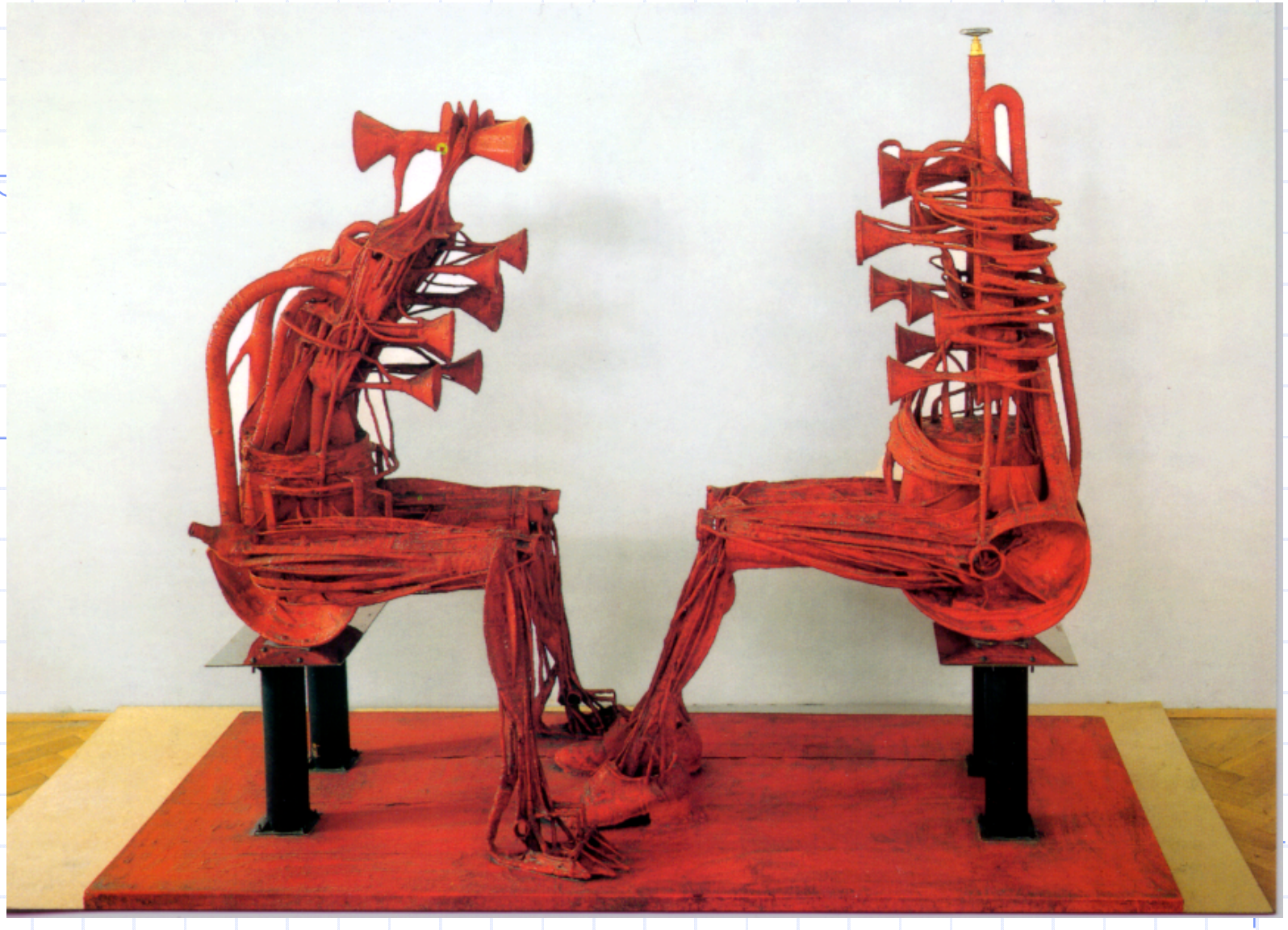
Beyond One-to-One Feature Correspondence: The Need for Many-to-Many Matching and Image Abstraction

Sven J. Dickinson

Department of Computer Science

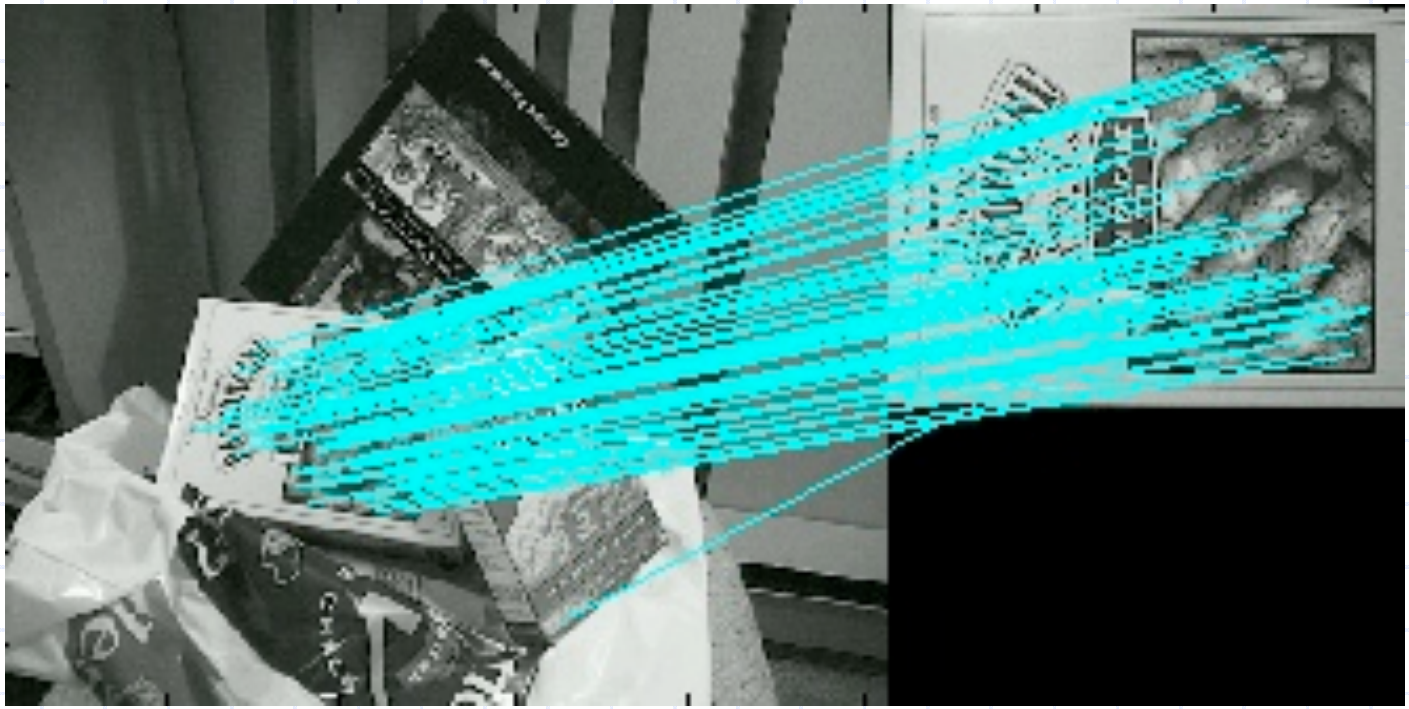
University of Toronto

SIG Workshop, June 21, 2009

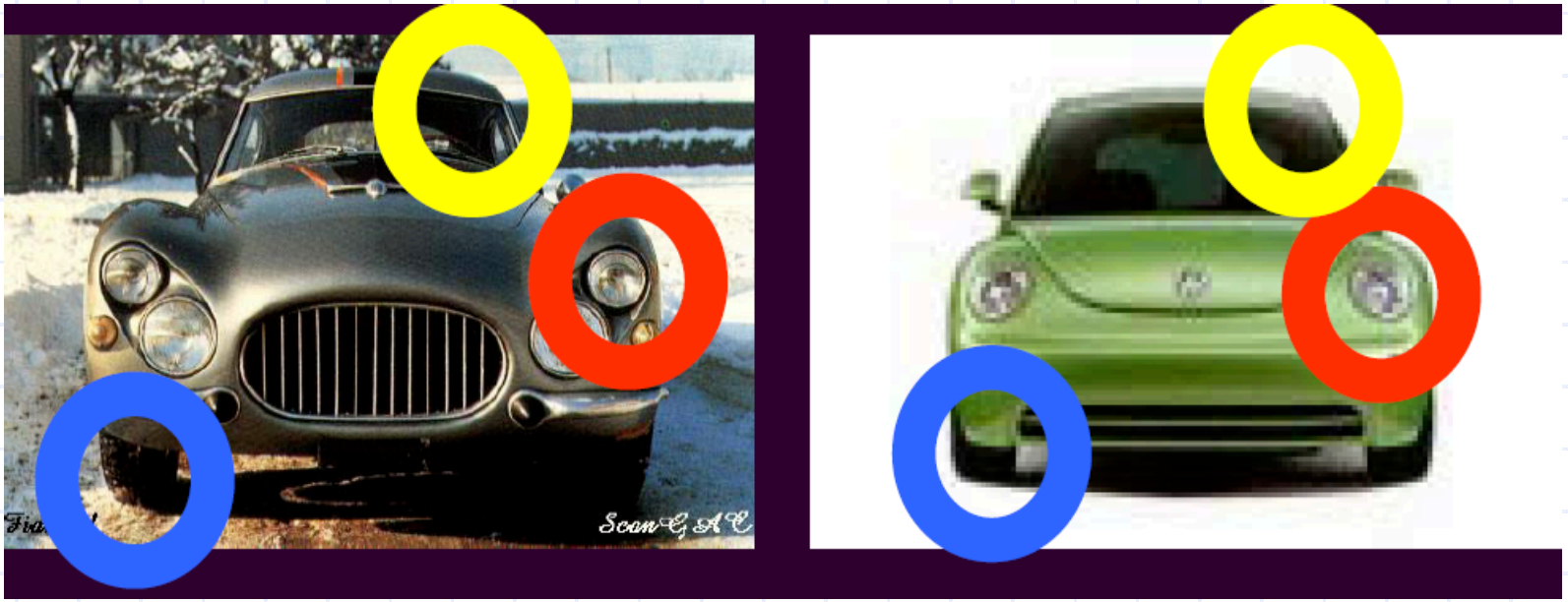


Great Dialog, Karel Nepras, 1966 (Prague National Gallery)

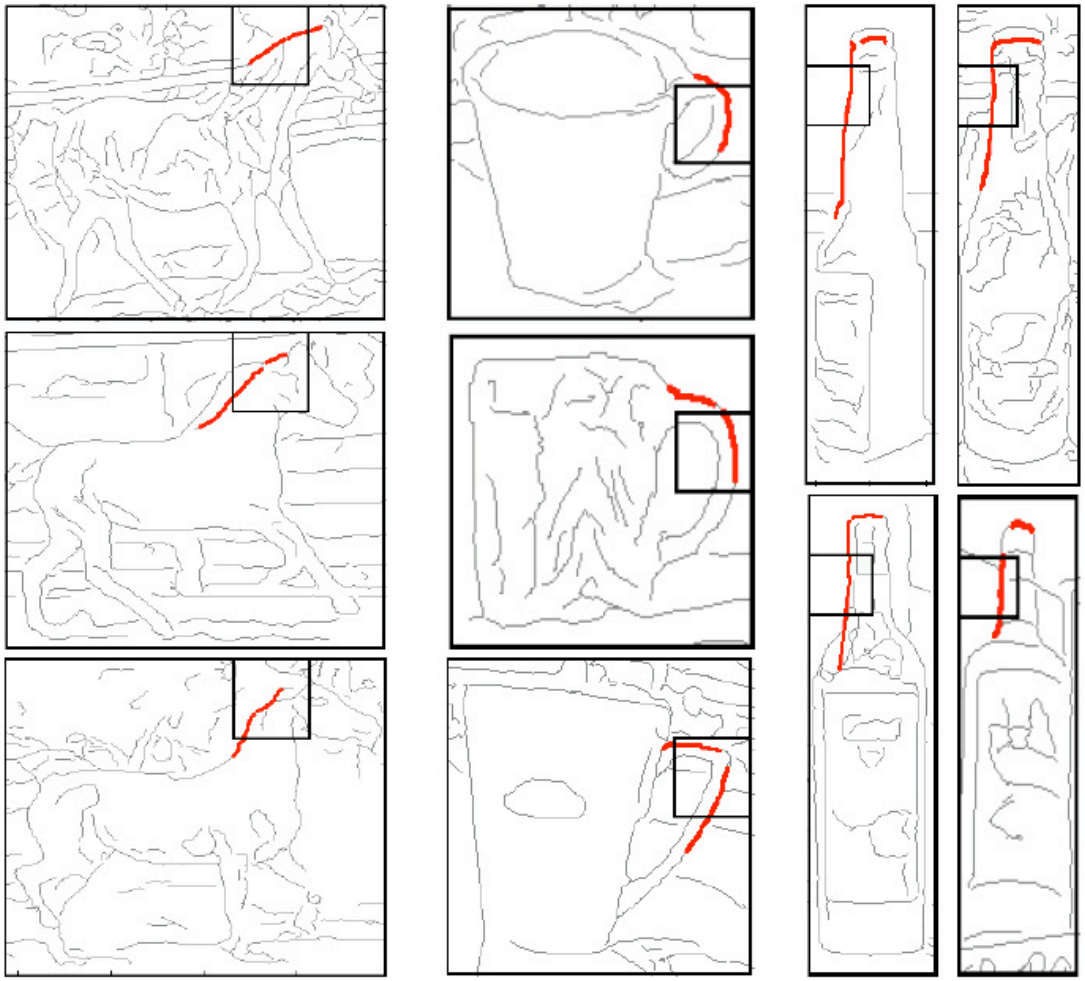
Great Dialog, Karel Nepras, 1966 (Prague National Gallery)
Memory Figure Sitting on a Stool, Akan Culture, Ghana



Lowe (IJCV, 2004)

