Matching Hierarchies of Deformable Shapes

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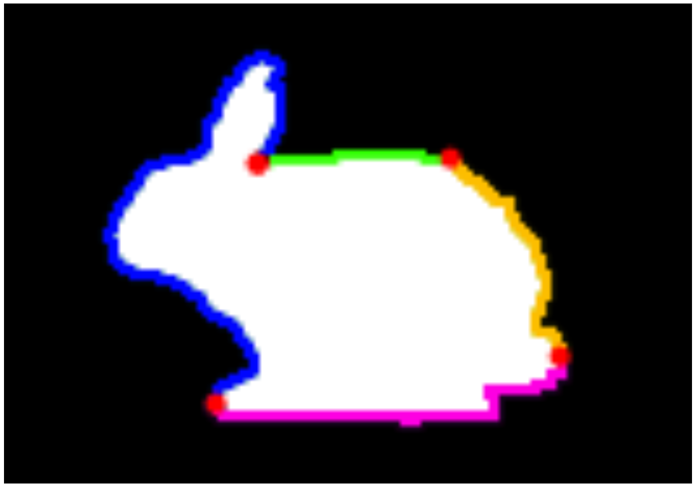
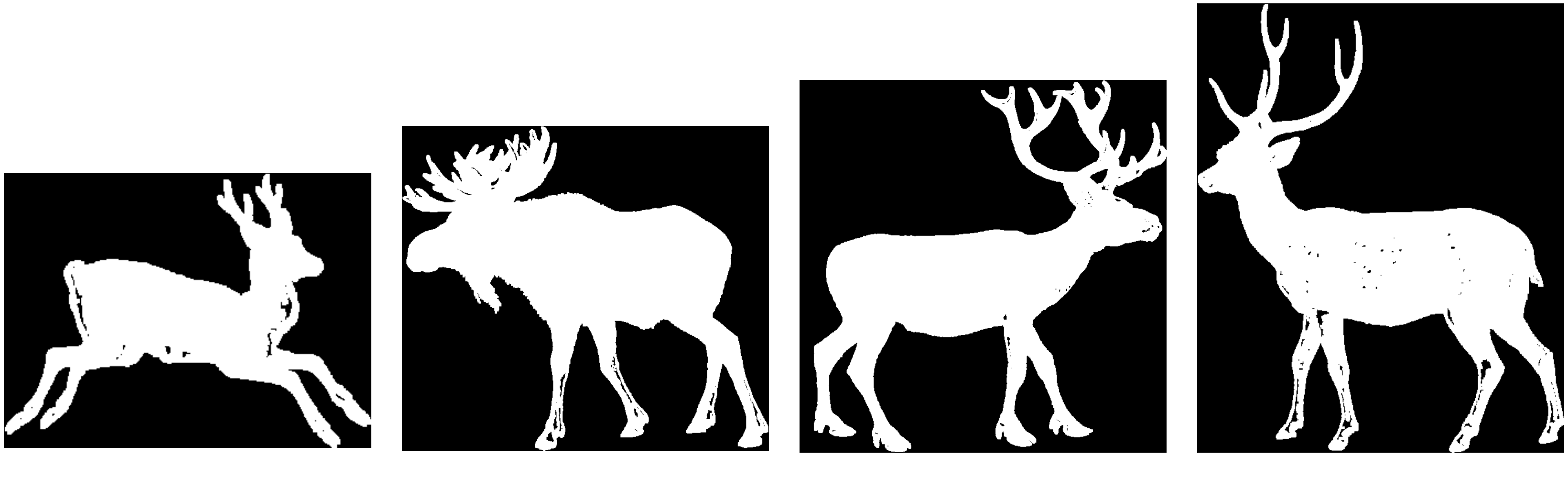
Goal

- Identify similar parts of deformable shapes
- Part = shape segment between two consecutive salient points
- Similar
  - Color, length, orientation
  - Neighbors
  - Subparts



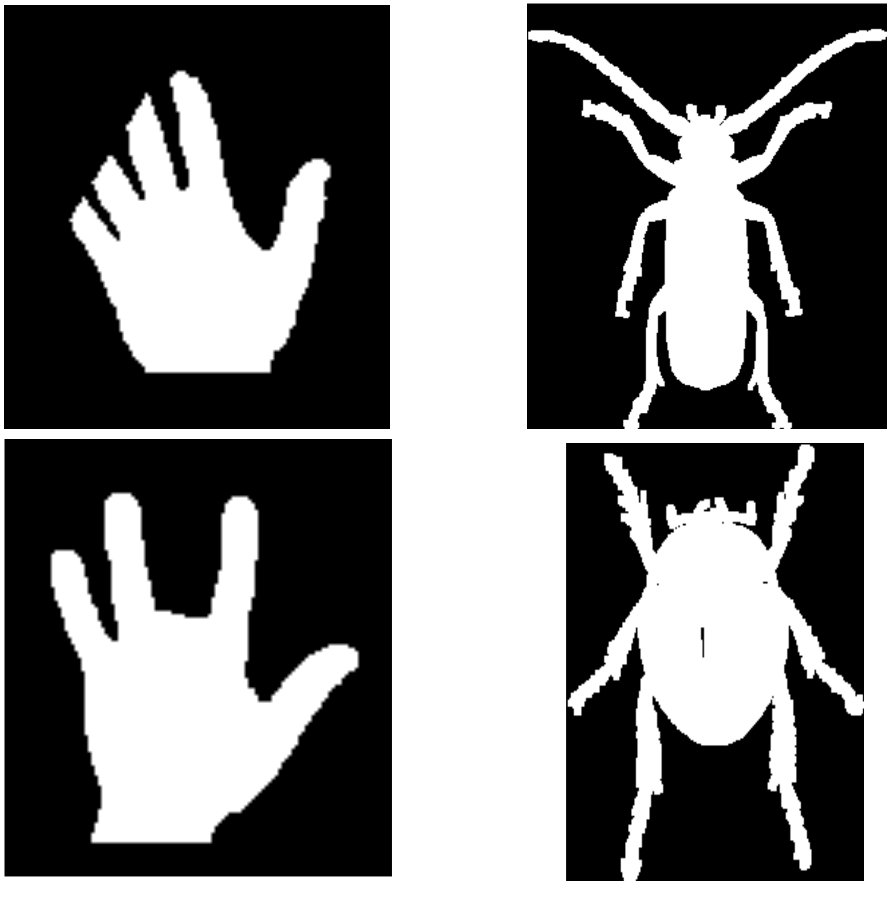
Goal

- Identify similar parts of deformable shapes
- Similar deformable shapes = Shapes of objects in the same class whose parts are subject to various transformations



