Feature Correspondence and Deformable Object Matching via Agglomerative Correspondence Clustering

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MOTIVATION

Object-based Feature Correspondence

Feature correspondence considering **geometric distortion** of **objects** and background **clutter**

■ **Previous methods** for deformable image matching assumed weakly supervised cases with a single common object and low clutter
→ low outlier ratio, a single group with geometric consistency
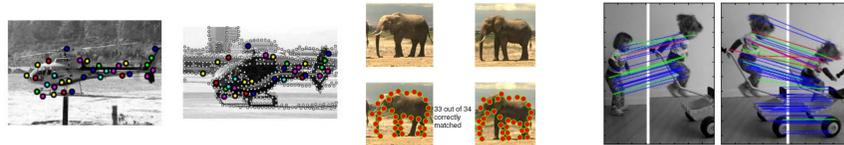
Berg *et al.* CVPR2005   Leordeanu & Hebert ICCV2005   Torresani *et al.* ECCV2008

33 out of 34 correctly matched

■ However, **real-world cases** have significant clutter, multiple objects, even many-to-many object correspondences
→ High outlier ratio, multiple groups with geometric consistency

input image pair   Initial correspondences with local features

■ Feature correspondence problem needs to be interleaved with *object-level clustering against distracting outliers* in an unsupervised way.
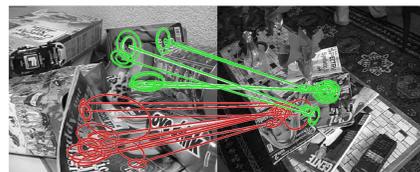
Goal (our result)

MAIN IDEA

Agglomerative correspondence clustering considering connectedness between deformed parts

■ **Bottom-up aggregation strategy**

Starting from confident correspondences, progressively merge them with reliable neighbors until deformation is tolerable

→Hierarchical Agglomerative Clustering (HAC) framework

■ **Distance measure for deformed parts**

For deformable objects, feature correspondences do not form global *compact*ness in their pairwise geometric similarity, but deformed parts are *connect*ed by some mediating parts.
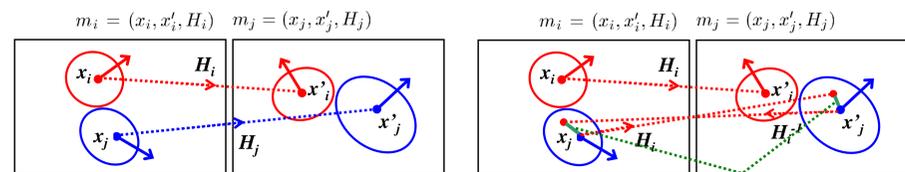
→ **An adaptive linkage model** in HAC framework

Robust distance measure btw correspondence clusters

+

HAC framework

Verification

Object-based clusters against distracting outliers
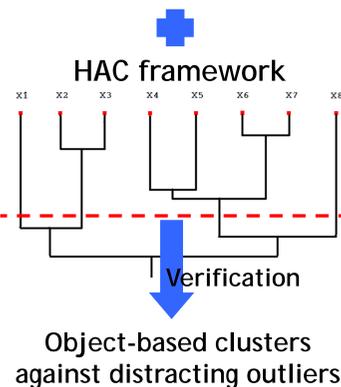
PROPOSED METHOD

Distance between Two Correspondences

$m_i = (x_i, x'_i, H_i)$ $m_j = (x_j, x'_j, H_j)$ $m_i = (x_i, x'_i, H_i)$ $m_j = (x_j, x'_j, H_j)$

$$d_{geo}(m_i, m_j) = \frac{1}{2}(d_{geo}(m_j|m_i) + d_{geo}(m_i|m_j)) \Leftarrow d_{geo}(m_j|m_i) = \frac{1}{2}(|x'_j - H_i x_j| + |x_j - H_i^{-1} x'_j|)$$

a mutual projection error, small if H_i and H_j are similar to each other

Distance between Two Clusters

*Note that each element in clusters represents a correspondence

■ **Conventional linkage models** and their properties

min   max   avg

C_1 C_2 C_1 C_2 C_1 C_2

Single Linkage   Complete Linkage   Average Linkage
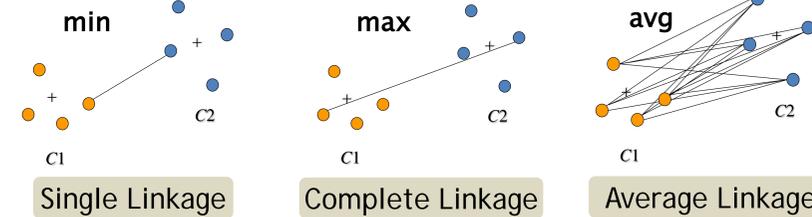
● **Connectedness** criterion
● Strong **chaining** effect
● Sensitive to chaining outliers

● **Compactness** criterion
● Tends to make **spherical** clusters
● Robust to outliers

