Discovering Similarities in 3D Data

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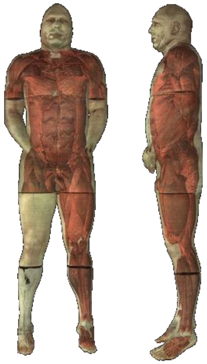
Steve Diverdi, Wilmot Li, Niloy Mitra, Yaron Lipman,
Thomas Funkhouser

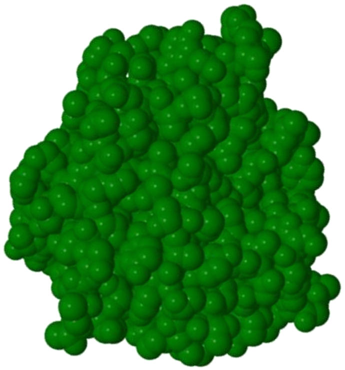
Motivation

3D data is widely available

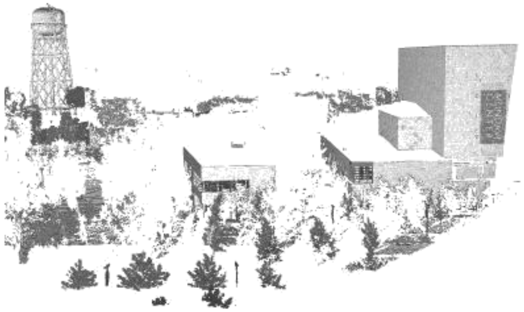


Medicine

Mechanical CAD



Molecular Biology



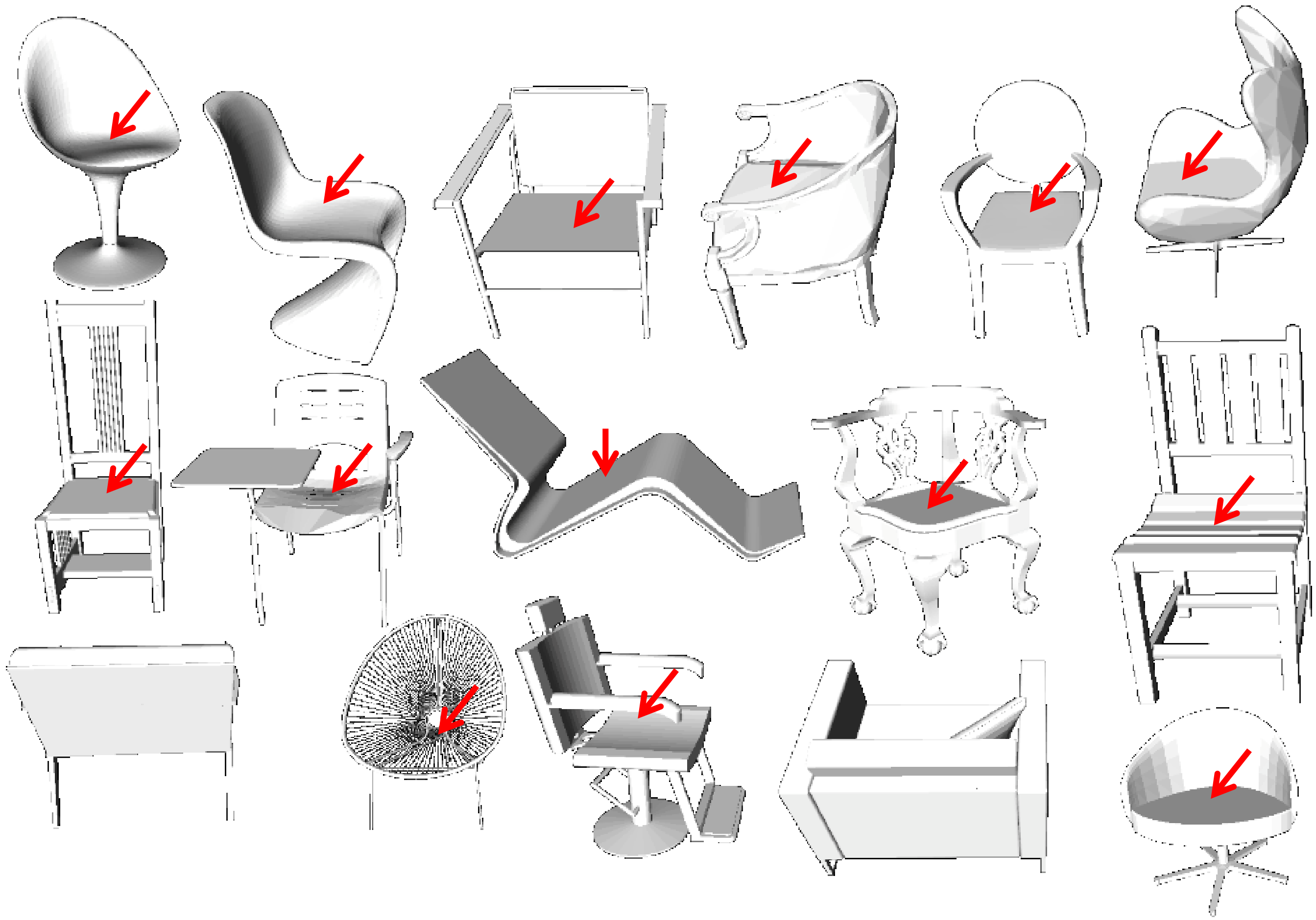
LIDAR Scans

Cultural Heritage

Computer Graphics

Motivation