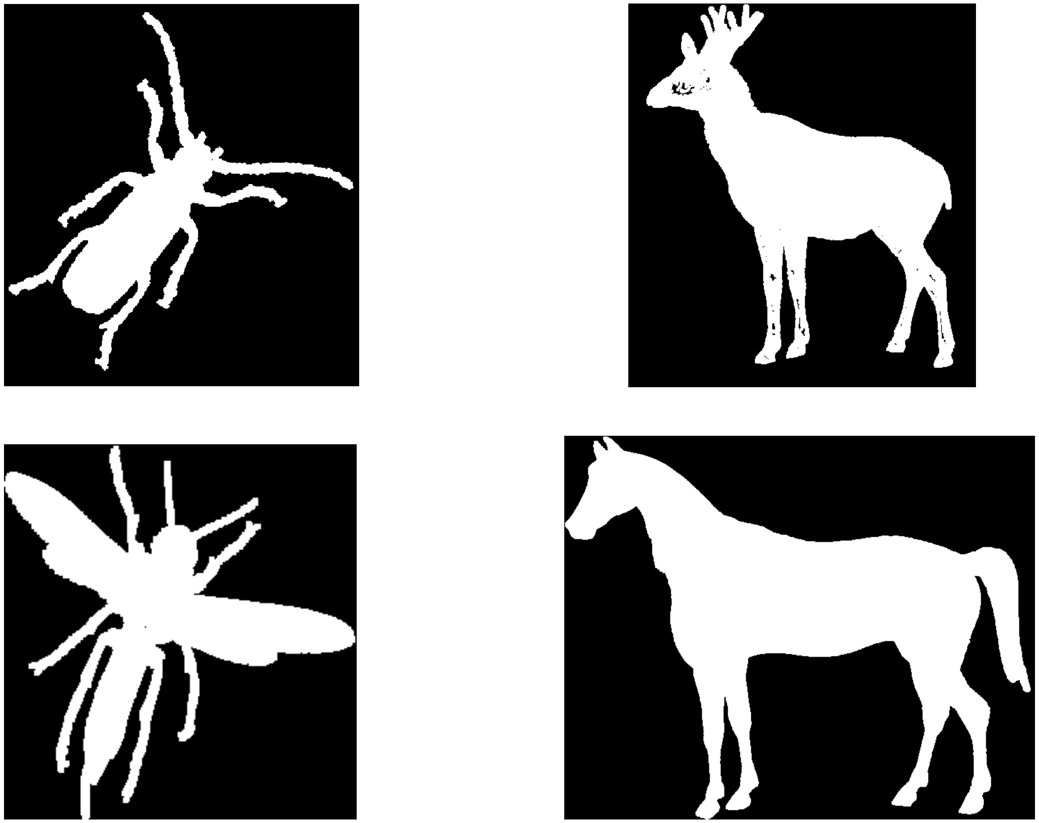
Example - Transformations

Some parts may be missing, or in excess



Challenges - Perception

Objects in different classes may have similar parts



Prior Work - Shape representation

- Arc trees [Günther et al. CVGIP 90]
  - Not invariant to part transformations
- Curvature scale-space [Mokhtarian et al. PAMI 92]
  - Requires image blurring and subsampling => info loss
- Markov-tree [Fan et al. ICCV 05]
  - Must specify the number, size and scale of parts
- Part-based signatures [Ling et al. PAMI 07]
  - Correct estimation of shape landmark points is critical
- Binary trees [Felzenszwalb et al. CVPR 07]
  - Fixed branching factor for all shapes

Prior Work – Shape Matching

- Edit distance [Bunke et al. PRL 83, Sebastian et al. PAMI 04]
  - Computationally expensive on large graphs
- Spectral [Siddiqi et al. IJCV 99, Shokoufandeh et al. PAMI 05]
  - Gives a match score, but not which parts got matched
- EM learning [Tu et al. ECCV 04]
  - No optimal solution, heuristic assumptions
- Max-clique of association graph [Pelillo et al. PAMI 99]
  - Appealing

Our Approach

- Accounting for shape parts is essential
  - Part representation => hierarchical graph
  - Identify similar parts => graph matching
- But how to formulate matching that
  - is invariant to transformations, and
  - gives perceptually valid solutions
- We use many to many matching

Problem statement

Given 2 shapes

Find all parts that have similar

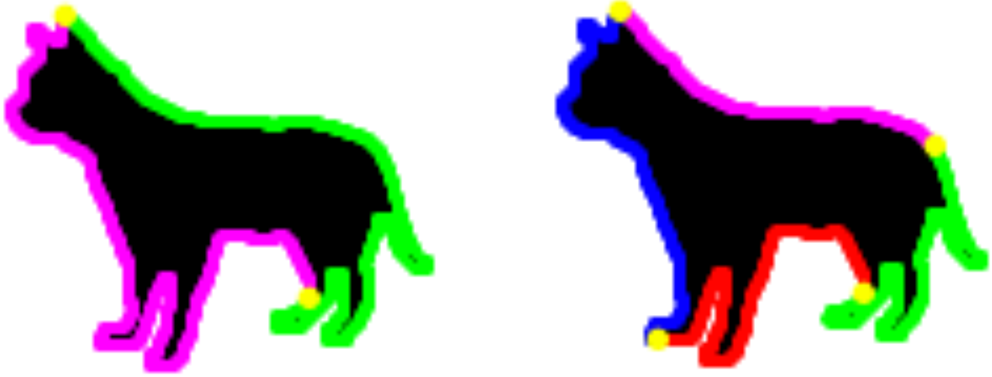
- Photometric properties (color)
- Geometric properties (length, orientation)
- Their neighbors relationships are similar
- Their subparts are similar

So that the matches maximally cover the two shapes

What are shape parts?

Shape parts

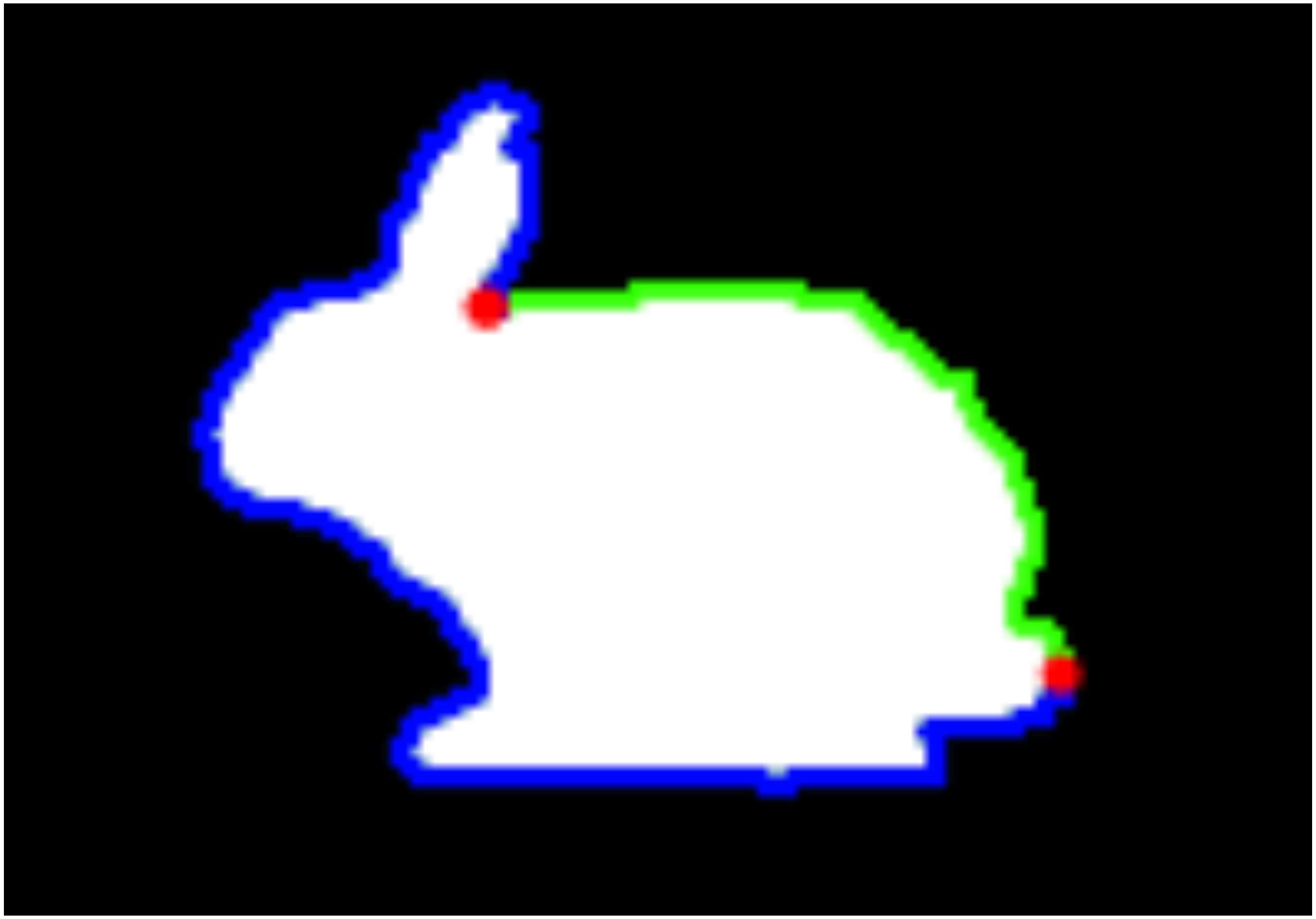
- Shape = Ordered sequence of salient points
- Salient points = Points with high [Teh,Chin PAMI 89]:
  - Curvature
  - Region of support
- Part = shape segment between 2 consecutive salient points
- Saliency is a matter of scale



