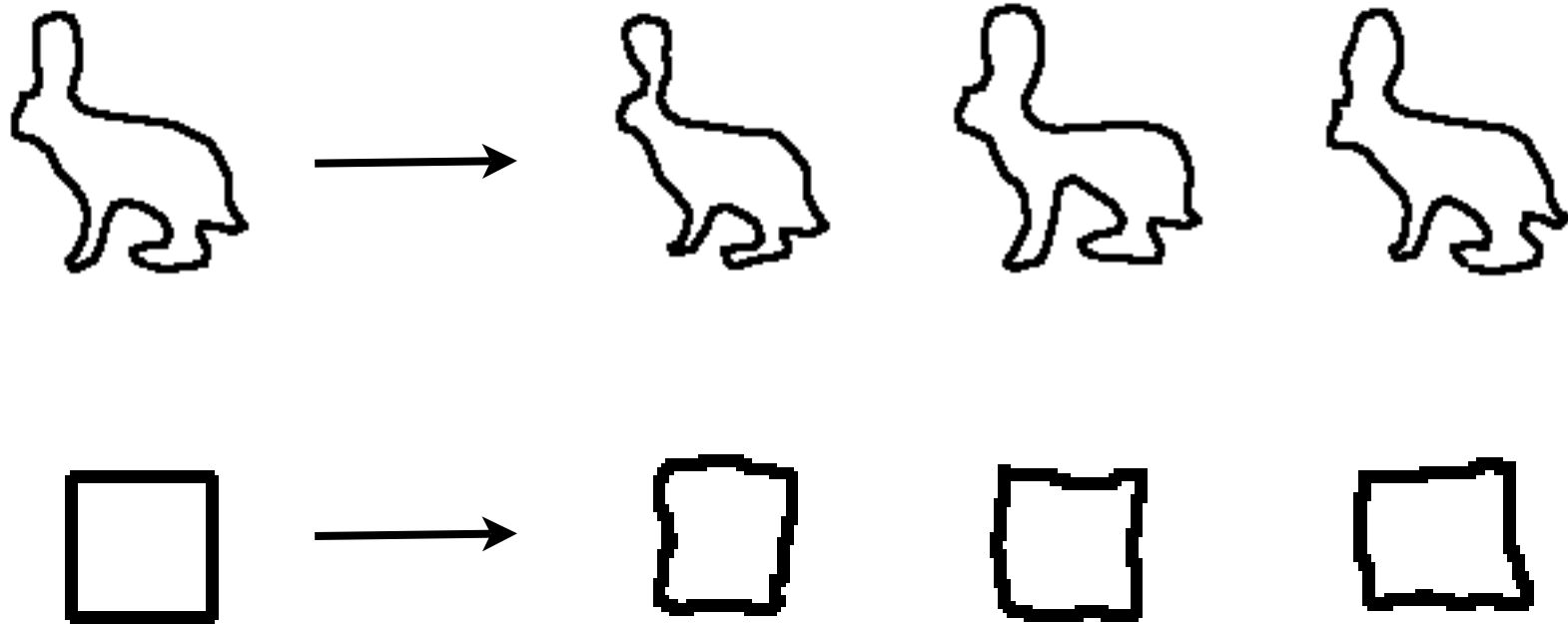
# Shape-tree

- Invariant to similarity transformation
- Subtree is shape-tree of sub-curve
- Given placement for a,b we can reconstruct the curve
- Bottom nodes captures local curvature
- Top nodes capture curvature of sub-sampled curve



# Deformations

- Perturb relative locations stored in a shape-tree
  - Reconstructed curve is perceptually similar to original
  - Global properties are preserved



# Distance between curves

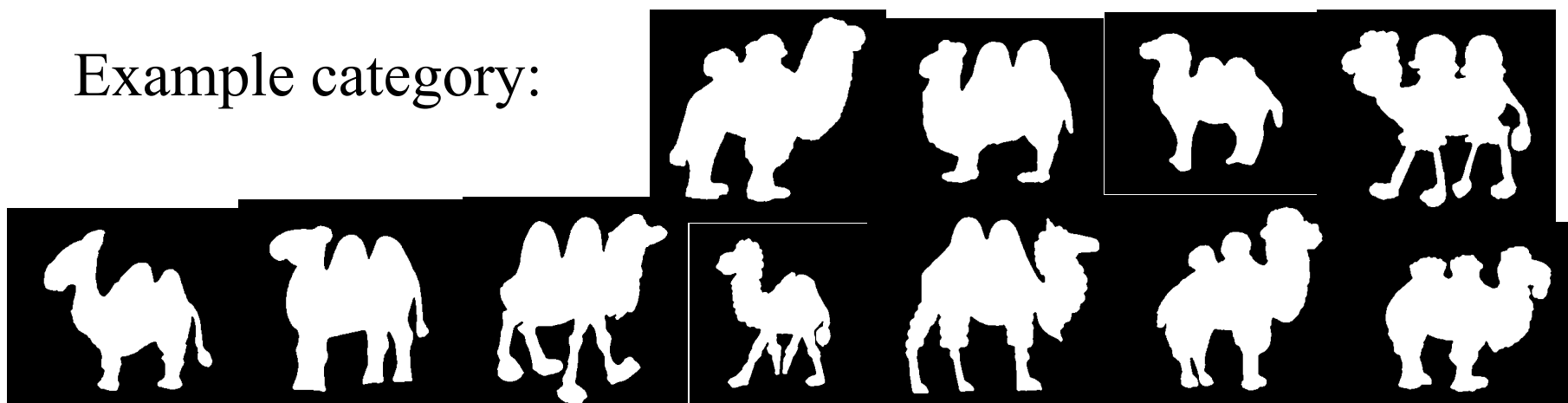
- Define distance between shape-trees in terms of deformations applied to each node
- But a curve can be represented with multiple shape-trees!
  - We need to search over possibilities
- Given curves A,B
  - Fix shape-tree for A, search over shape-trees for B:  $O(n^4)$
  - Jointly find correspondences and common tree:  $O(n^4 \log n)$
- Reason about missing parts by cutting off sub-trees