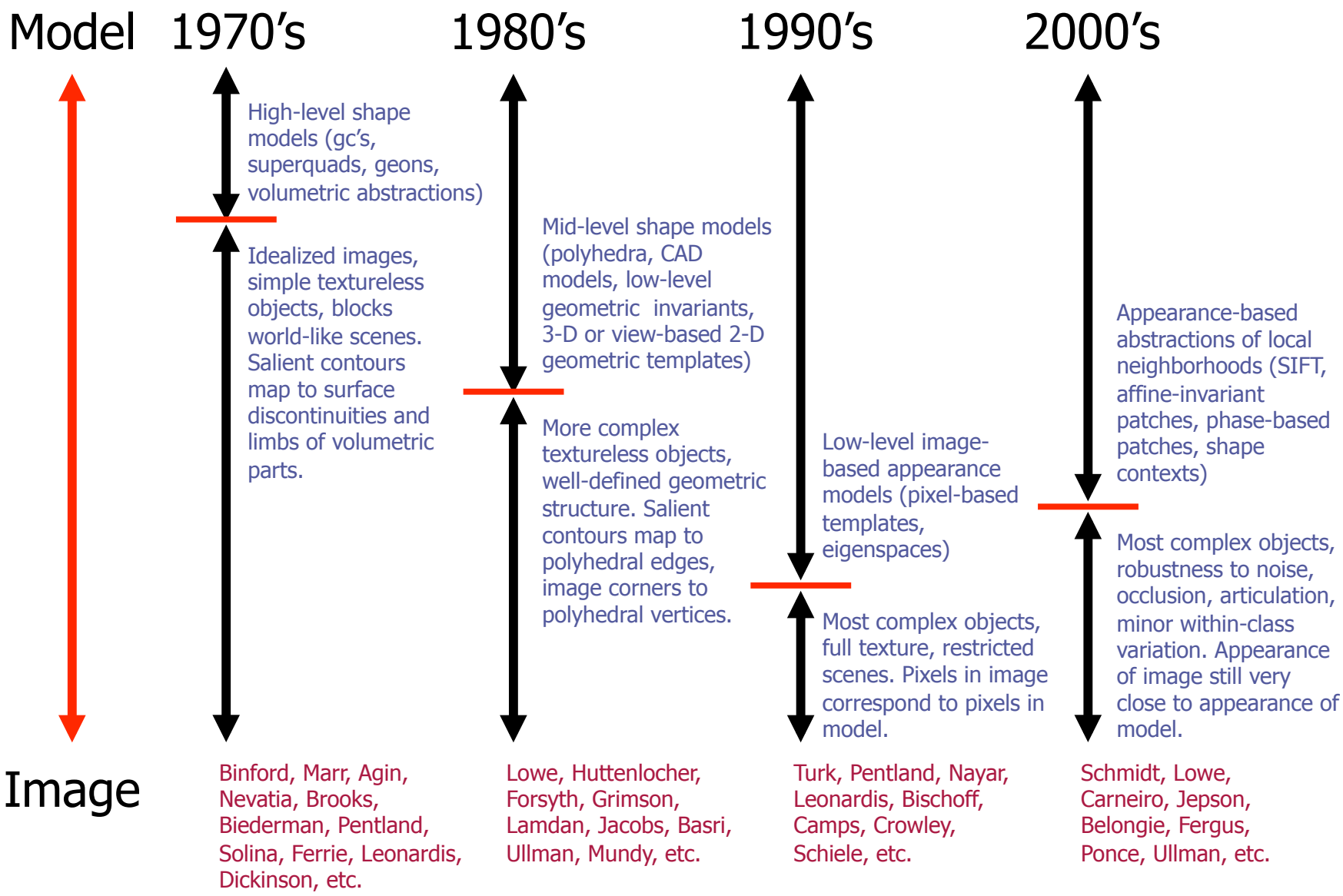


Fergus, Perona, and Zisserman (IJCV, 2007)

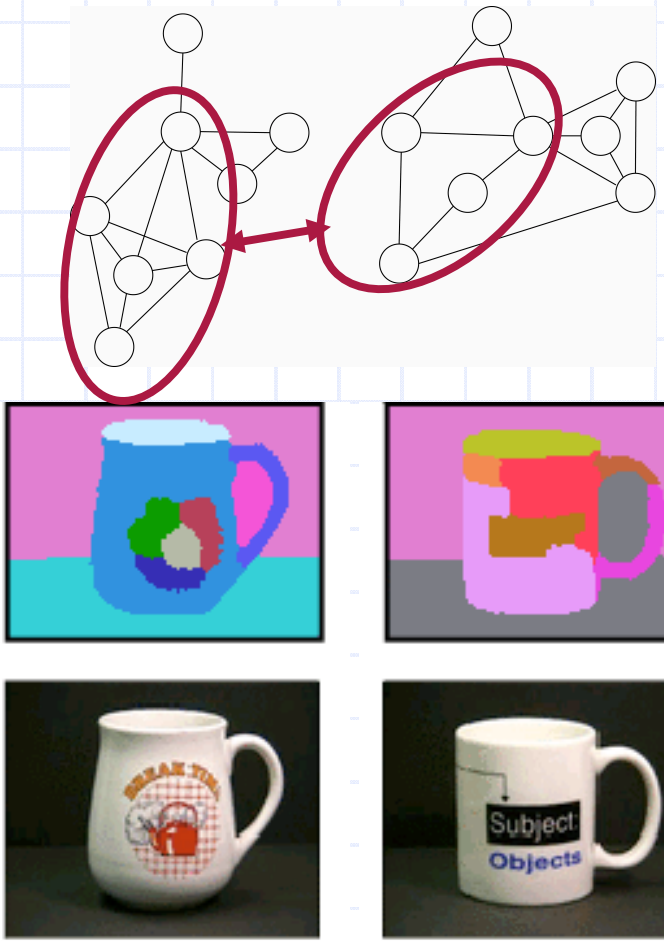


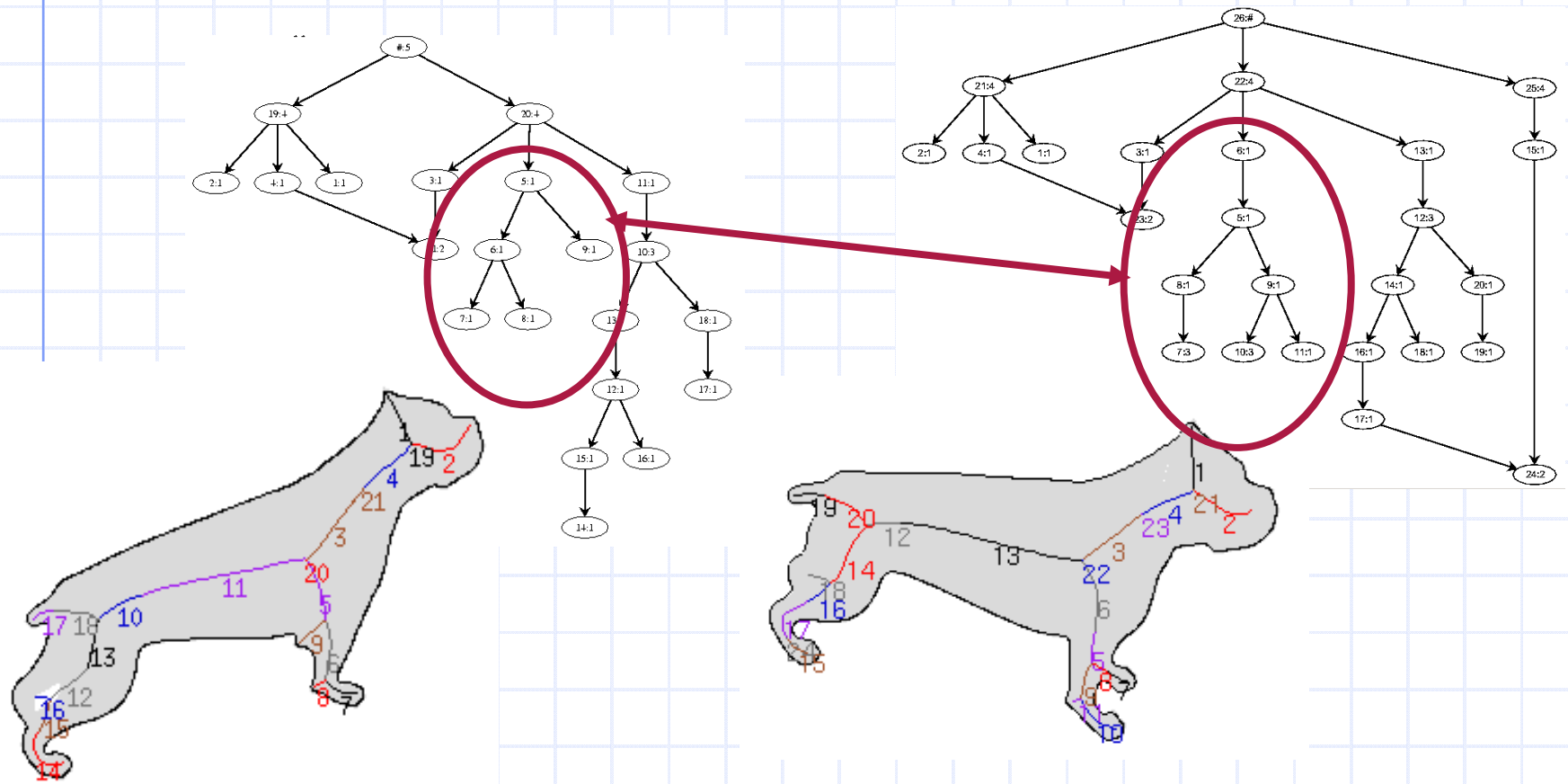
V. Ferrari, L. Fevrier, F. Jurie, and C. Schmid (PAMI, 2008)