Hierarchical Shape Tree

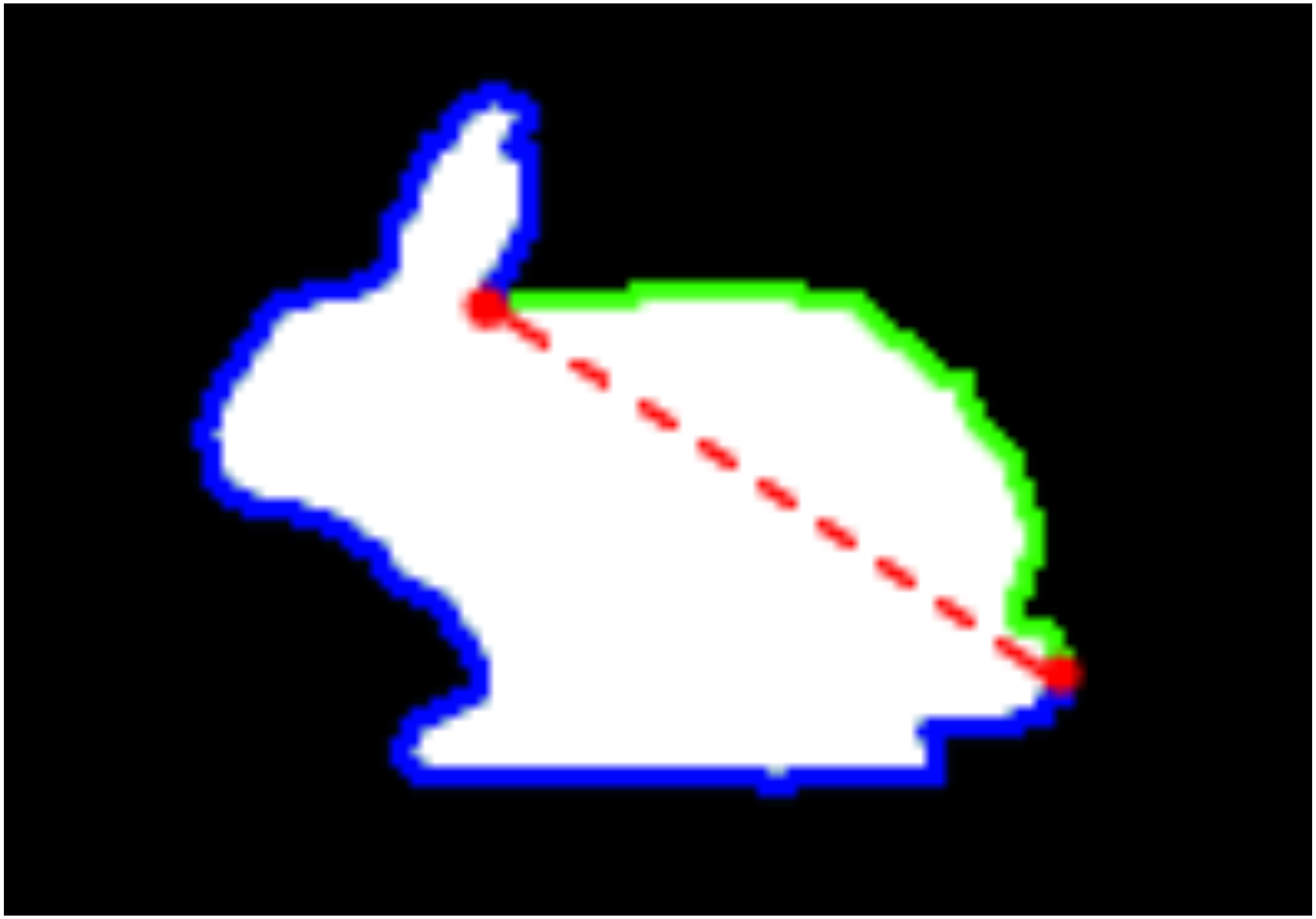
Original shape

Hierarchical Shape Tree



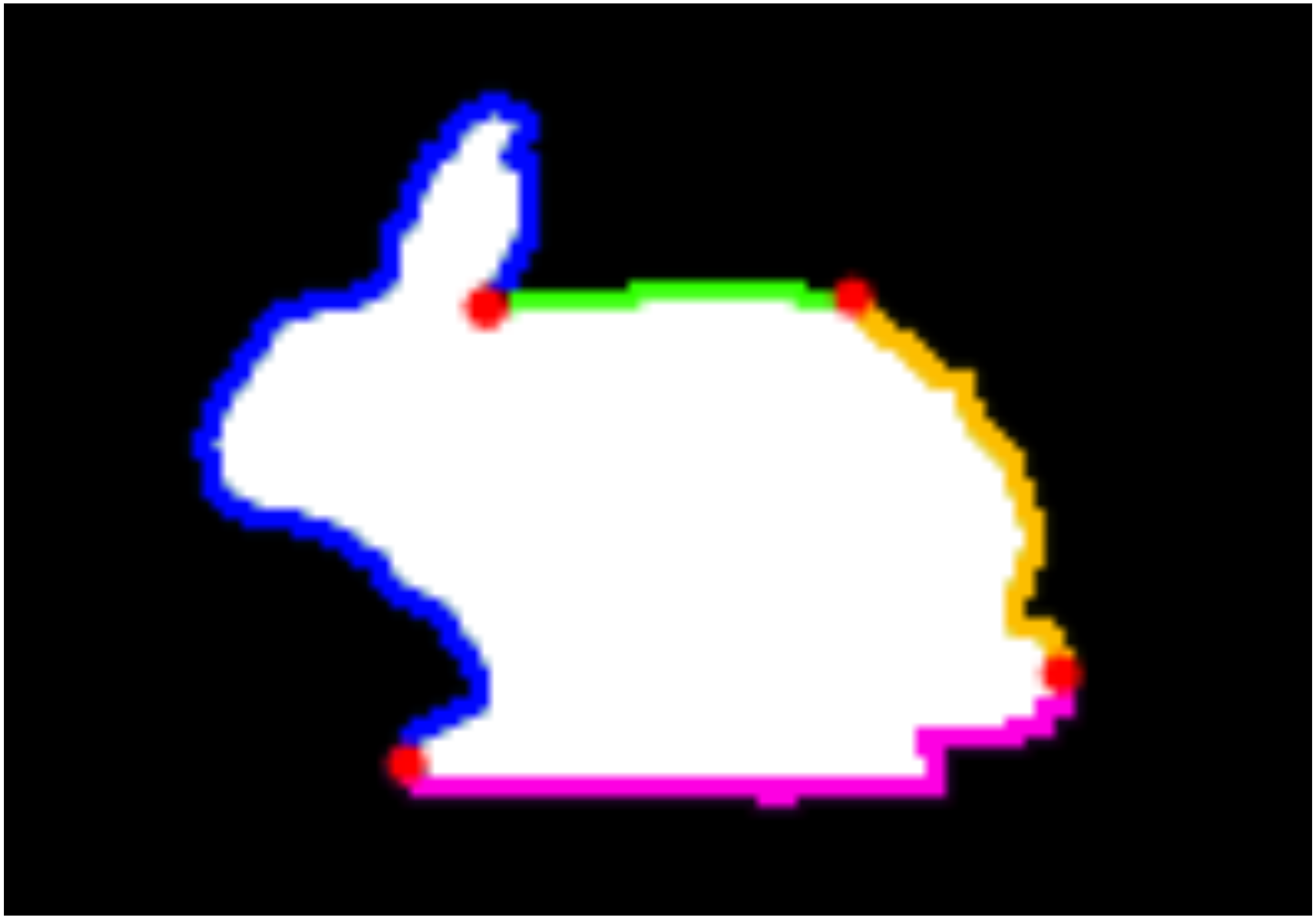
First level

Hierarchical Shape Tree



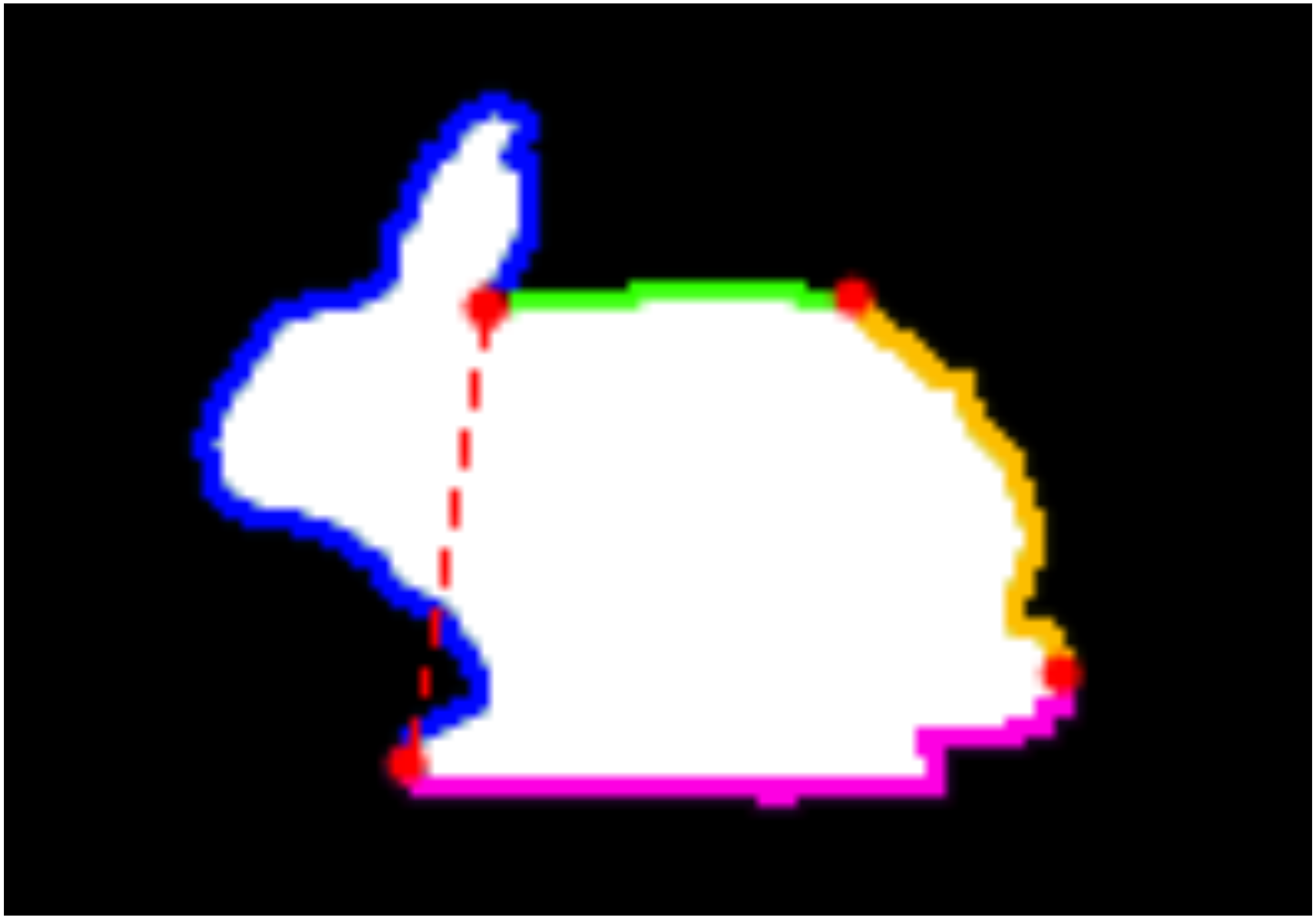
Error estimation