# Recognition results

MPEG7		
Shape-tree	Inner distance	G. M.
85.30	85.40	80.03

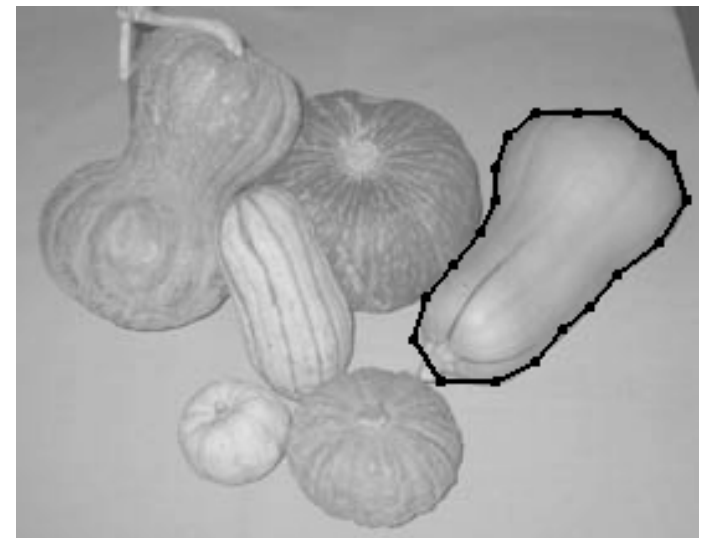
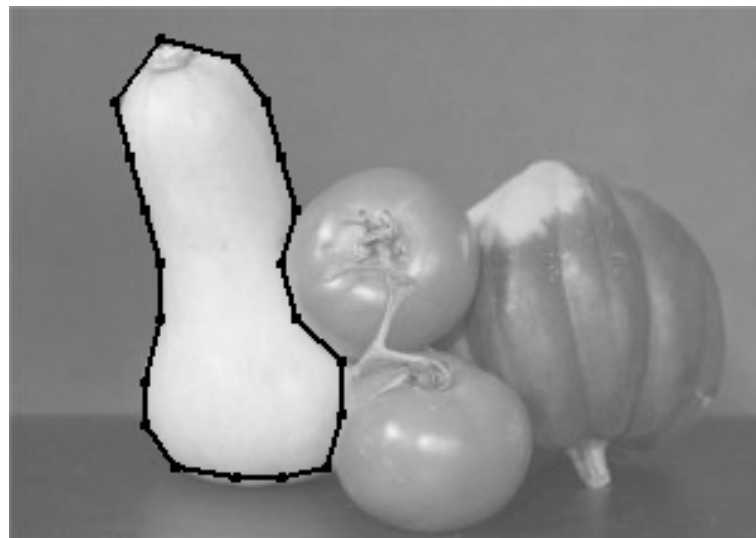
Example category:



Swedish leaves		
Shape-tree	Inner distance	Shape context
94.31 (mean)	94.13	88.12

# Cluttered images

- Consider embedding deformed curve in images
  - Cost depends on deformation + image evidence
  - No edge detection
- Combine partial embeddings with bottom-up algorithm
  - Generalization of Dijkstra's shortest path (with D. Mcallester)
  - Find best match without considering bad ones



# Problems

- Current local evidence measurement too weak
- Often place object at strange location
  - Close inspection shows that gradient is high along boundary
- What is going on?
  - We may need NMS
  - We may need to capture internal coherence
  - Could try finding multiple good solutions

# Parts

- Sub-trees represent generic curves
- We can share sub-trees among different models
  - Useful for bottom-up matching
- Look for a context-free grammar for compactly representing all shape-trees of a big data set
  - Terminals  $l(a,b)$  are line segments from  $a$  to  $b$
  - Sentences are curves
  - Non-terminals  $N(a,b)$  represent curve fragments

# Examples

- $L(a,b)$  generates an “almost straight curve” from  $a$  to  $b$
- Productions
  - $L(a,b) \rightarrow L(a,c) L(c,b)$  where  $c \sim (a+b)/2$
  - $L(a,b) \rightarrow l(a,b)$  if  $a$  near  $b$
- Can also define  $B(a,b)$  to generate an elongated branch anchored at  $a$  and  $b$
- etc.
- Learning is a challenge