➡ All are not adequate for object-based feature correspondence clustering

■ **Proposed linkage model**
   for connectedness without chaining effect

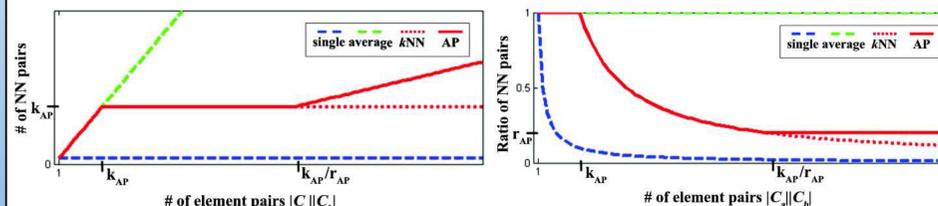◆ *k*NN **linkage**: use the average of *k*NN supporting distances
   ➡ More robust than single, but chaining arises btw large clusters

*k*NN (e.g. *k*=3)

C_1 C_2 C_1 C_2

◆ **Adaptive Partial linkage**: increase *k* of *k*NN according to **cluster sizes**
   ➡ Two control parameters: *k*NN number k_{AP}, partial rate r_{AP}

single average *k*NN AP

# of NN pairs   Ratio of NN pairs

# of element pairs $|C_a||C_b|$ # of element pairs $|C_a||C_b|$

Early stage ➡ Intermediate ➡ Late stage

● Average linkage
● All as supporters
● Compact clusters
● Avoids chaining outliers

● *k*NN linkage
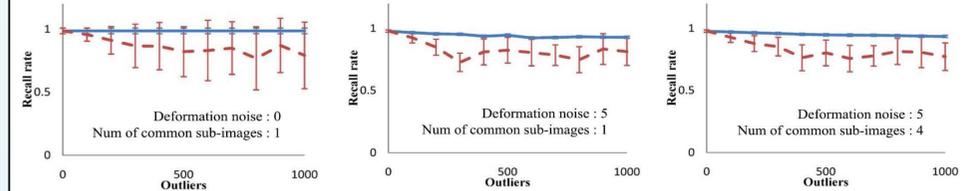● k_{AP} supporting NNs
● Connected clusters

● Partial linkage
● $r_{AP} |C_a||C_b|$ supporting NNs
● Connected clusters
● Avoids asymptotic chaining effect

Local compactness & **global connectedness** for deformable objects!
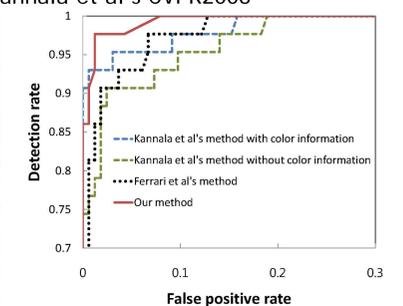
EXPERIMENTS

Feature Correspondence using Synthetic Images

● TSP warping by 9 x 9 control points perturbed with Gaussian noise

● Initial matching using MSER & Hessian-affine detectors with SIFT descriptor

● k_{AP}=10, r_{AP}=0.05
● One-to-one constraint
● Comparison with Leodeanu & Hebert '05

Recall rate   Recall rate   Recall rate

Deformation noise : 0   Deformation noise : 5   Deformation noise : 5
Num of common sub-images : 1   Num of common sub-images : 1   Num of common sub-images : 4

Outliers   Outliers   Outliers

Object Recognition

● The ETHZ toys dataset
● Comparison with Ferrari et al's IJCV2006 & Kannala et al's CVPR2008

Detection rate

Kannala et al's method with color information
Kannala et al's method without color information
Ferrari et al's method
Our method

False positive rate

Object-based Image Matching

● Object-based image matching on all the test images of the ETHZ toys dataset

recall
precison

# of top score pairs
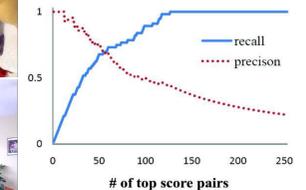
● Object-based image matching examples on various web images
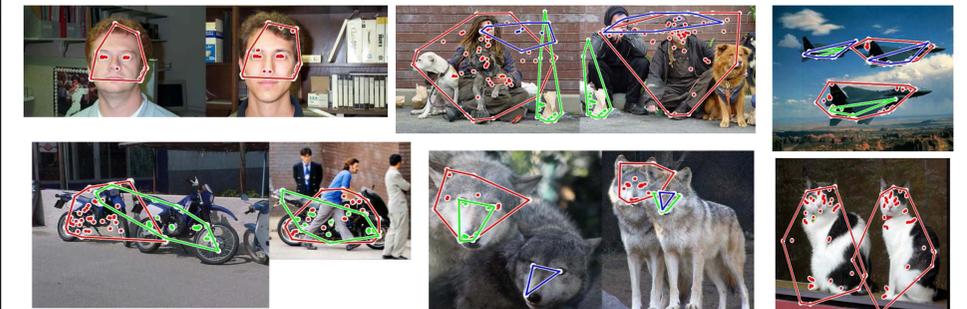
CONCLUSION

● Simple and efficient method for object-based feature correspondence
● Highly robust to outliers and deformation