Hierarchical Shape Tree



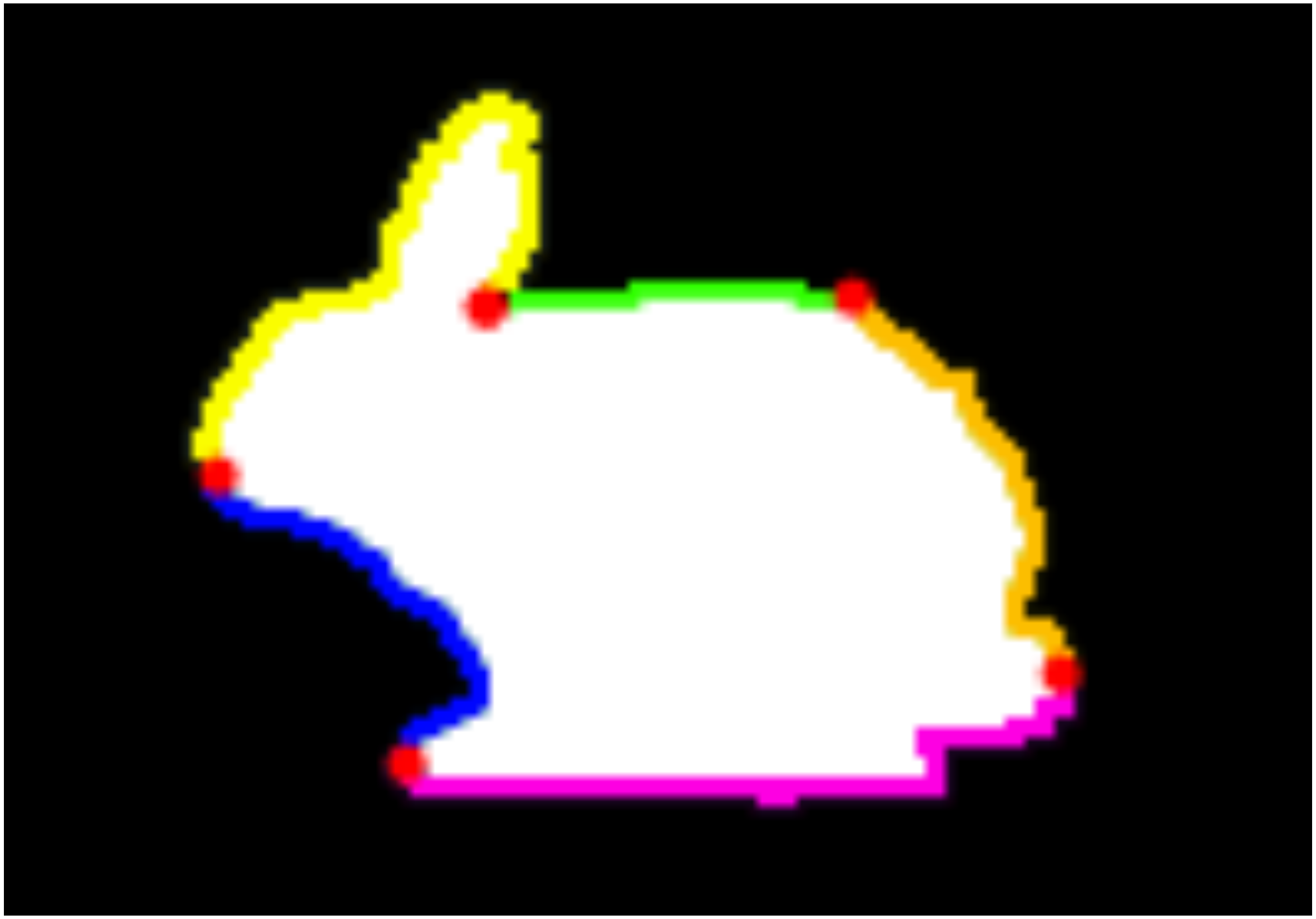
Second level

Hierarchical Shape Tree



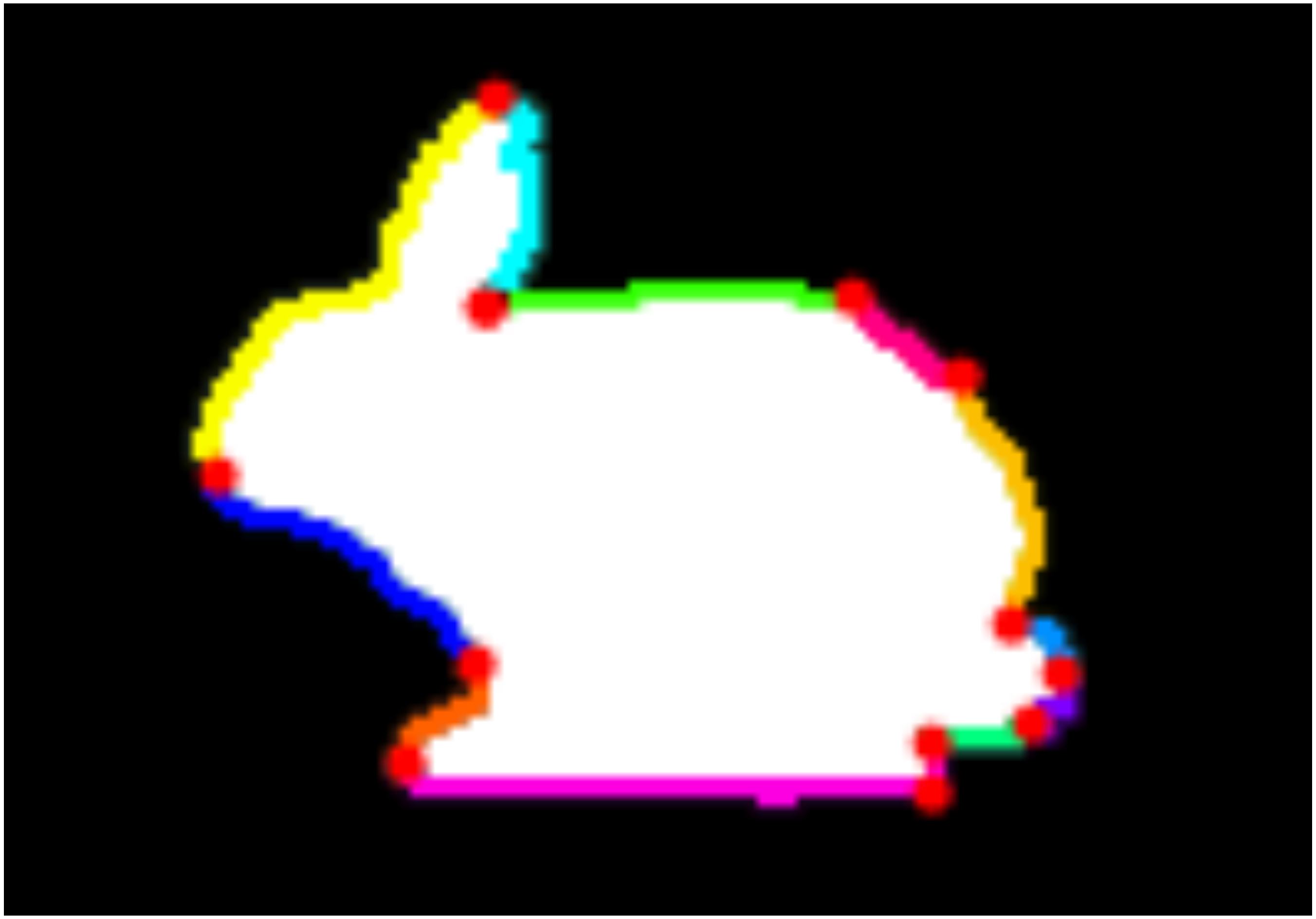
Error estimation

Hierarchical Shape Tree



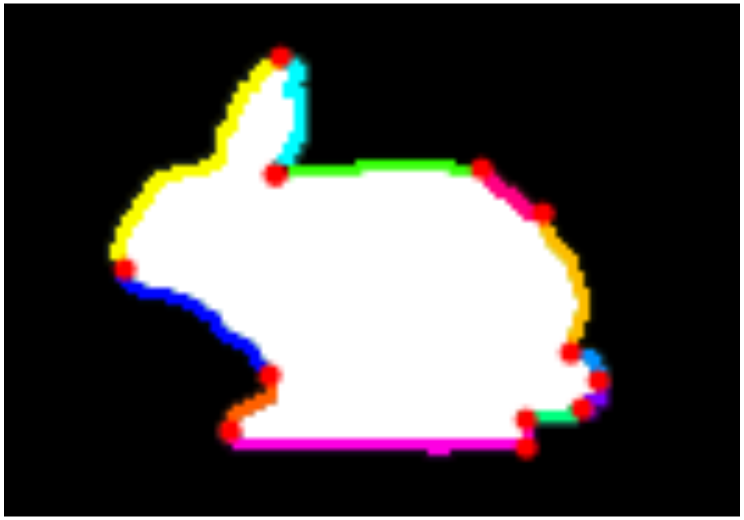