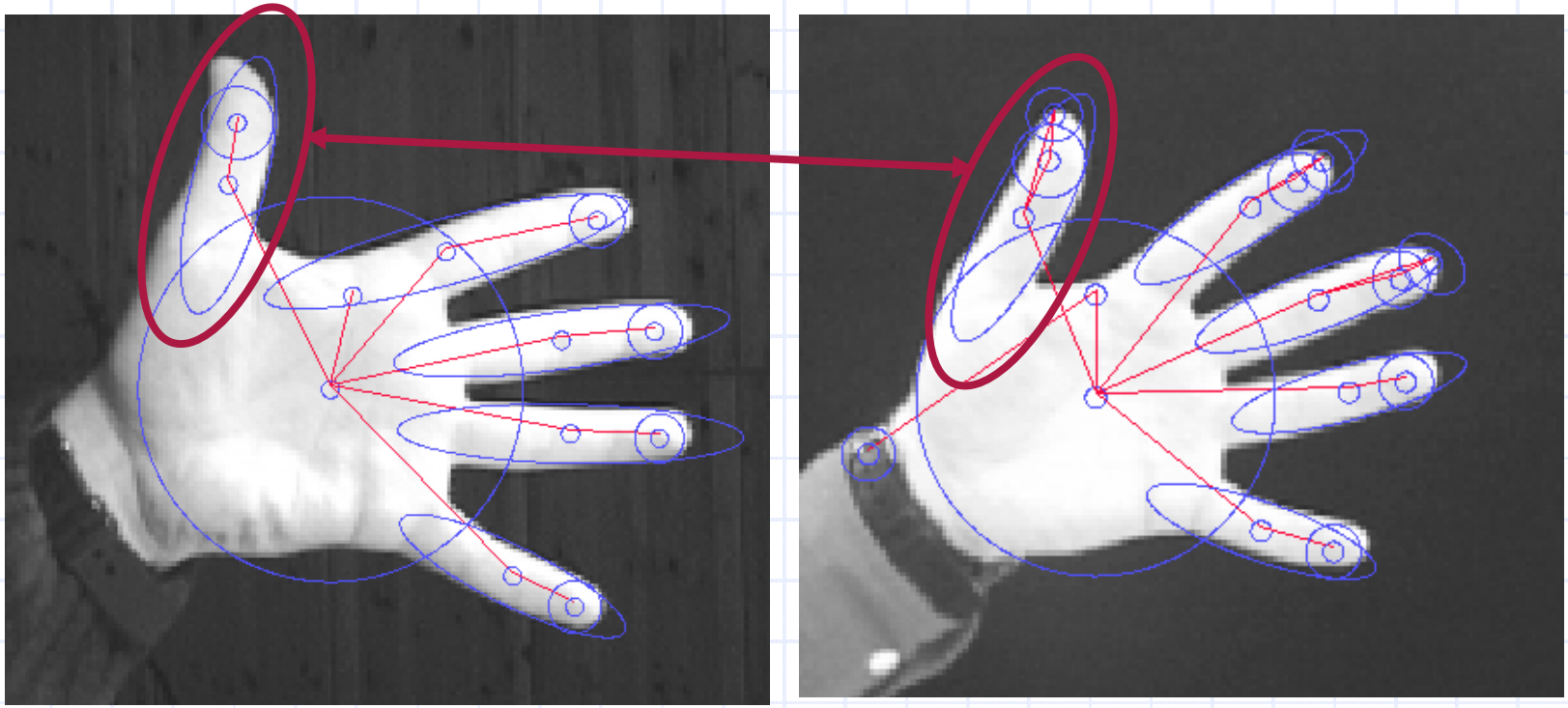
A Clear Trend



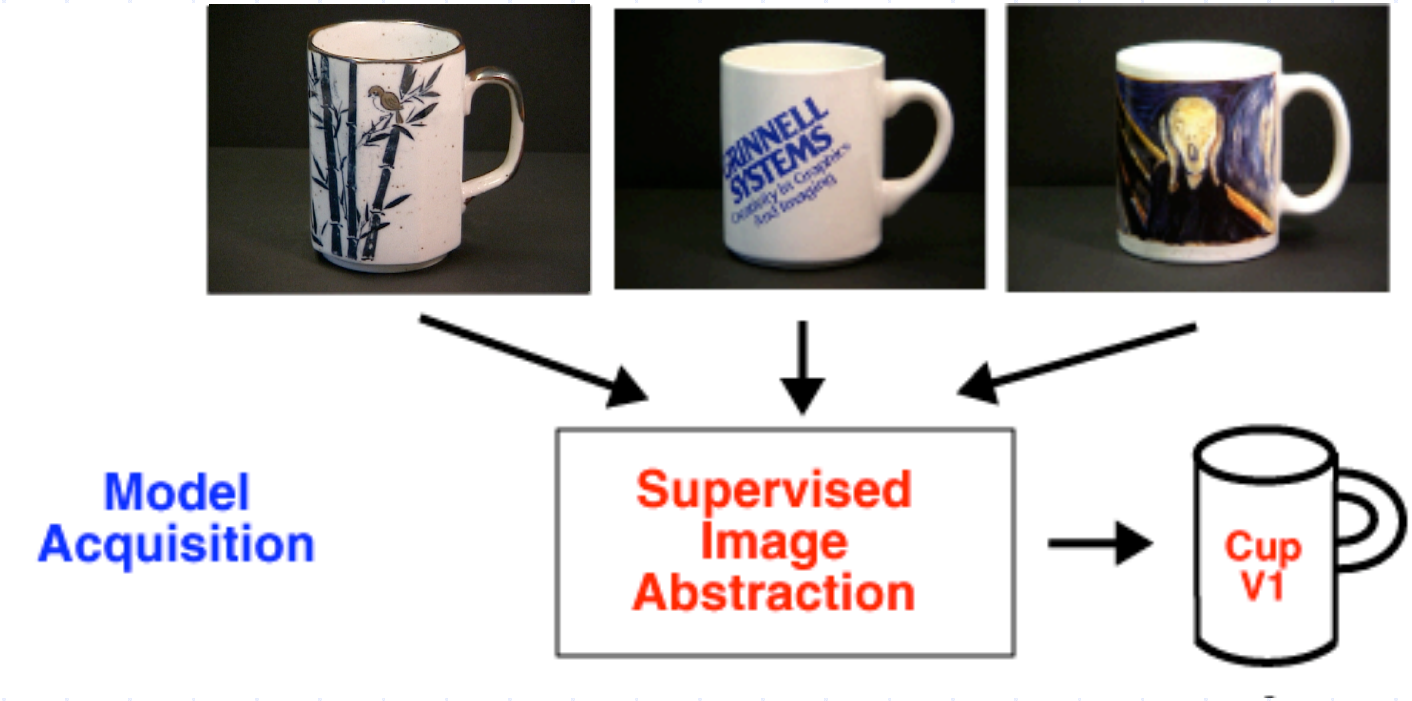
Example Domains




#:5
19:4
20:4
2:1
4:1
1:1
3:1
5:1
11:1
12:2
6:1
9:1
10:3
7:1
8:1
13:1
18:1
17:1
12:1
15:1
16:1
14:1
26:#
21:4
22:4
25:4
2:1
4:1
1:1
3:1
6:1
13:1
15:1
23:2
5:1
12:3
8:1
9:1
14:1
20:1
7:3
10:3
11:1
16:1
18:1
19:1
17:1
24:2



1. Model-Based Graph Abstraction from Examples



Keselman and Dickinson (PAMI 05)

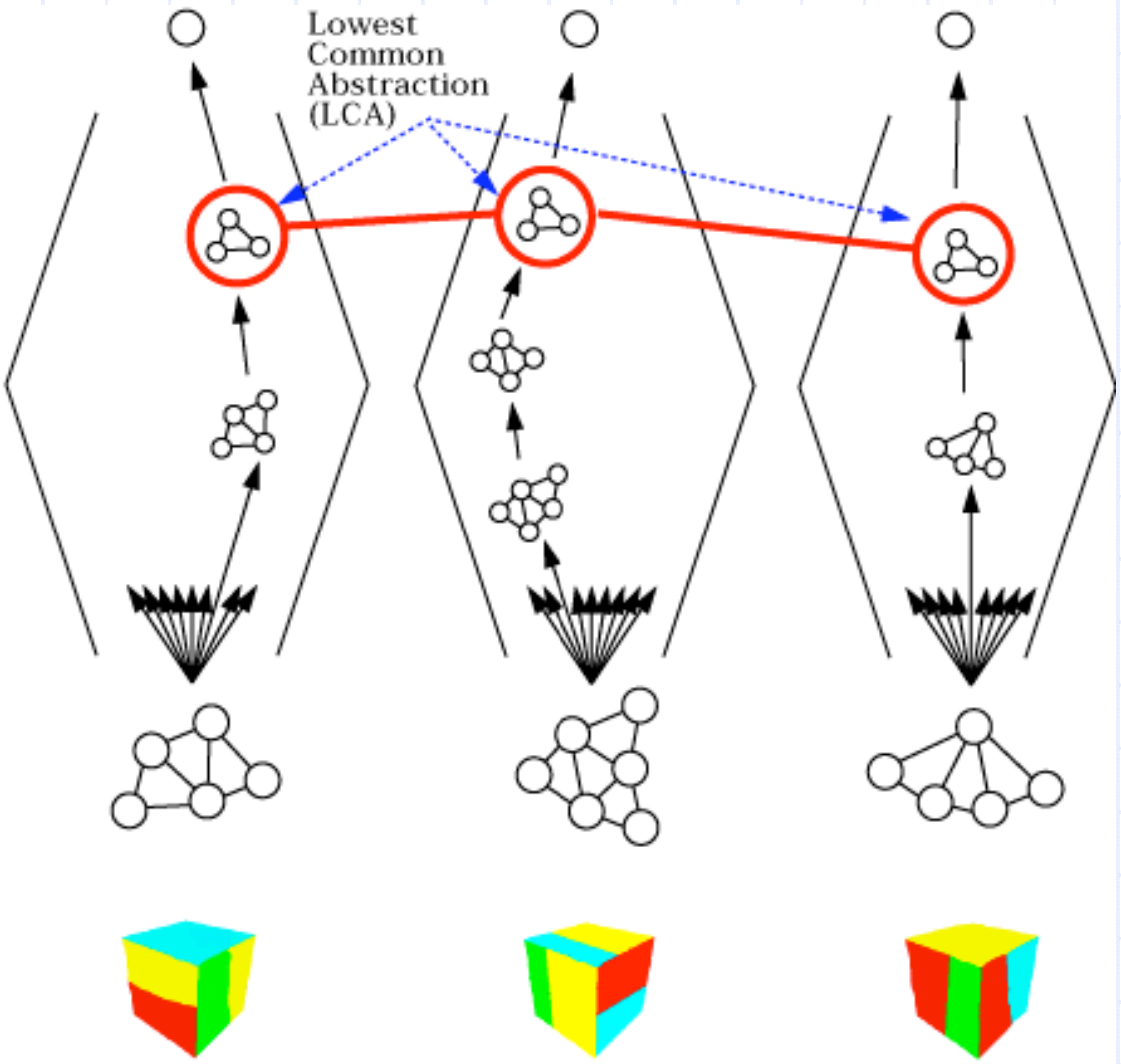
Problem Formulation

The top of the lattice is the silhouette (all regions merged into one)

Lattice representing the space of all possible region adjacency graphs resulting from merging a pair of adjacent regions

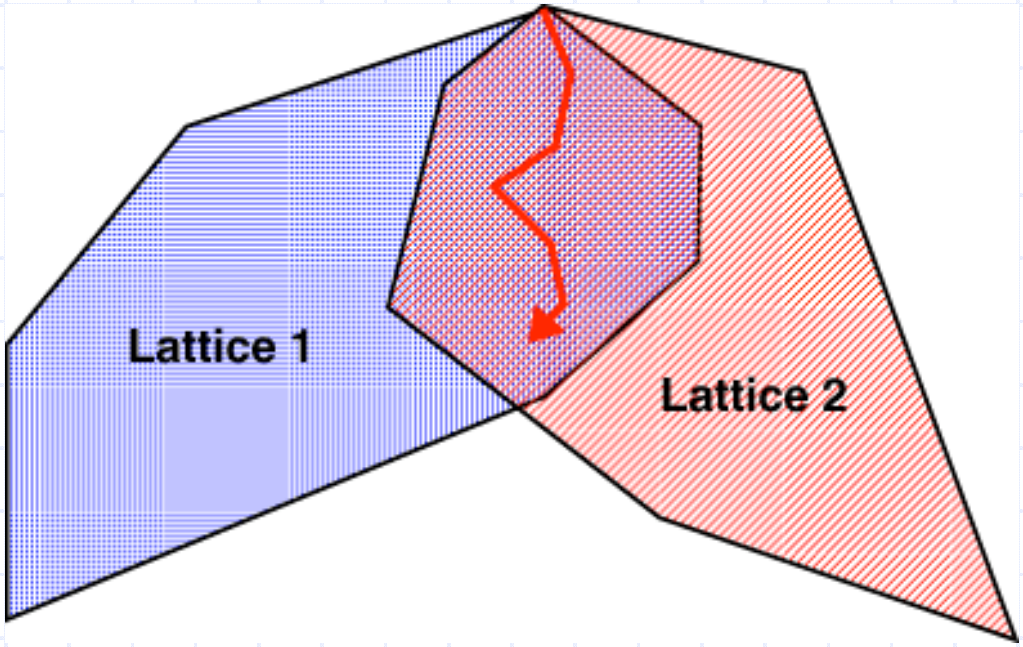
Initial region adjacency graph

Input image containing exemplar object



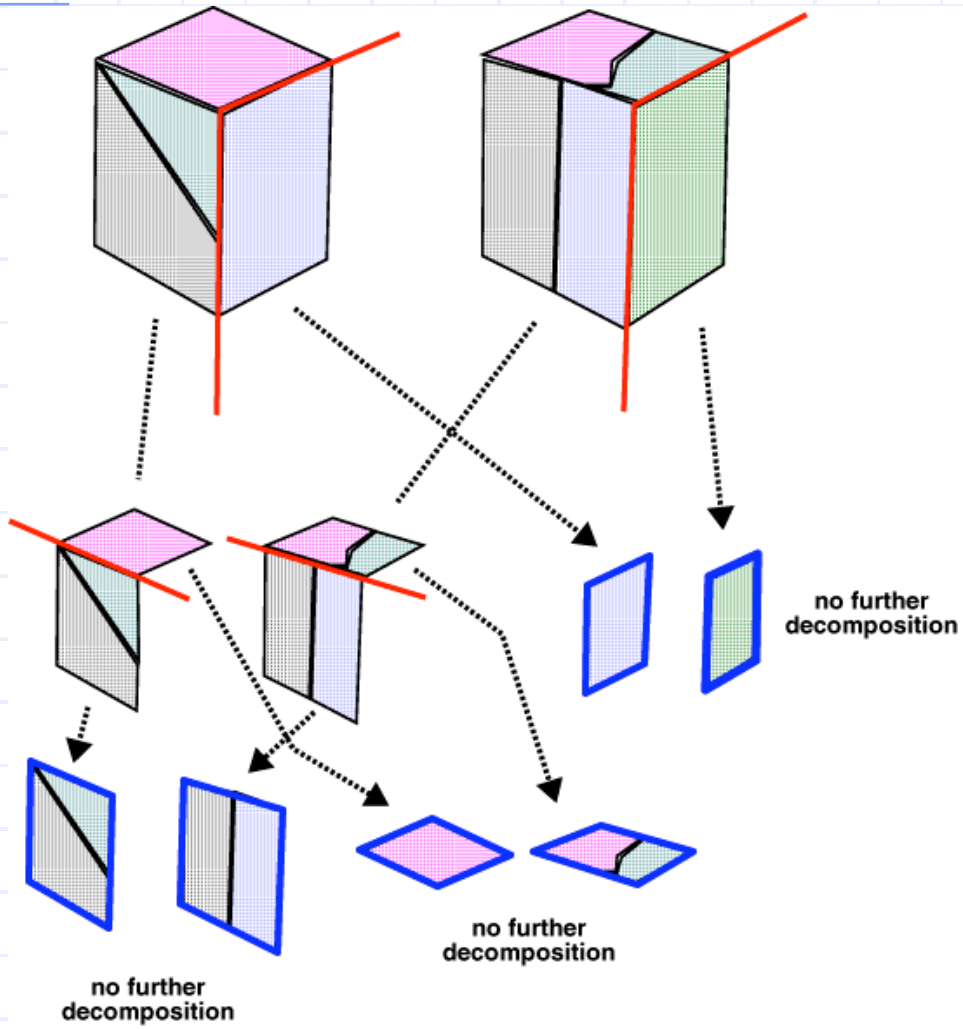
The LCA of Two Lattices

Computing the intersection of two lattices is still intractable.



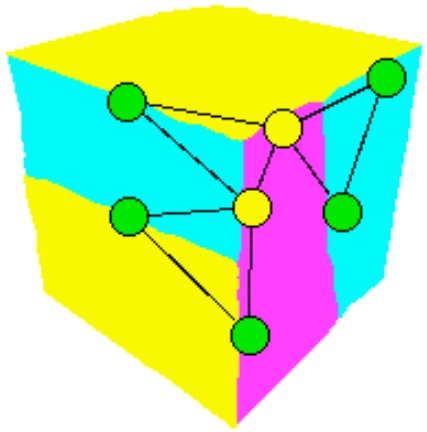
However, we do know one element of the intersection set!

Recursive Decomposition



The Search for Corresponding Cuts

First, form a dual graph representation:

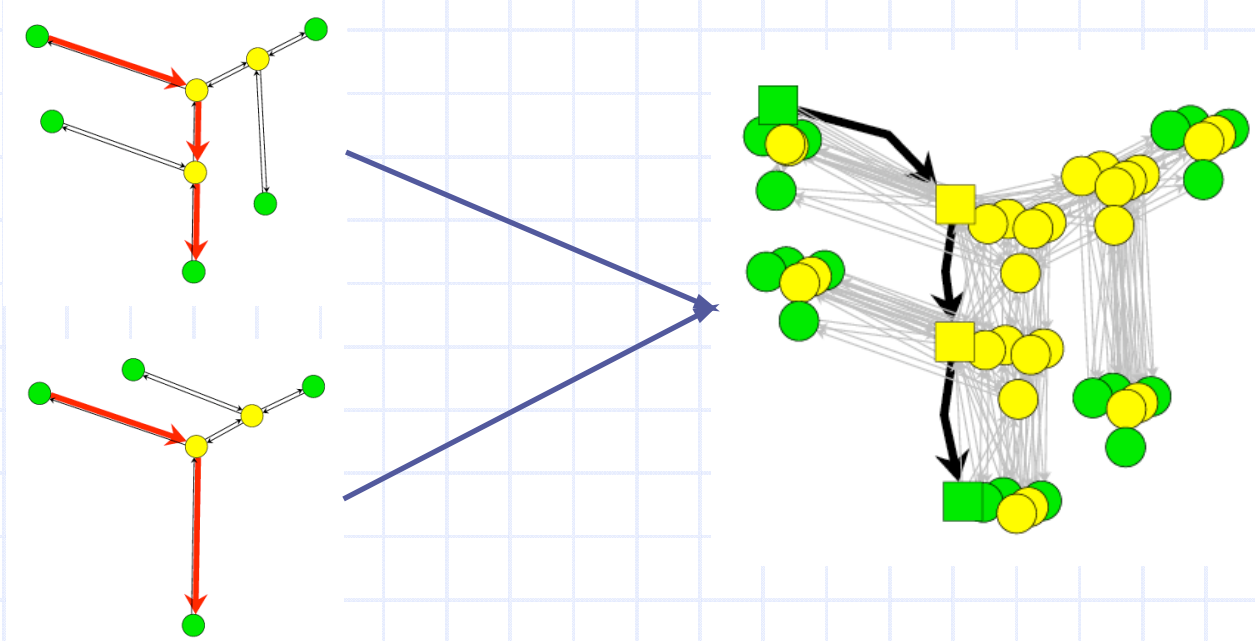


boundary segment graph.