Finding correspondences is important for understanding relationships in 3D data



Motivation

Applications:

- Annotation transfer
- Similarity measurement
- Surface alignment
- Collection analysis
- Saliency estimation
- Surface interpolation
- Symmetry detection
- Object recognition
- Visualization
- Clustering
- etc.

Motivation

Applications:

- ➢ Annotation transfer
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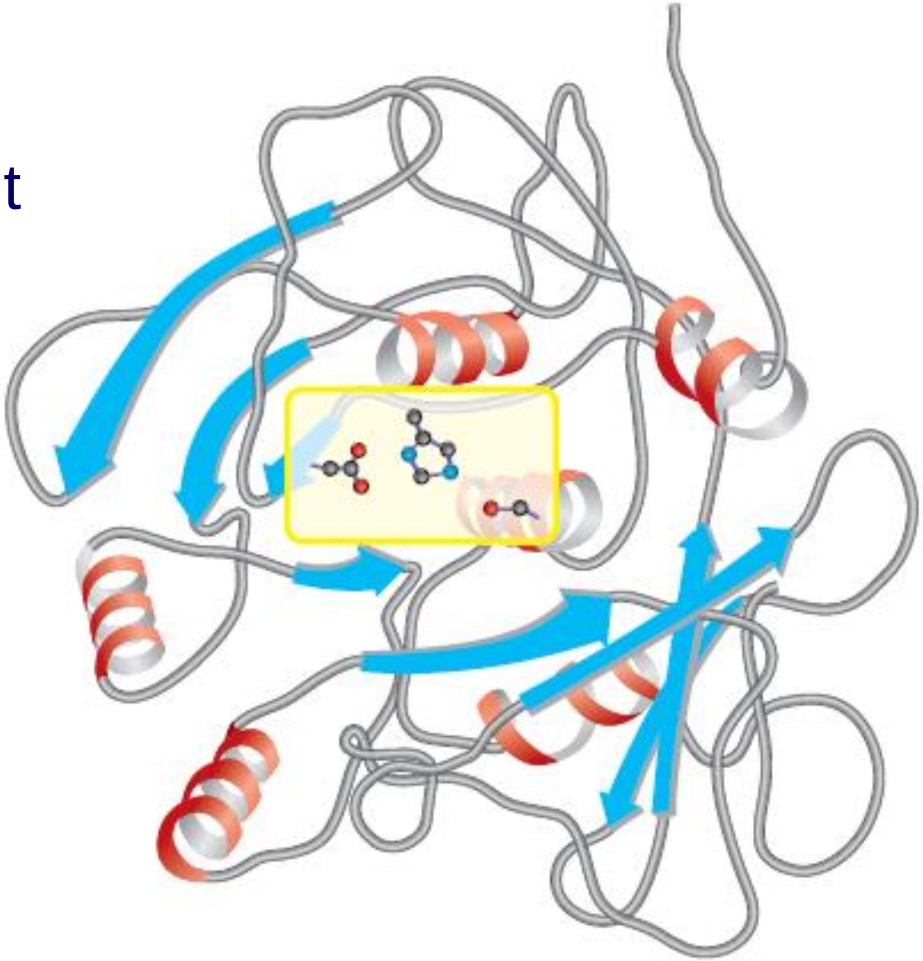