Third level

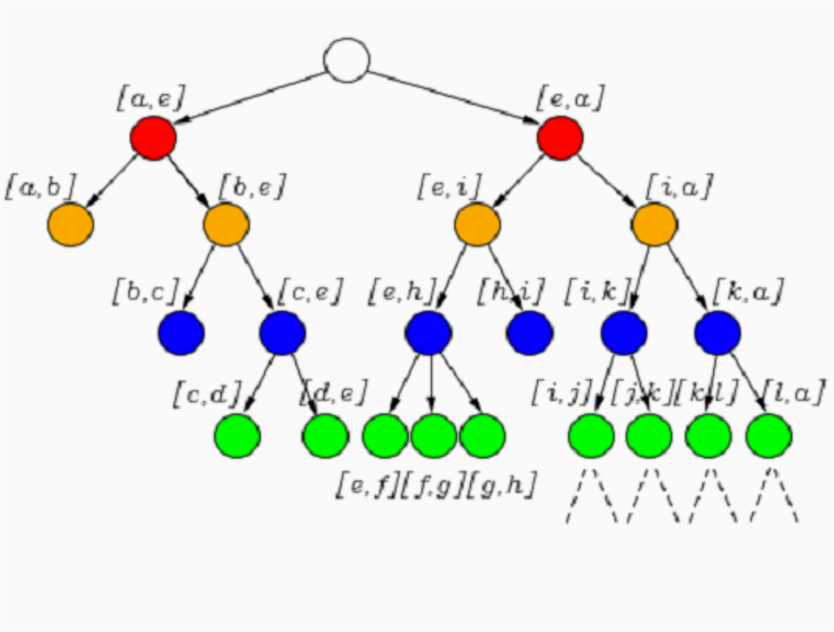
Hierarchical Shape Tree



Final level

Hierarchical Shape Tree





- Data-driven
  - number of nodes
  - hierarchical levels
  - branching factors
- Approximately 50 nodes per shape