A cut in the original region adjacency graph is a path through its dual boundary segment graph.

Combining the Dual Graphs

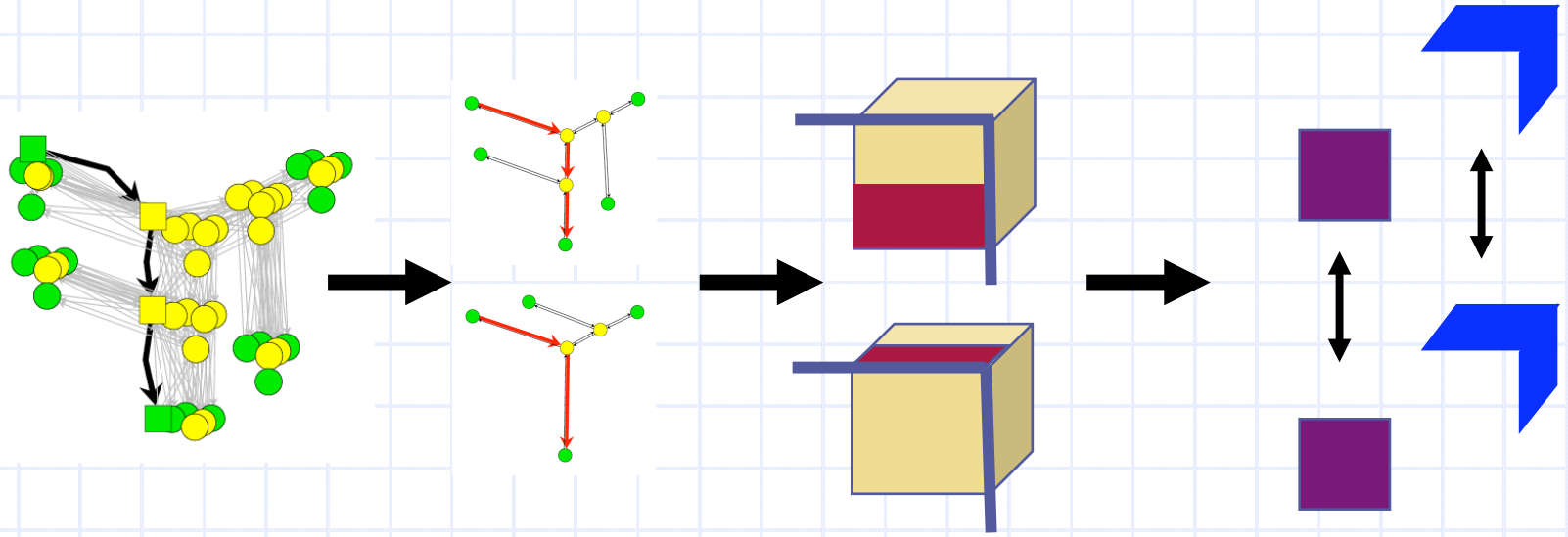
Next, combine the dual graphs to form an association graph.



Boundary segment graphs

Association graph

A Shortest Path Formulation



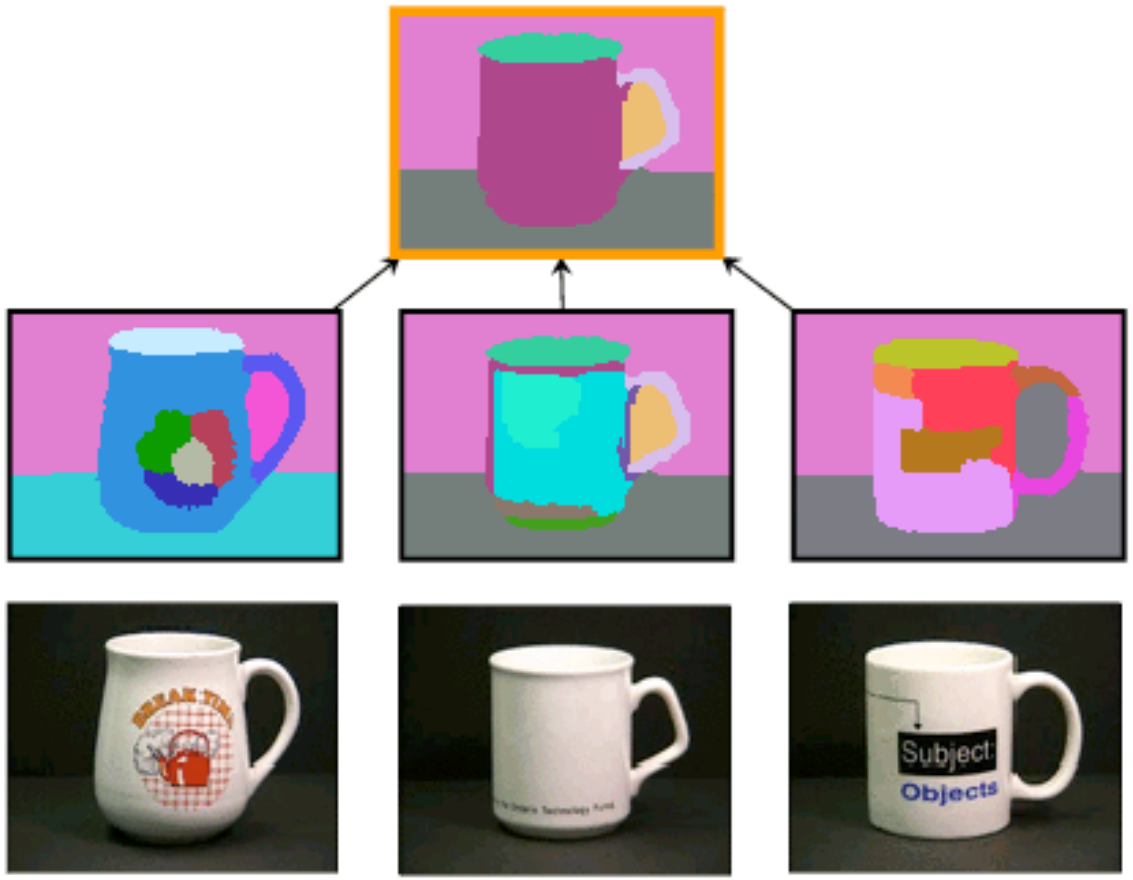
shortest path in association graph

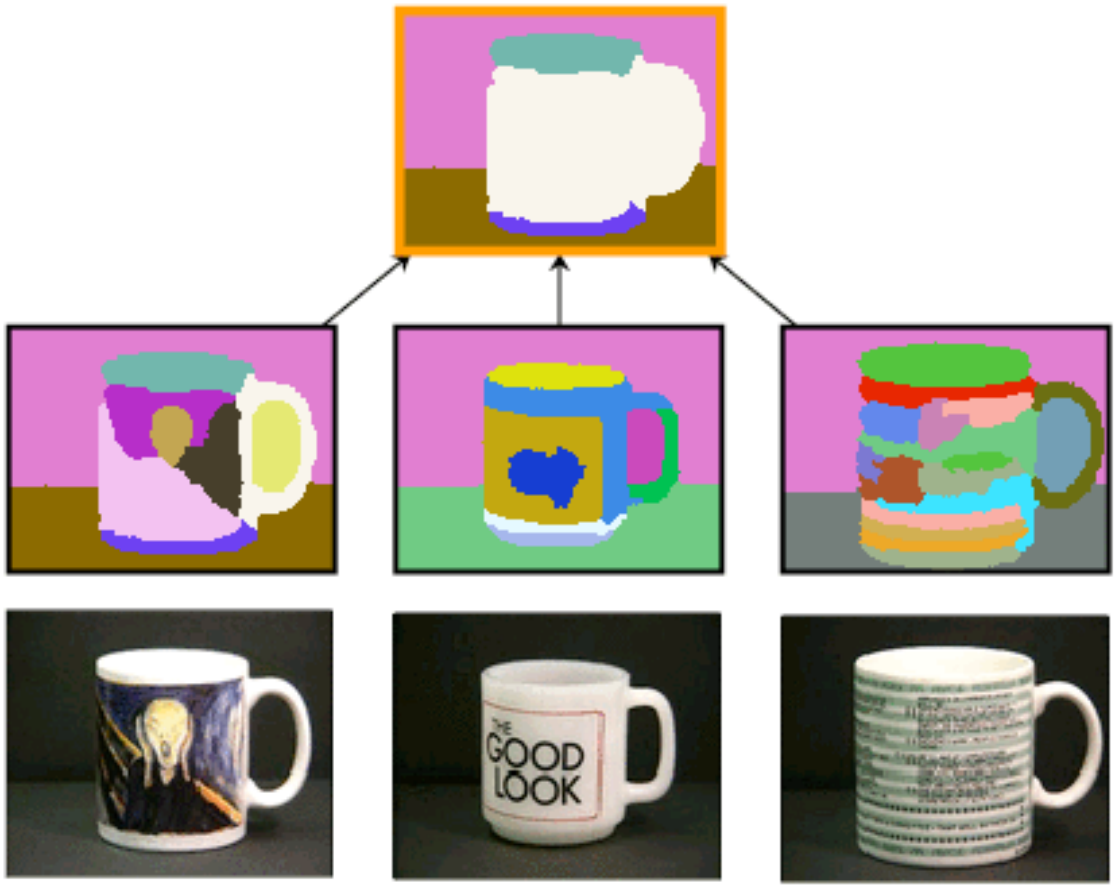
pair of paths in dual graphs

pair of cuts in RAGs

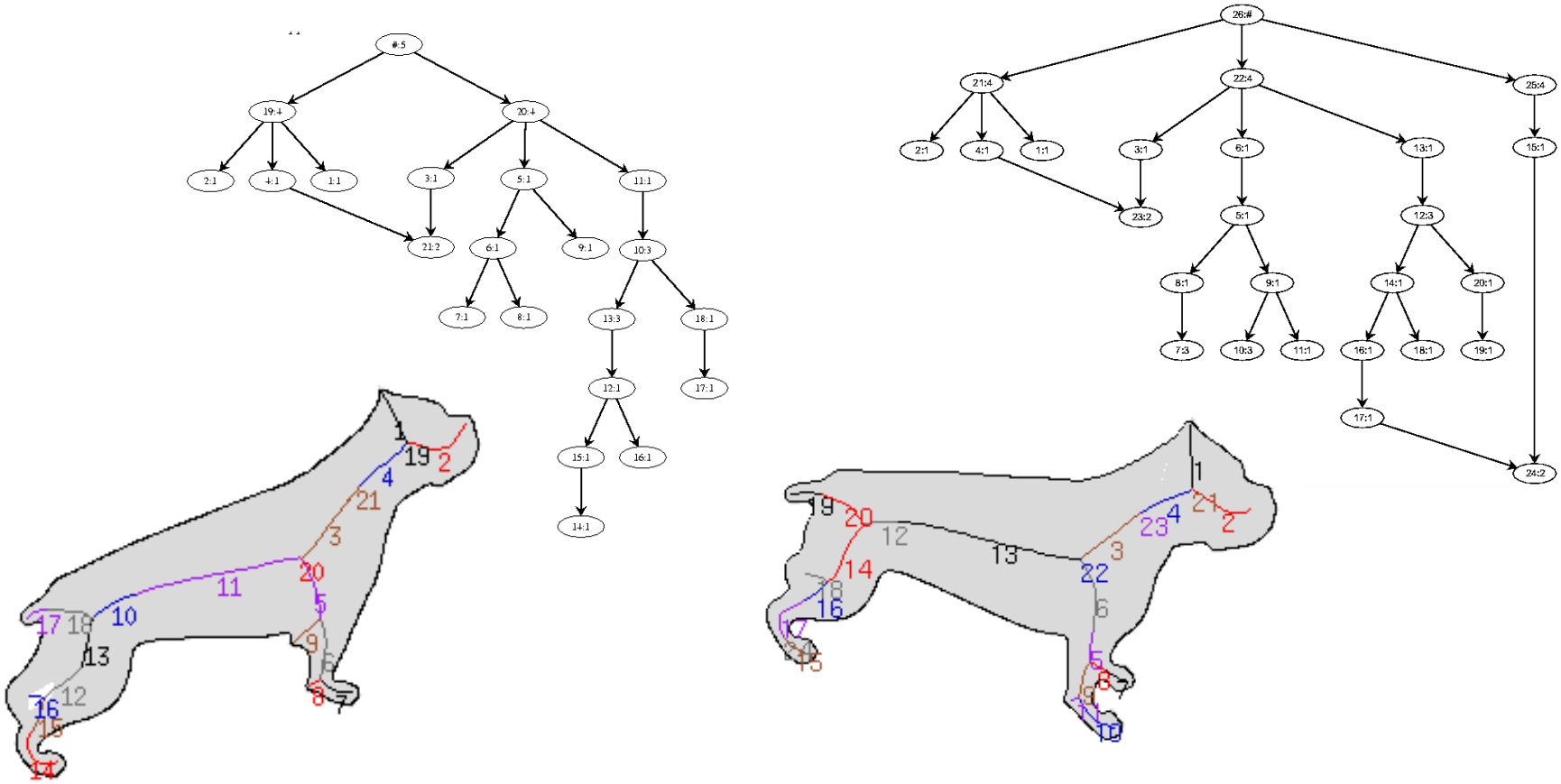
pairs of similarly shaped regions

Demonstration



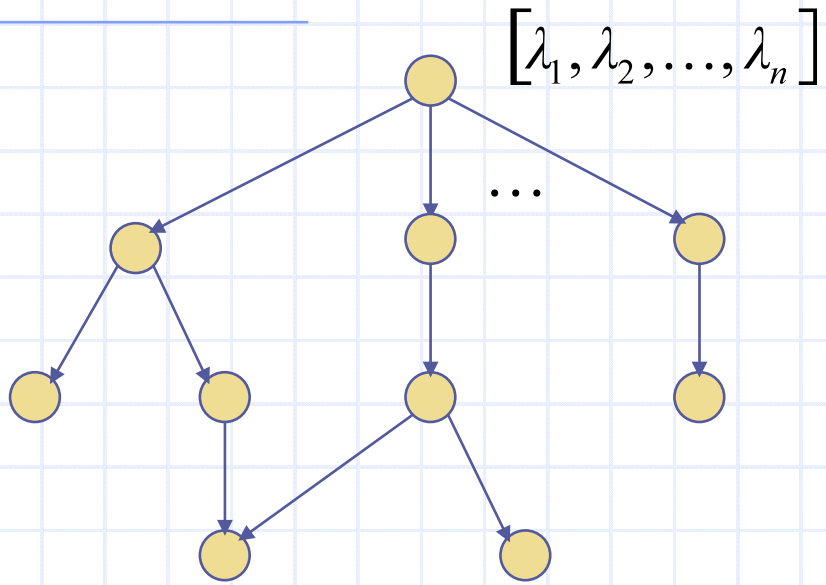

THE
GOOD
LOOK

2. Indexing/Matching Spectral Abstractions of Graph Structure



Shokoufandeh, Macrini, Dickinson, Siddiqi, and Zucker
(IJCV 99, PAMI 05)