Attributes Associated with Nodes

- Pixel-intensity contrast
- Relative length wrt parent
- Relative orientation wrt parent
- Error of straight line approximation
- Bookstein coordinates of middle point

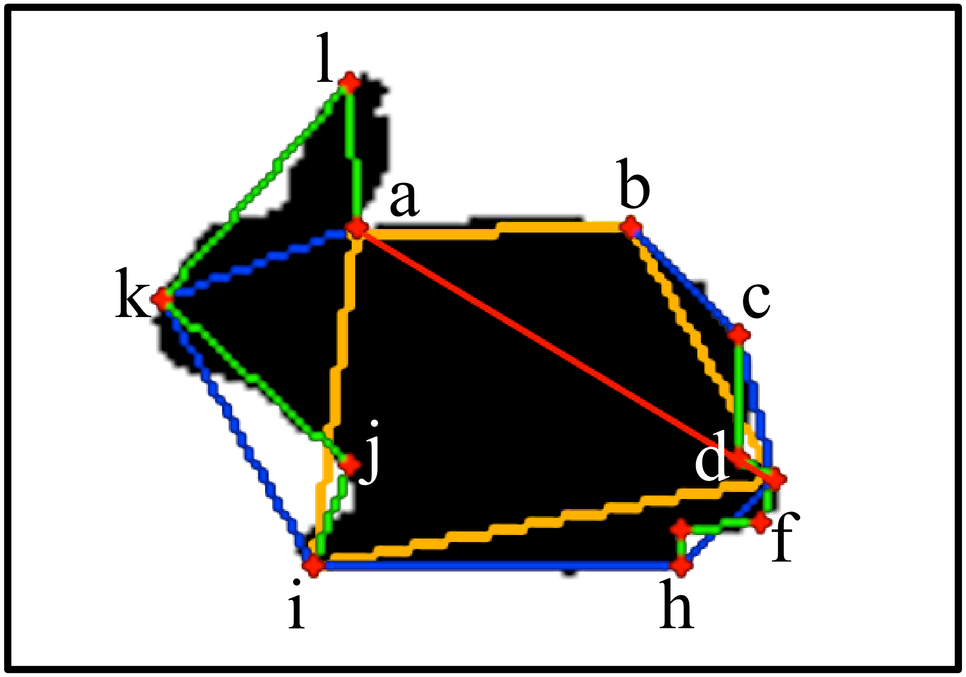
Edges

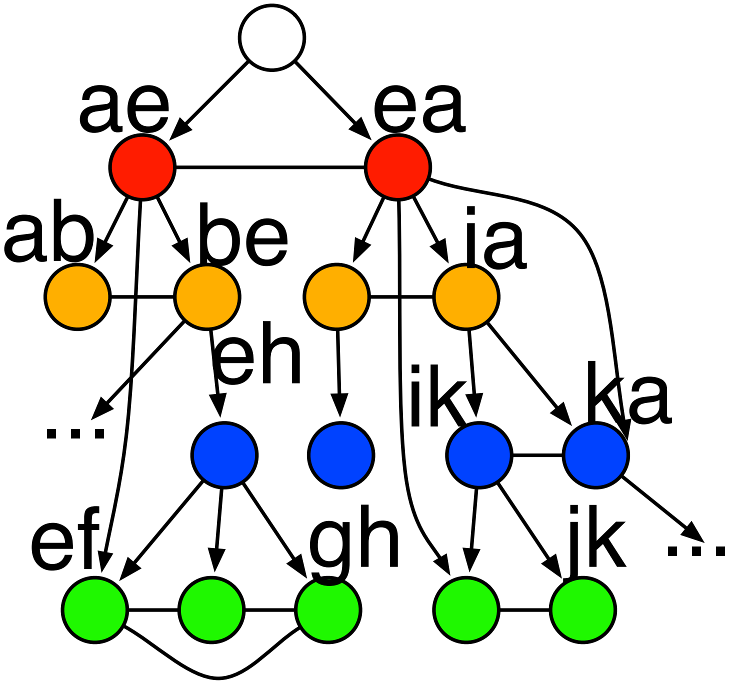
- Capture neighbor relationships
  - Two parts are neighbors if
    - Touch
    - Are siblings
- Capture scale relationships
  - Two parts are ascendant-descendant if
    - Part of

Attributes Associated with Edges

- Neighbor edge
  - Strength of neighbor relationship (distance)
- Ascendant/Descendant edge
  - Strength of part-of relationship (ratio of lengths)

Hierarchical Shape Representation





For clarity, we present only a few nodes and edges

Matching

- Given two graphs G=(V,E) and G'=(V',E')
- Minimize the cost

$$C = \beta \sum_{v \in V} c_1(v, f(v)) + (1-\beta) \sum_{(v,u) \in E} c_2(v, f(v), u, f(u))$$

c_1 = cost of matching nodes v and *v'=f(v)*

c_2 = cost of matching edges *(v,u)* and *(v',u')*

β = weights the relative significance of c_1 vs. c_2

Linearization and Relaxation

$$C=\beta\sum\nolimits_{v\in V}c_1(v,f(v))+(1-\beta)\sum\nolimits_{(v,u)\in E}c_2(v,f(v),u,f(u))$$

$$\Downarrow$$

$$X=[010010010...]^{\mathrm{T}},\quad x_{vv'}\in\left\{0,1\right\}\text{ indicator}$$

Linearization and Relaxation

$$C = \beta \sum\nolimits_{v \in V} c_1(v, f(v)) + (1 - \beta) \sum\nolimits_{(v,u) \in E} c_2(v, f(v), u, f(u))$$

$$\Downarrow$$

$$X = [010010010\ldots]^{\mathrm{T}}, \quad x_{vv'} \in \{0,1\} \text{ indicator}$$

$$\Downarrow$$

$$x_{vv'} \in [0,1] \text{ real number}$$

Linearization and Relaxation

$$C = \beta \sum_{v \in V} c_1(v, f(v)) + (1 - \beta) \sum_{(v,u) \in E} c_2(v, f(v), u, f(u))$$

$$\Downarrow$$

$$\min_X [\beta A^T X + (1 - \beta) X^T B X],$$

$$s.t. \;\; \forall v' \in V, \;\; \sum_{v \in V} x_{vv'} = 1$$

$$and \;\; \forall v \in V, \;\; \sum_{v' \in V} x_{vv'} = 1$$

$$and \;\; x_{vv'} > 0$$

Solving

$$\min_X [\beta A^T X + (1-\beta) X^T B X]$$

- Build matrix $W = \beta \, \mathrm{diag}(A) + (1-\beta) B$

- Reverse costs to similarities: $S = 1 - W$

=>

$$\max_X X^T S X$$

$$\text{s.t. } X \in \Delta$$

=> Maximal clique solution

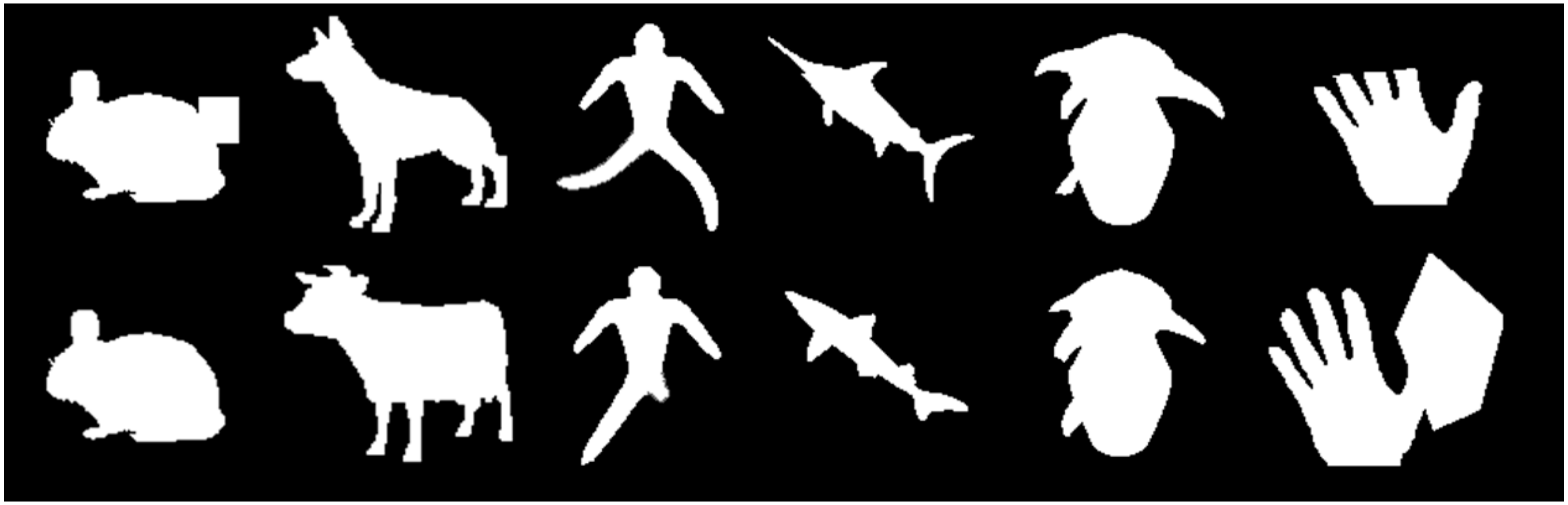
simplex

Many-to-Many Matching

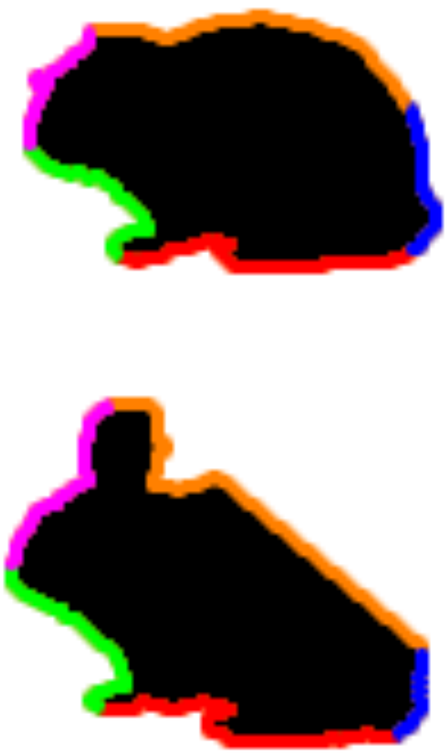
- One-to-many matching in one direction
- One-to-many matching in the other direction
- Take intersection of both matching

Results

- Brown dataset (99 images, 9 classes)
- MPEG-7 dataset (1400 images, 70 classes)
- Challenges: deformation, occlusion, missing parts



Qualitative Results – Same class



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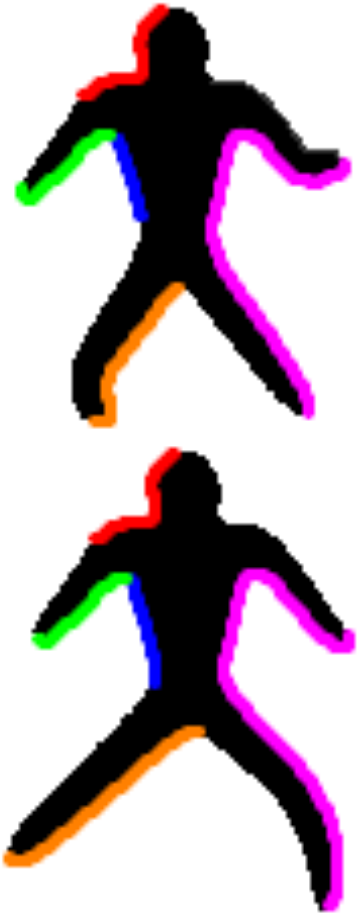

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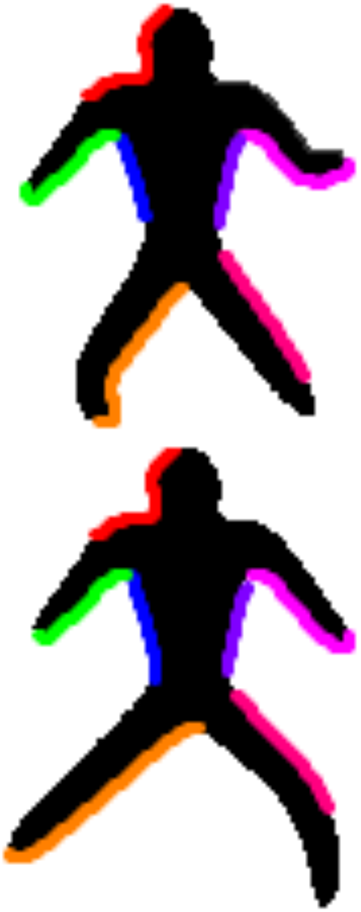

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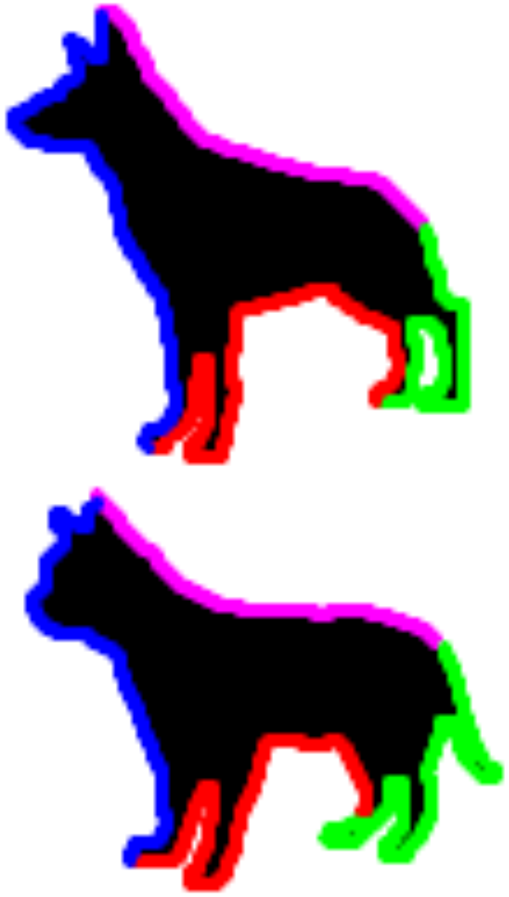