Modeling the Abstract "Shape" of a Graph

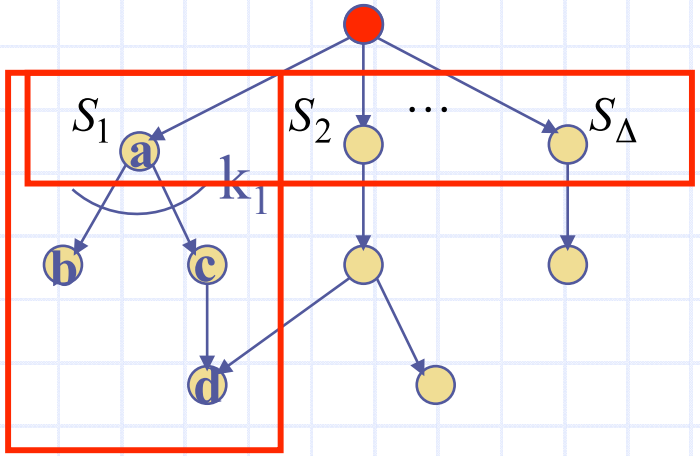


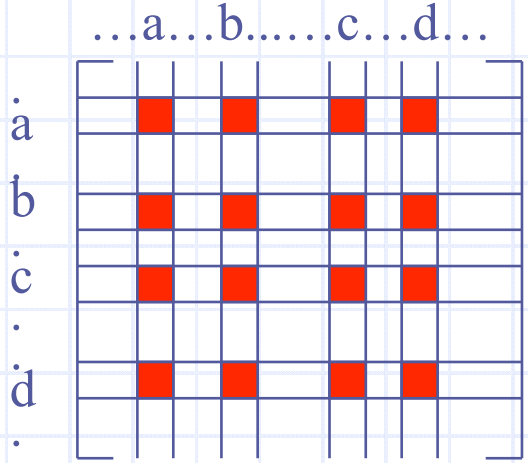
We *could* compute the graph's eigenvalues, sort them, and let them become the components of a vector assigned to the graph.

But:

1. Dimensionality grows with size of graph.
2. Eigenvalues are global! Therefore, can't accommodate occlusion or clutter.

A Topological Signature Vector



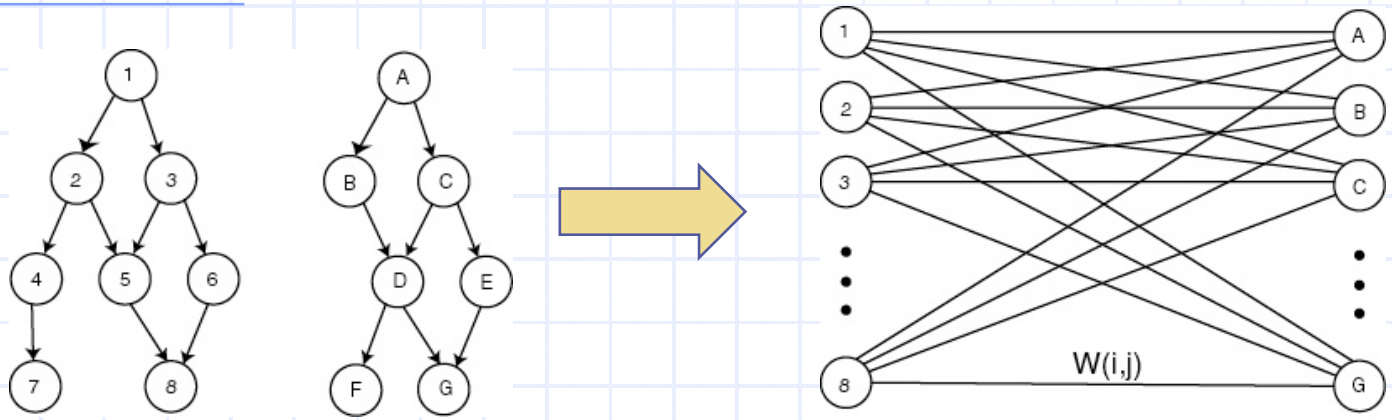


$$V = [S_1, S_2, S_3, \ldots, S_\Delta], \quad S_1 \geq S_2 \geq S_3 \geq \ldots S_\Delta \qquad S_i = |\lambda_1| + |\lambda_2| + \ldots |\lambda_{k_i}|$$

Why Sum the k largest Eigenvalues?

1. Summing reduces dimensionality.
2. Largest eigenvalues most informative.
3. Sums are "normalized" according to richness (k_i) of branching structure.

Generic vs. Specific Matching

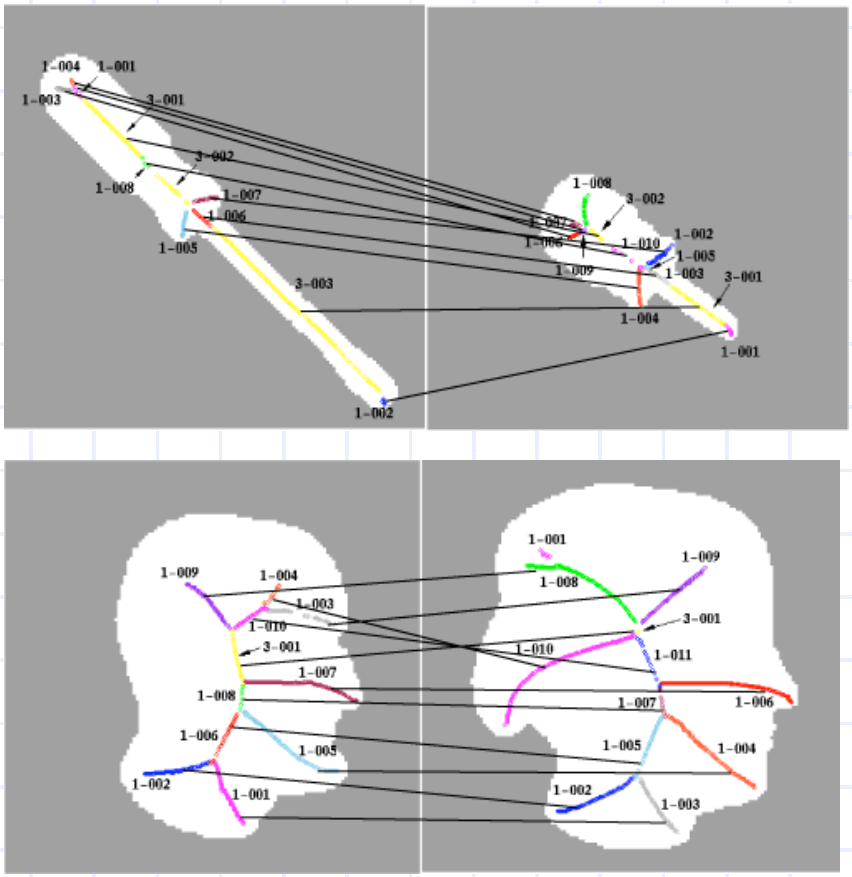


$$W(i,j) = e^{-\{\alpha_1 d_{struct}(i,j) + \alpha_2 d_{geom}(i,j)\}}$$

structural similarity

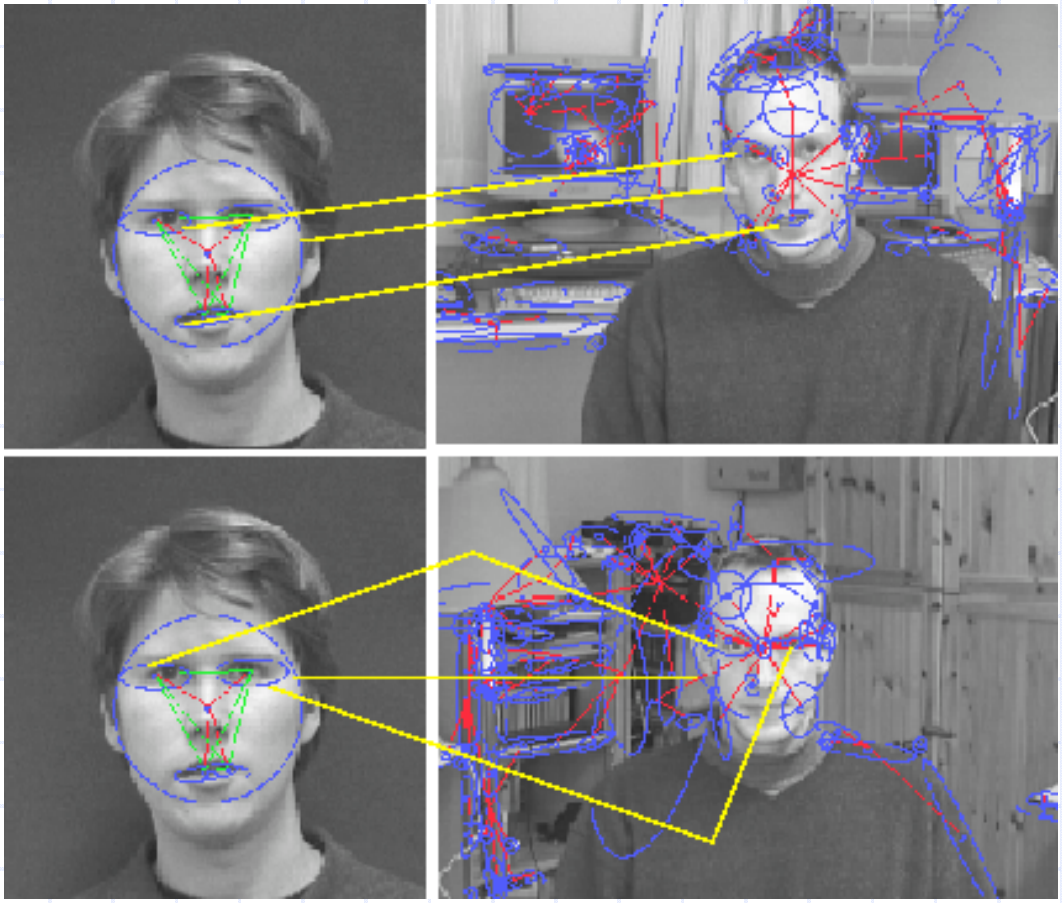
node contents similarity

Matching Shock Graphs



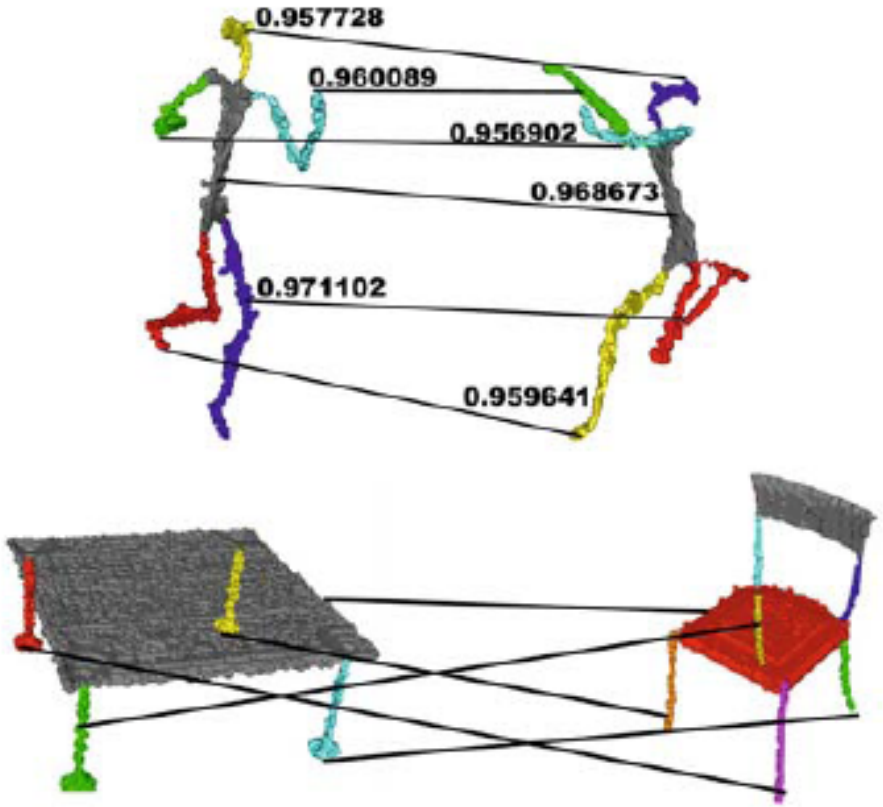
Siddiqi, Shokoufandeh, Dickinson, and Zucker (IJCV 99)