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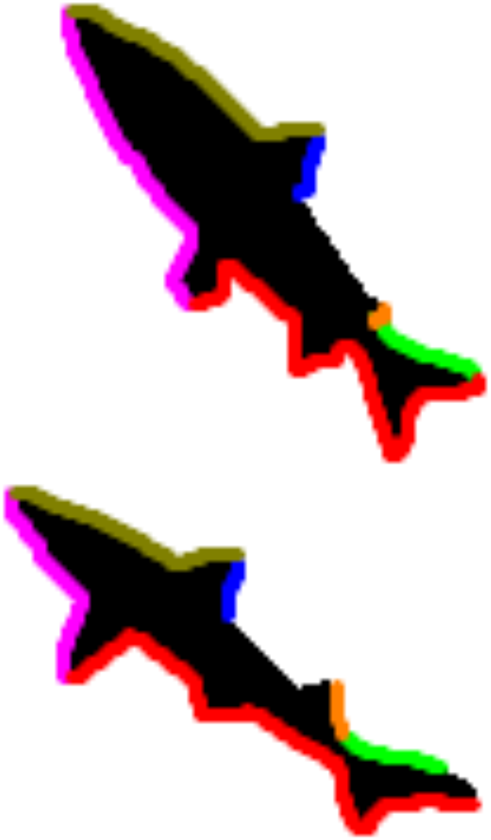
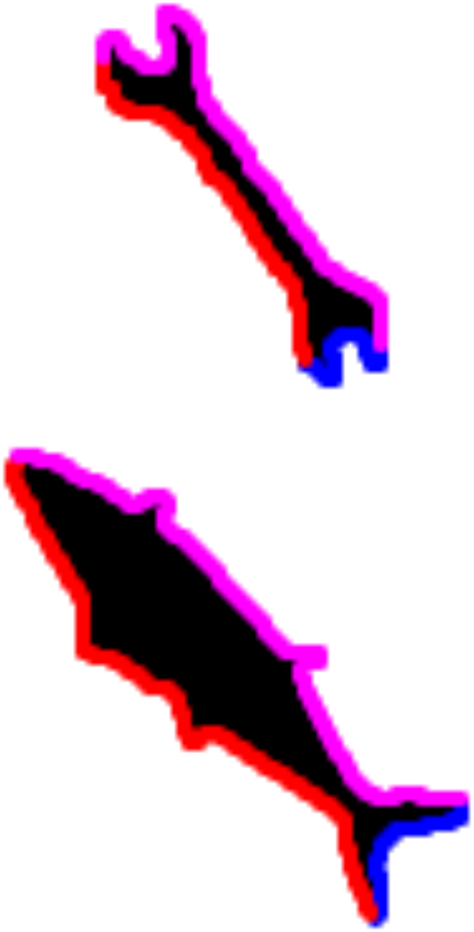
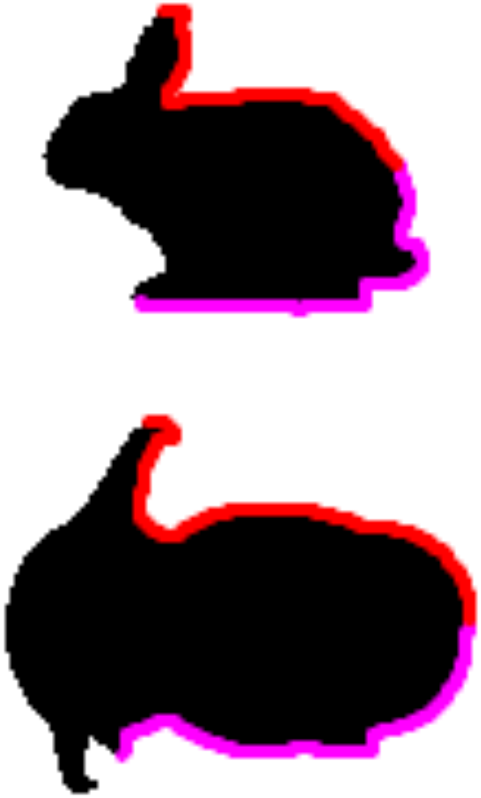


Qualitative Results – Different classes

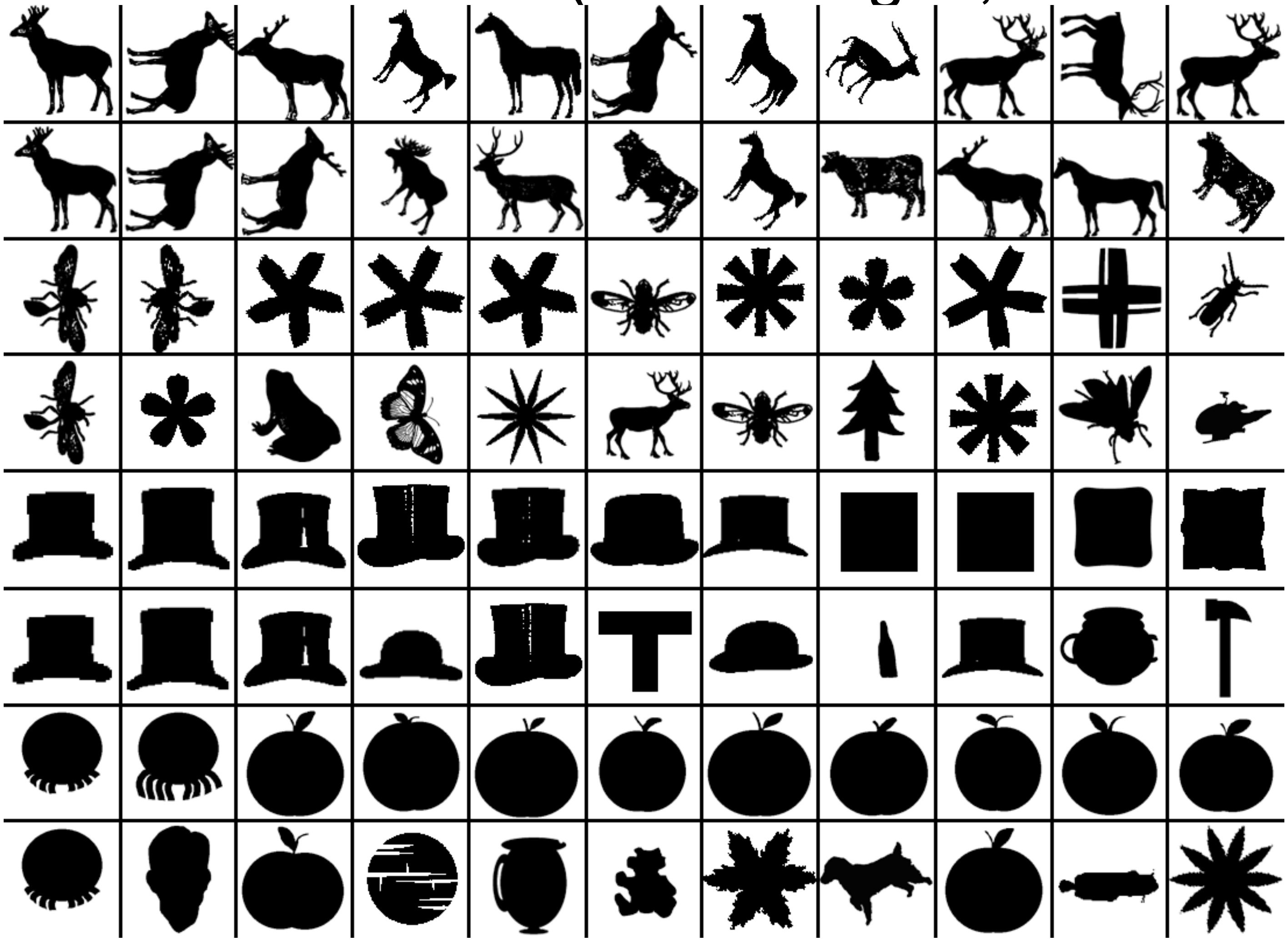


Qualitative Results – Different classes



Retrieval Results

- MPEG-7 dataset (1400 images, 70 classes)



Thank you!