Matching Blob and Ridge Graphs



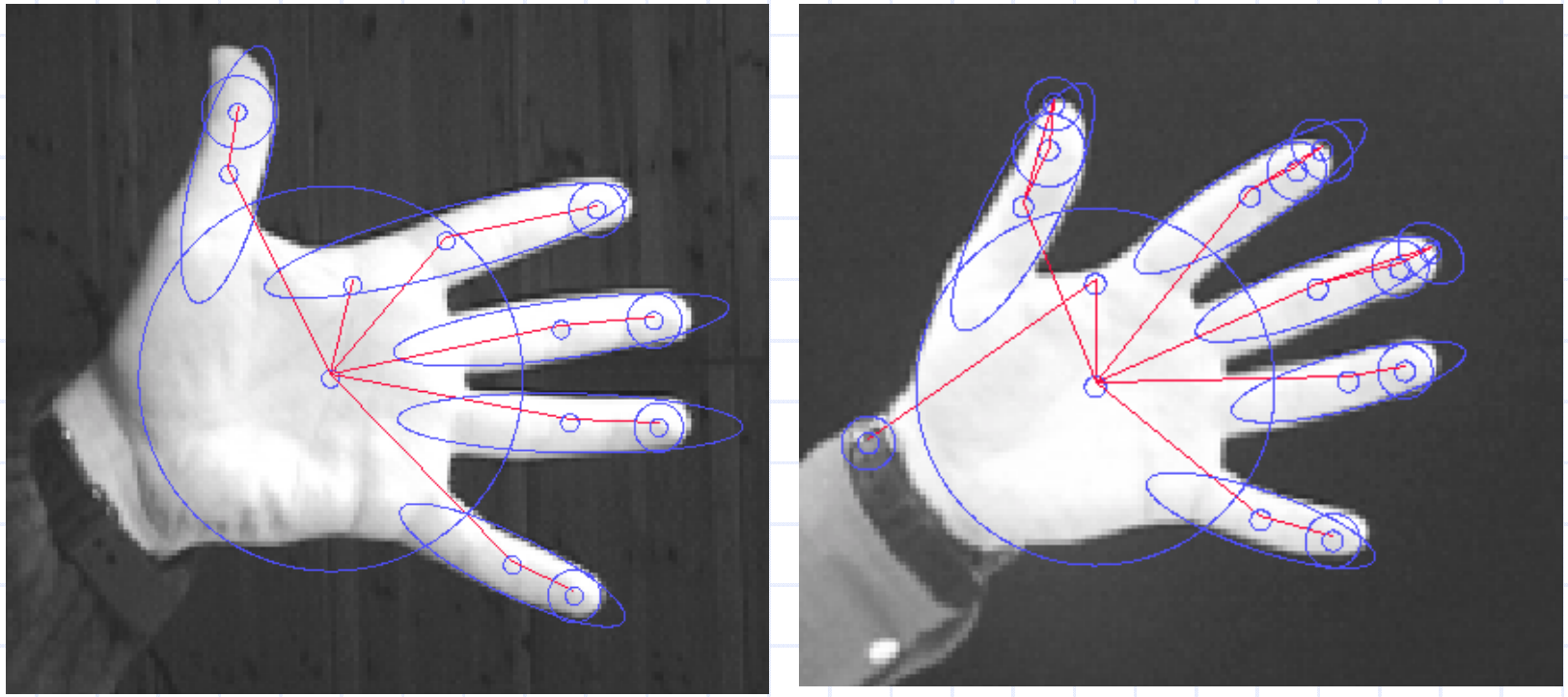
Shokoufandeh, Dickinson, Jönsson, Bretzner, Lindeberg (CVIU 06)

Matching Medial Surface Graphs



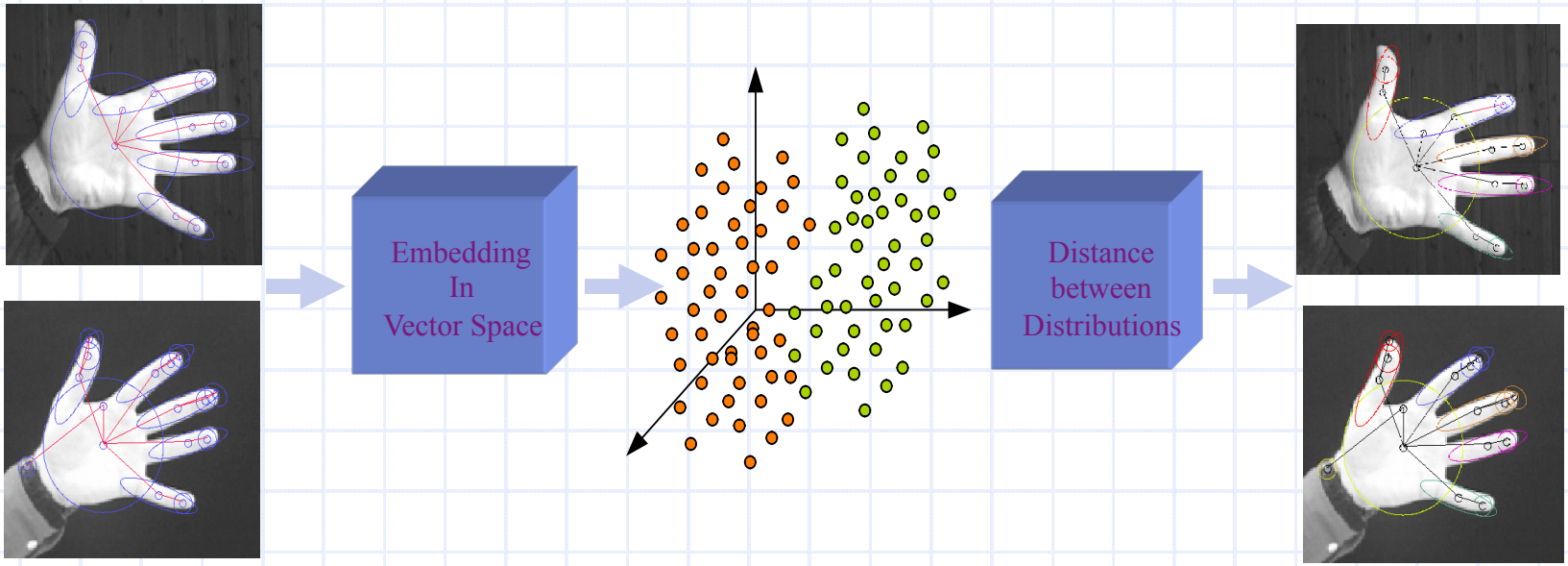
Zhang, Siddiqi, Macrini, Shokoufandeh, and Dickinson (JMVA 2008)

3. Many-to-Many Matching using Graph Embedding

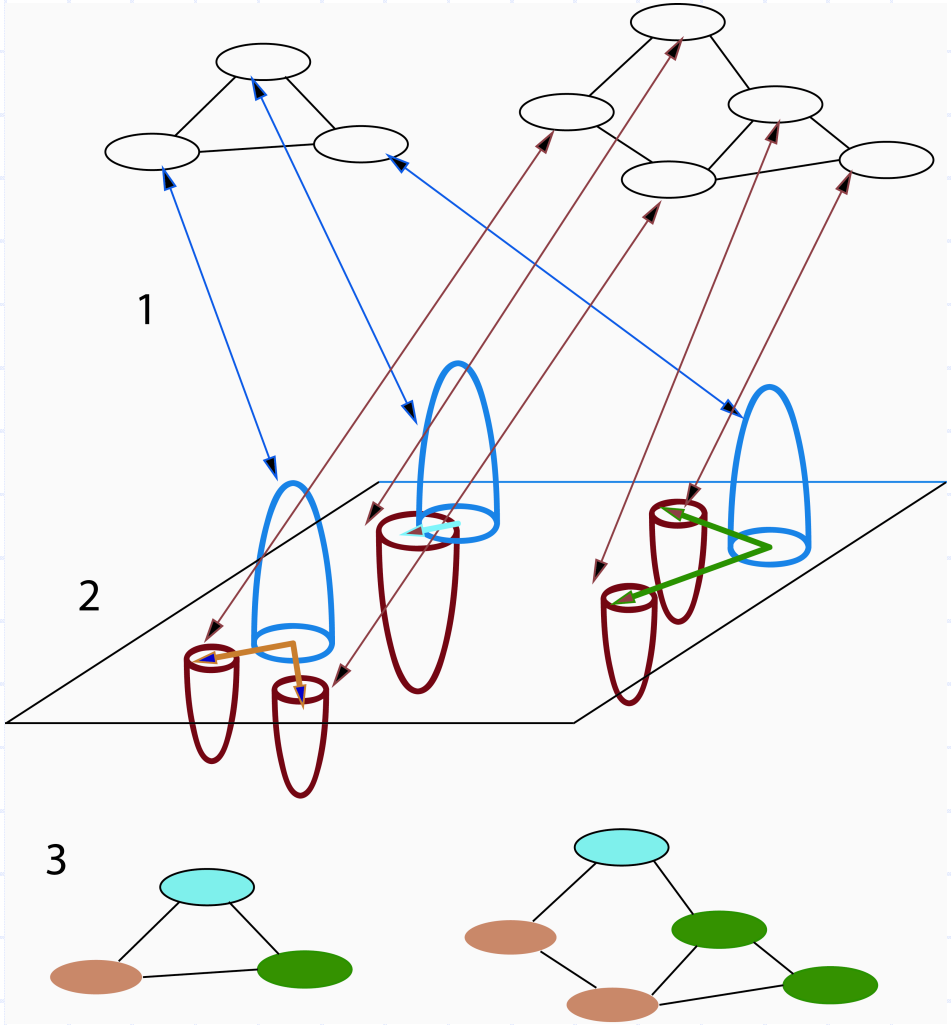


Keselman, Demirci, Shokoufandeh, Dickinson, and Bretzner (IJCV 06)

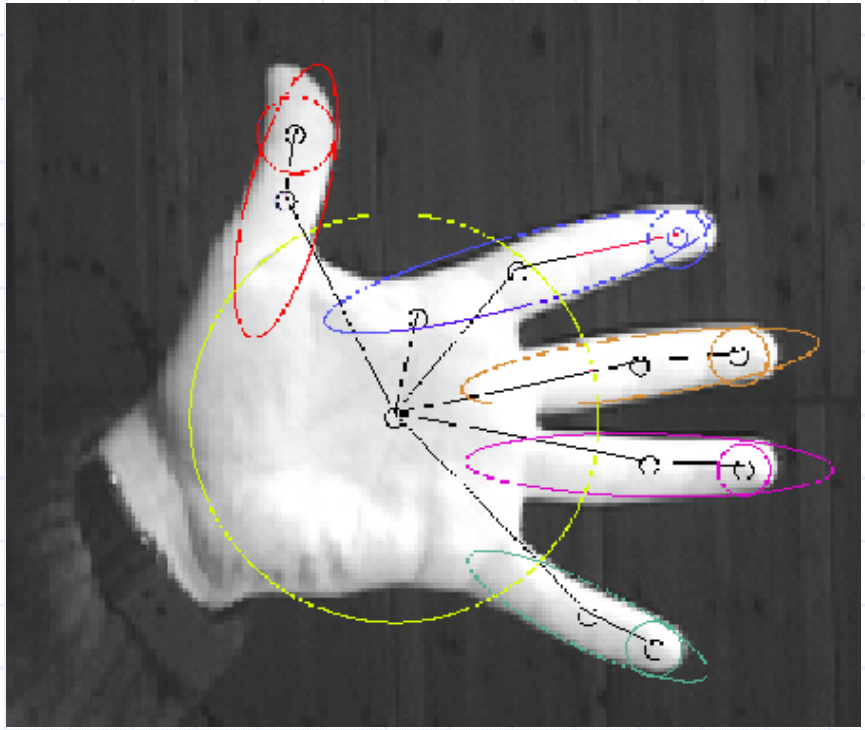
Matching Graphs as Weighted Point Sets in Euclidean Space

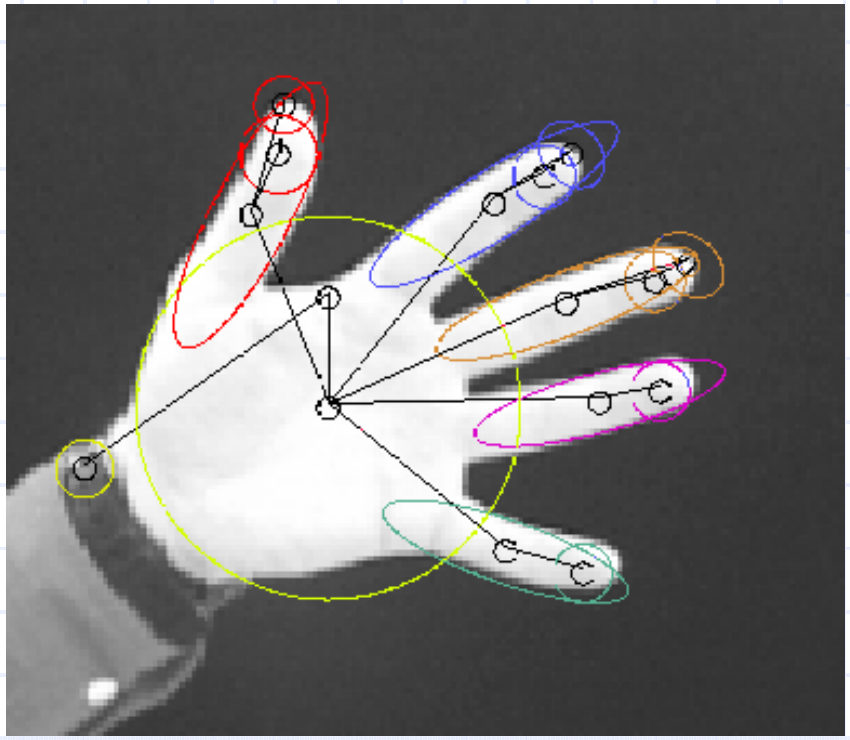


Matching the Embeddings using the Earth Mover's Distance (EMD)

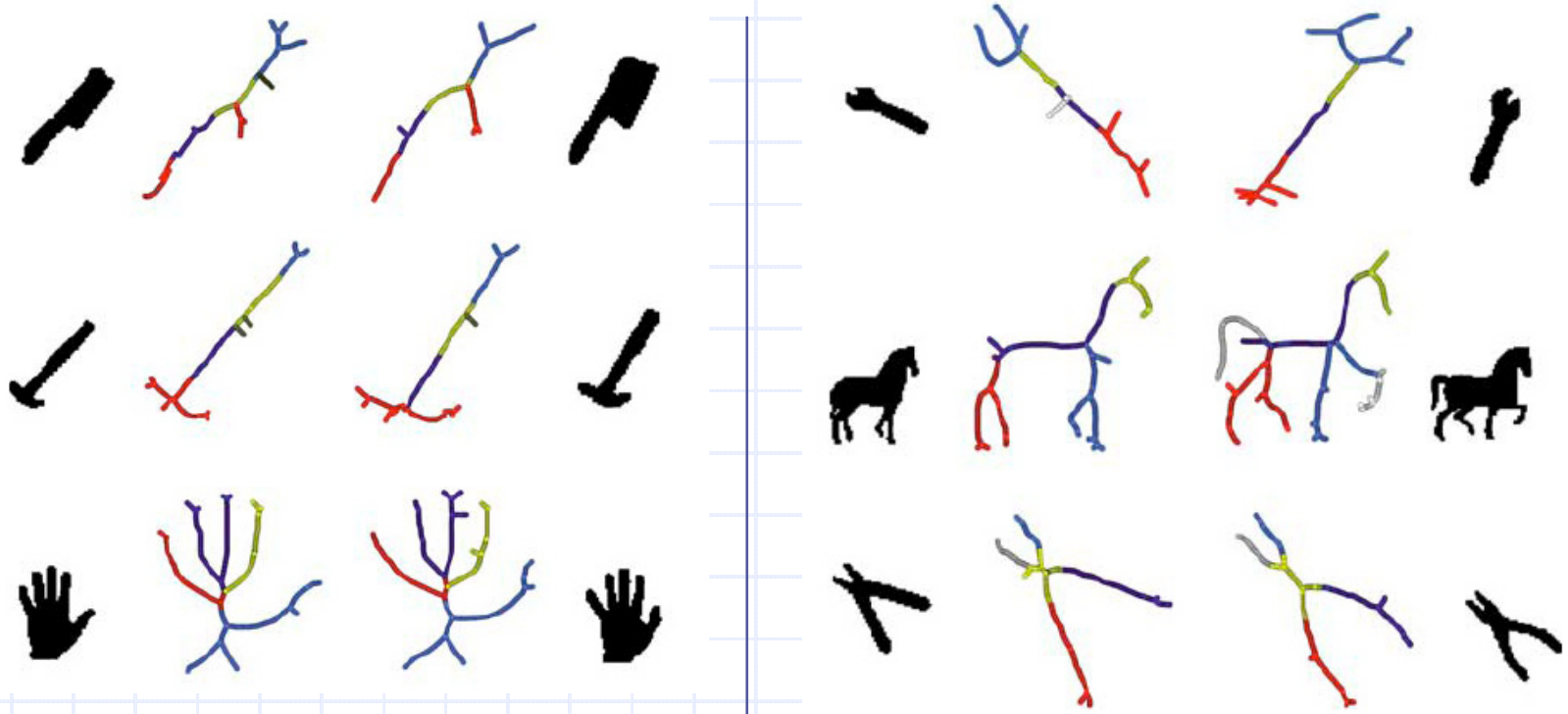


Demonstration (blob graphs)



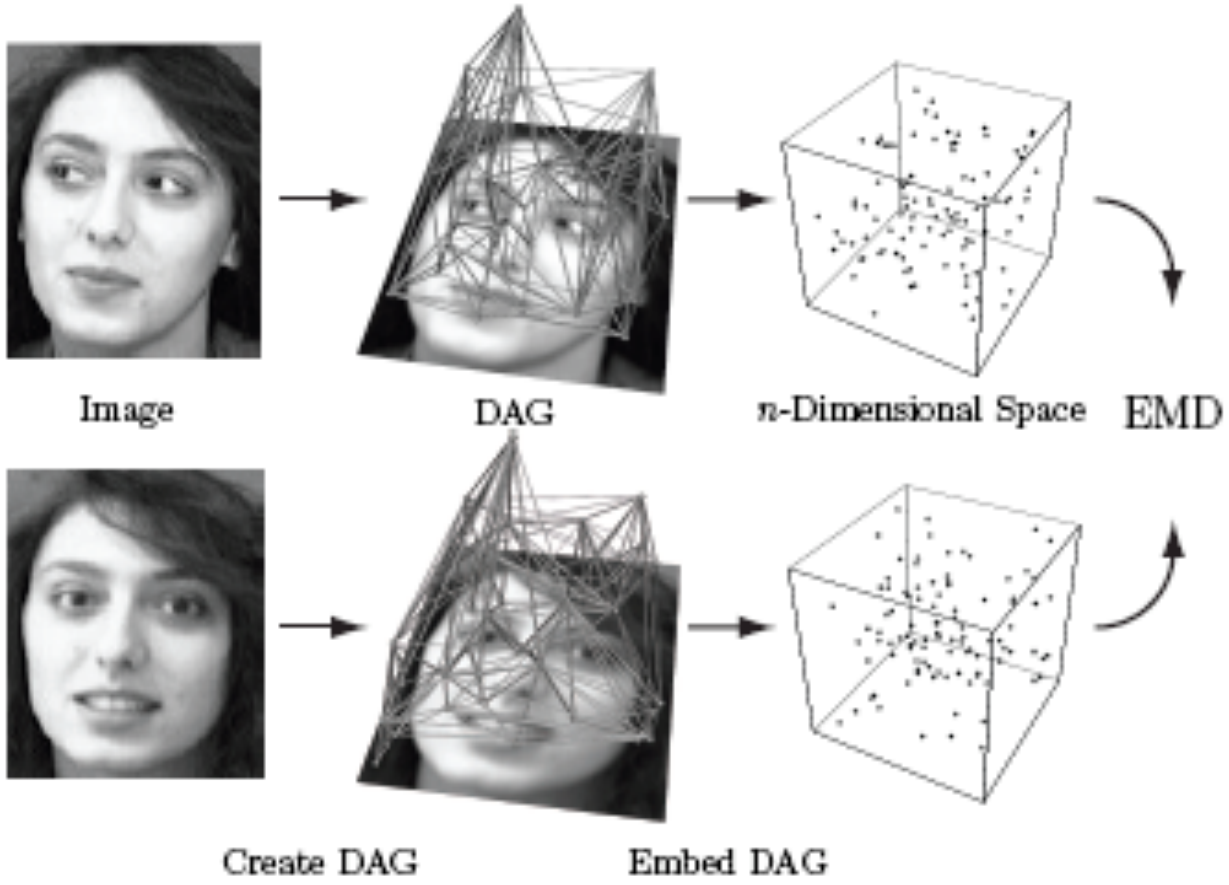


Demonstration (skeleton graphs)



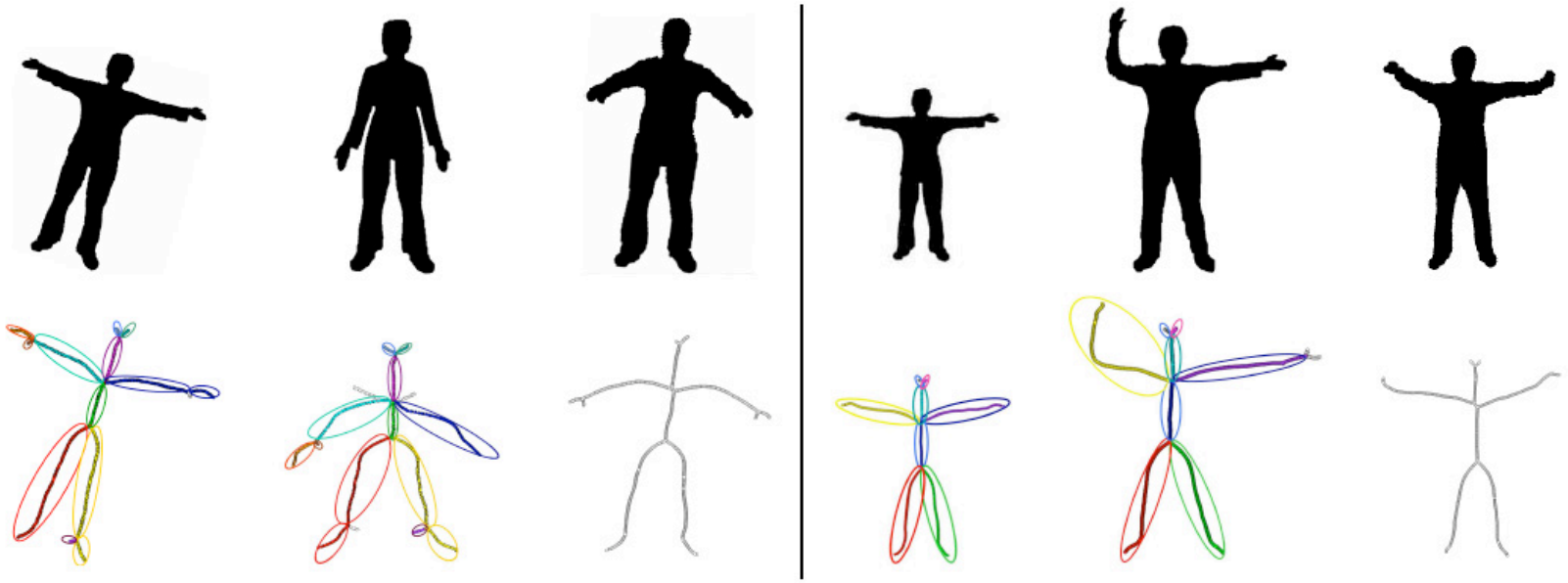
Keselman, Demirci, Shokoufandeh, Dickinson, and Bretzner (IJCV 06)

Demonstration (Top Point Graphs)



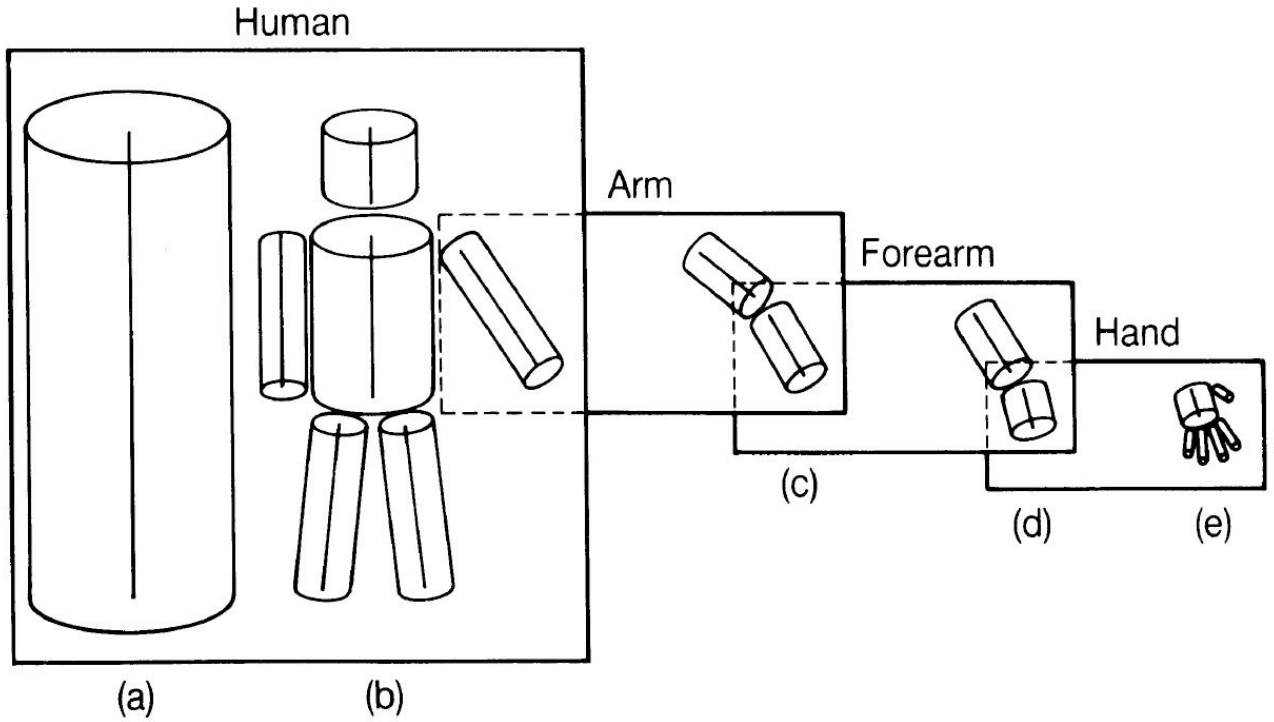
F. Demirci, B. Platel, A. Shokoufandeh, L. Florack, and S. Dickinson (JMIV 2009)

Demonstration (Skeletal Abstraction from Examples)

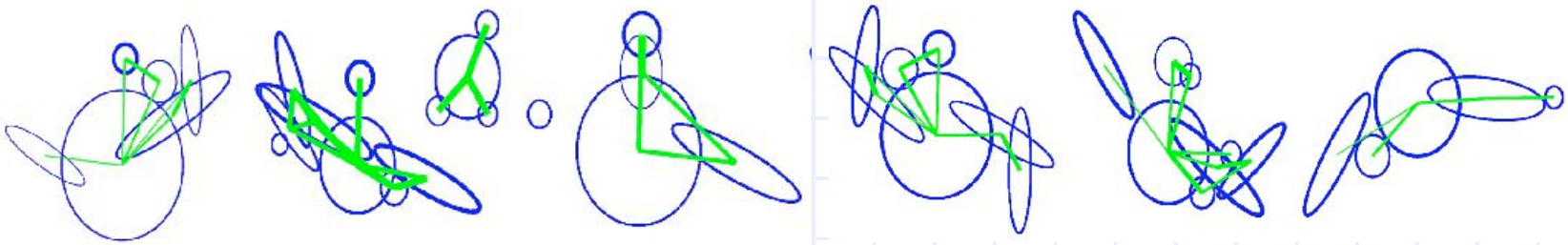


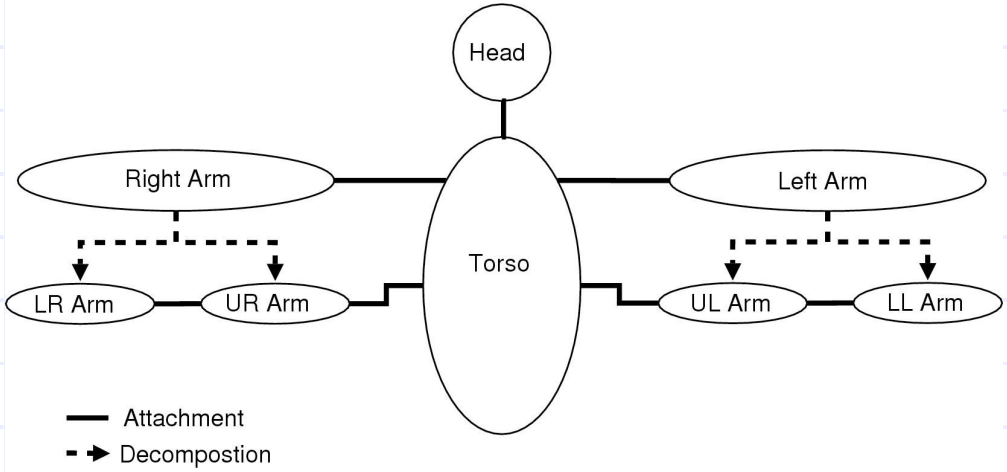
F. Demirci, A. Shokoufandeh, and S. Dickinson (PAMI 2009)

Application: Learning Abstraction Hierarchies from Examples

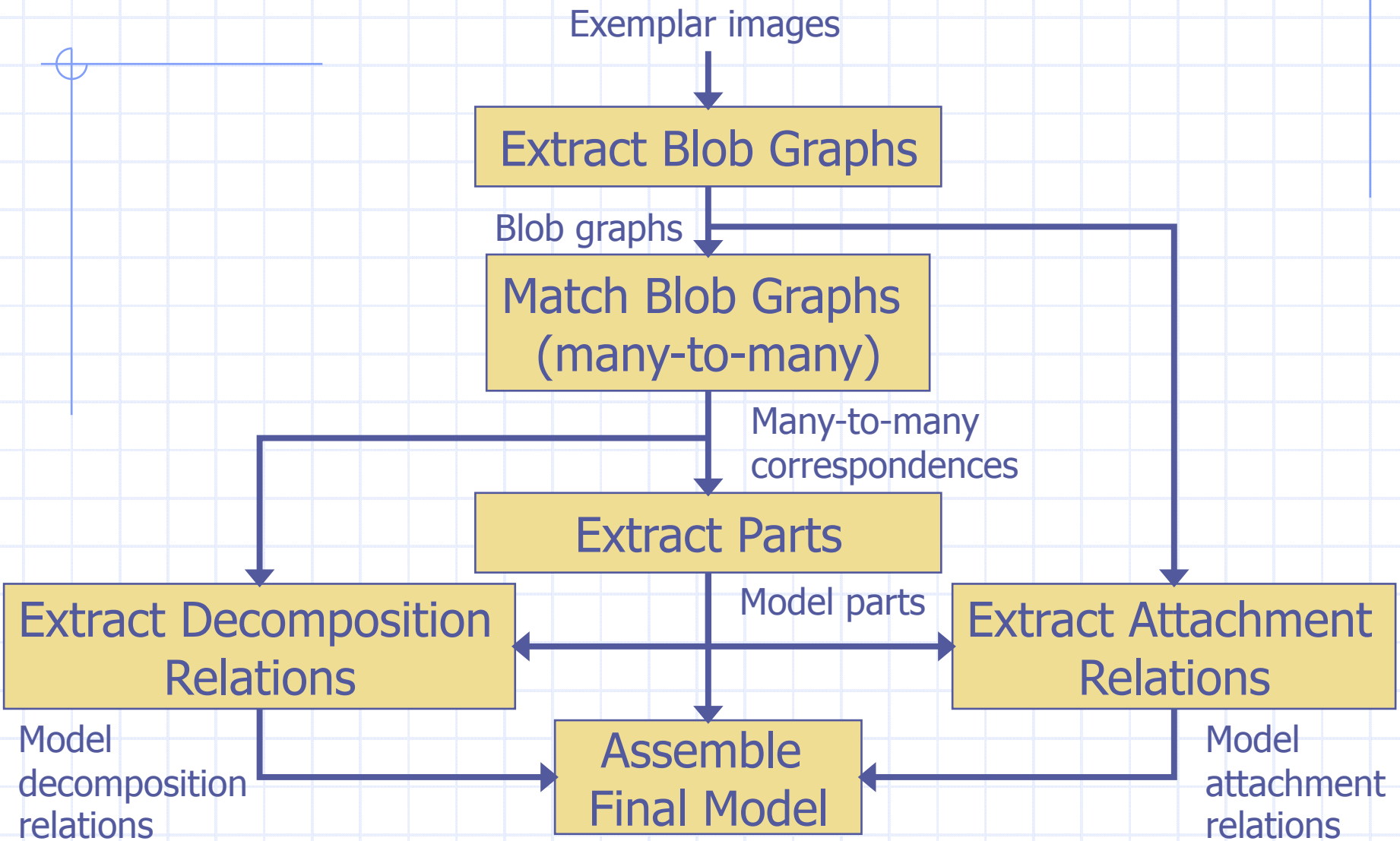


Levinshtein, Sminchisescu, and Dickinson (EMMCVPR 05)

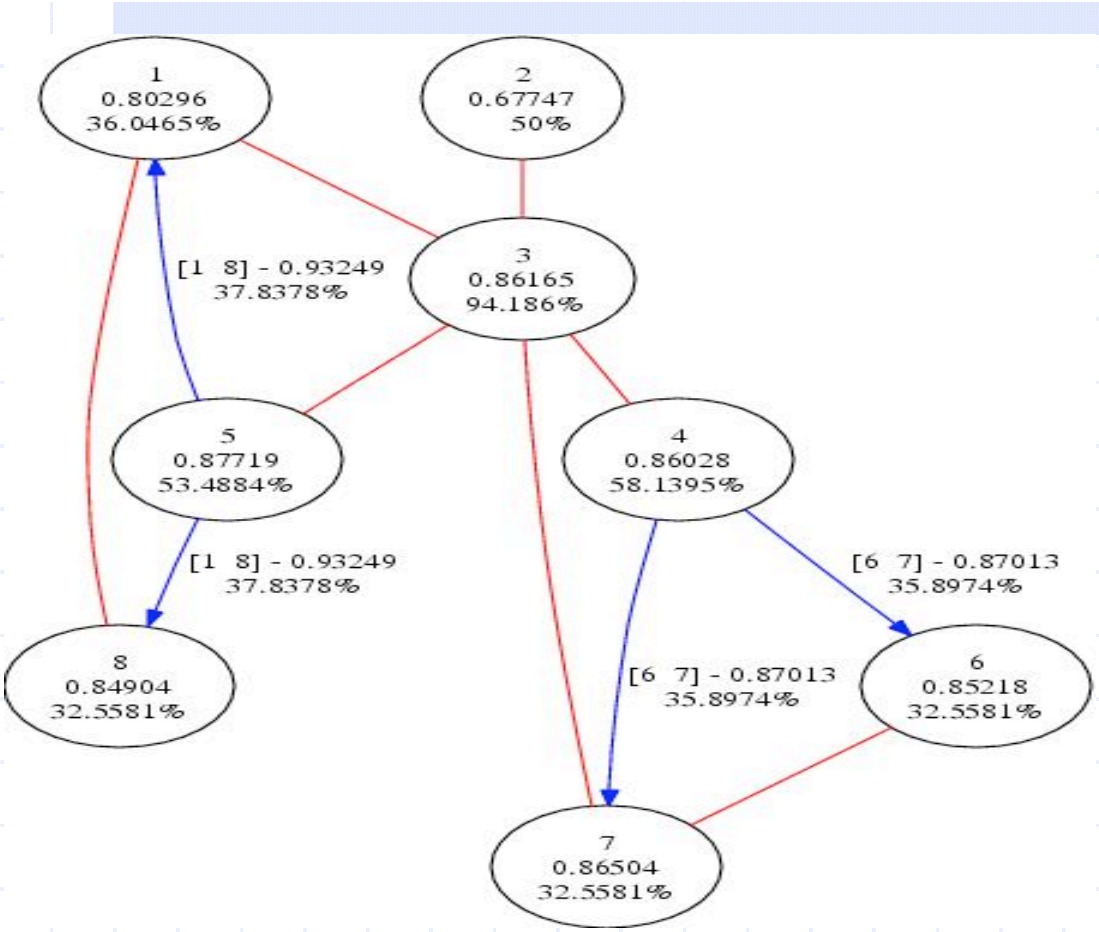


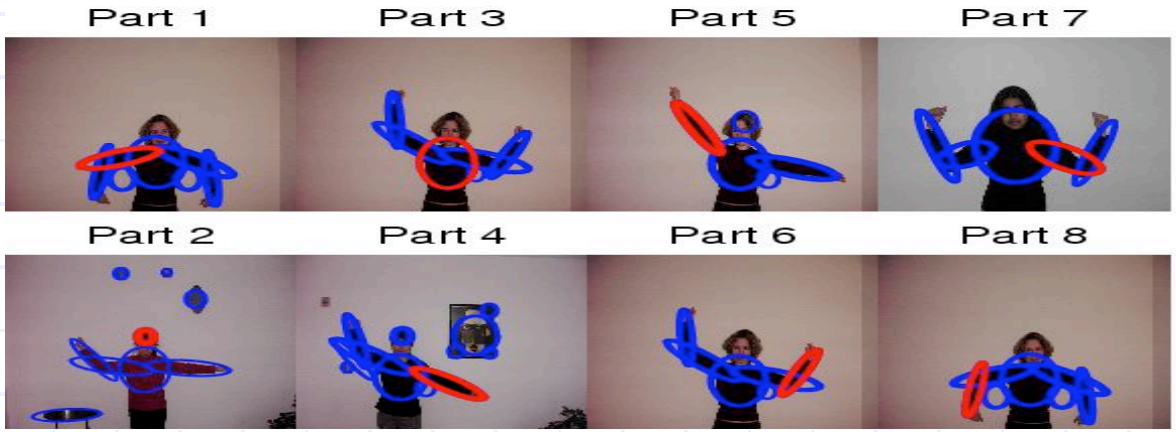

Head
Right Arm
Left Arm
Torso
LR Arm
UR Arm
UL Arm
LL Arm
Attachment
Decompostion

Processing Pipeline

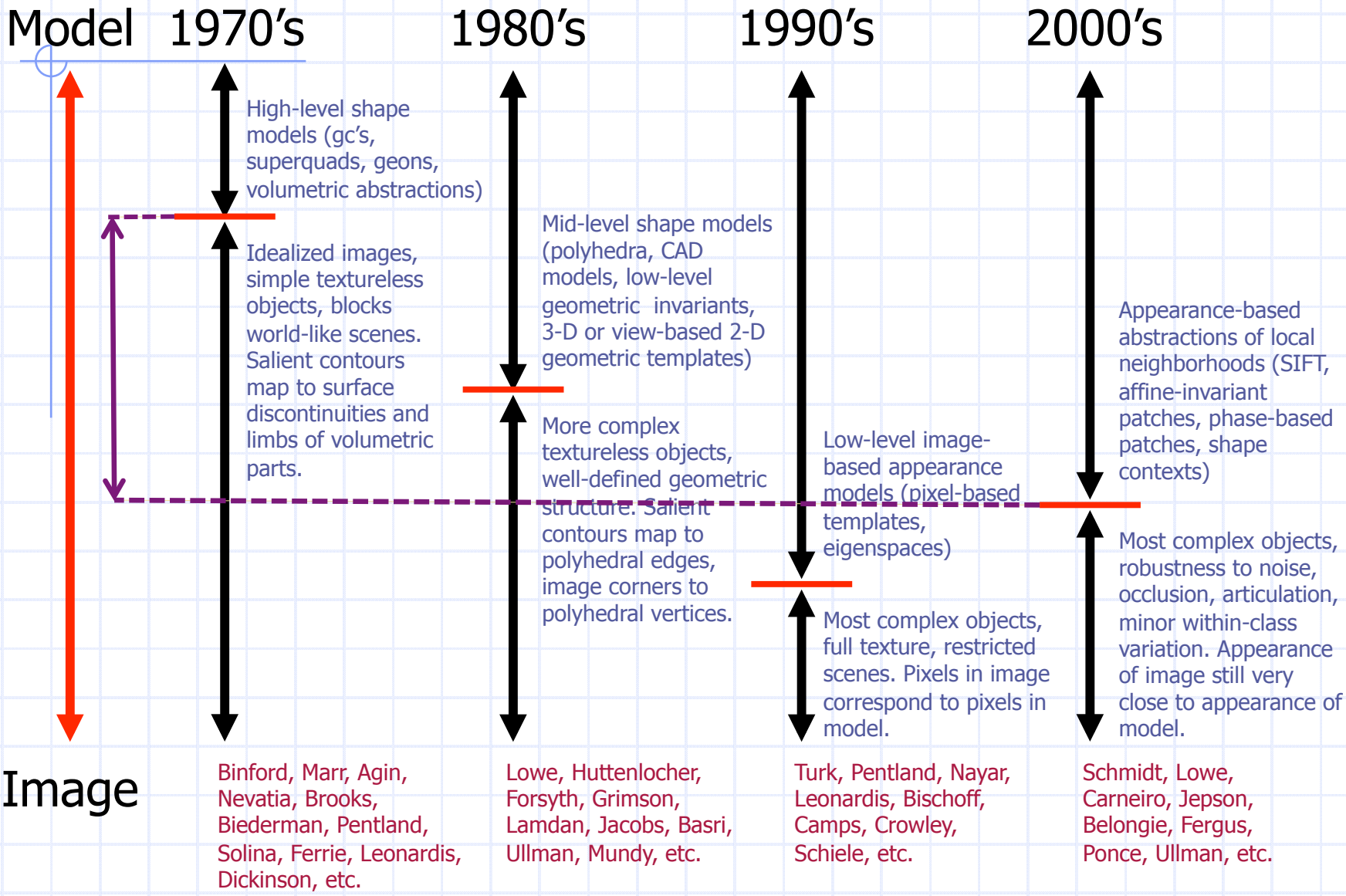


Results


1
0.80296
36.0465%
2
0.67747
50%
3
0.86165
94.186%
[1 8] - 0.93249
37.8378%
5
0.87719
53.4884%
4
0.86028
58.1395%
[1 8] - 0.93249
37.8378%
[6 7] - 0.87013
35.8974%
8
0.84904
32.5581%
[6 7] - 0.87013
35.8974%
6
0.85218
32.5581%
7
0.86504
32.5581%


Part 1
Part 3
Part 5
Part 7
Part 2
Part 4
Part 6
Part 8

Conclusions

- 1-1 correspondence → recognition of exemplars and highly restricted categories
- Structural variation, scale, articulation, and segmentation errors → m-to-m correspondence
- m-to-m regularities → image grammars (Rosenfeld, Fu → Zhu, Todorovic, Geman, Siskind, Ahuja, Mumford, etc.)
- More general m-to-m matching → this talk
- Main challenge facing recognition → effective abstraction mechanisms.

The Challenge of Image Abstraction