Predicting functional relationships between proteins based on similarities in their 3D structures

Motivation

Applications:

- Annotation transfer
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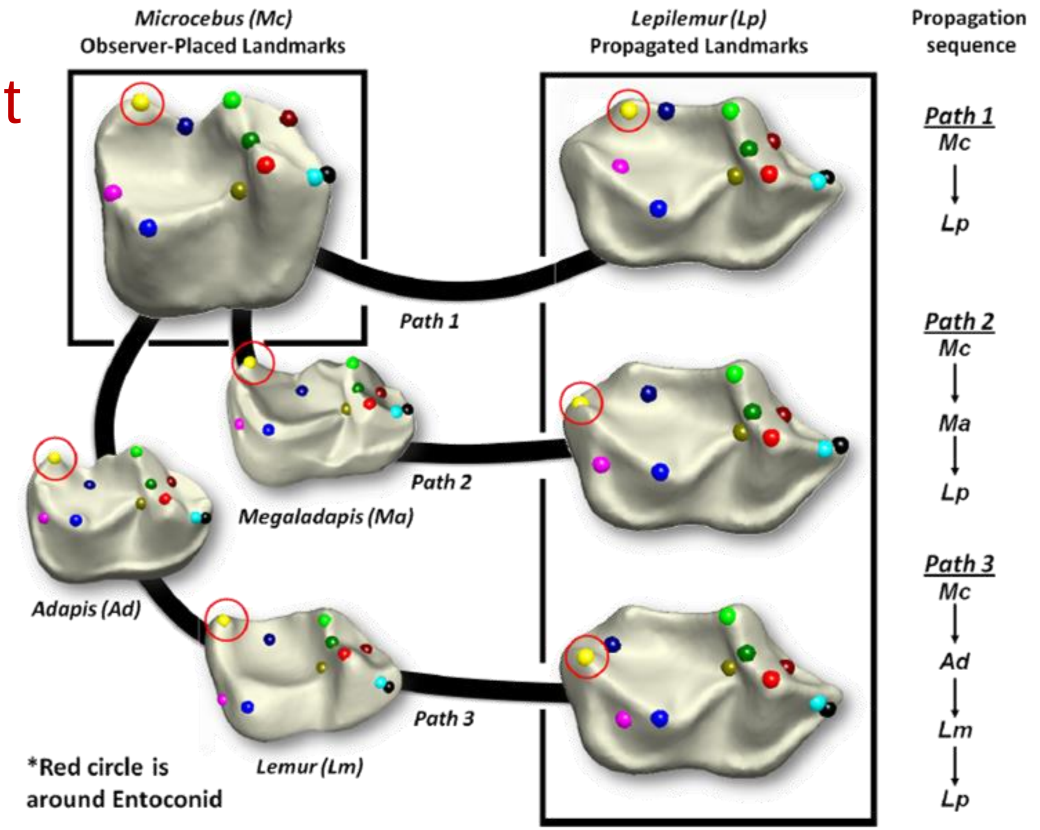

Predicting evolutionary relationships between fossils based on their morphological similarities

Motivation

Applications:

- Annotation transfer
- Similarity measurement
- ➢ Surface alignment
- Collection analysis
- Saliency estimation
- Surface interpolation
- Symmetry detection
- Object recognition
- Visualization
- Clustering
- etc.

Predicting how to re-assemble broken frescoes based on matching of fractured surfaces

Motivation

Applications:

- Annotation transfer
- Similarity search
- Surface alignment
- ➢Collection analysis
- Saliency estimation
- Surface interpolation
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- Object recognition
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- Clustering
- etc.

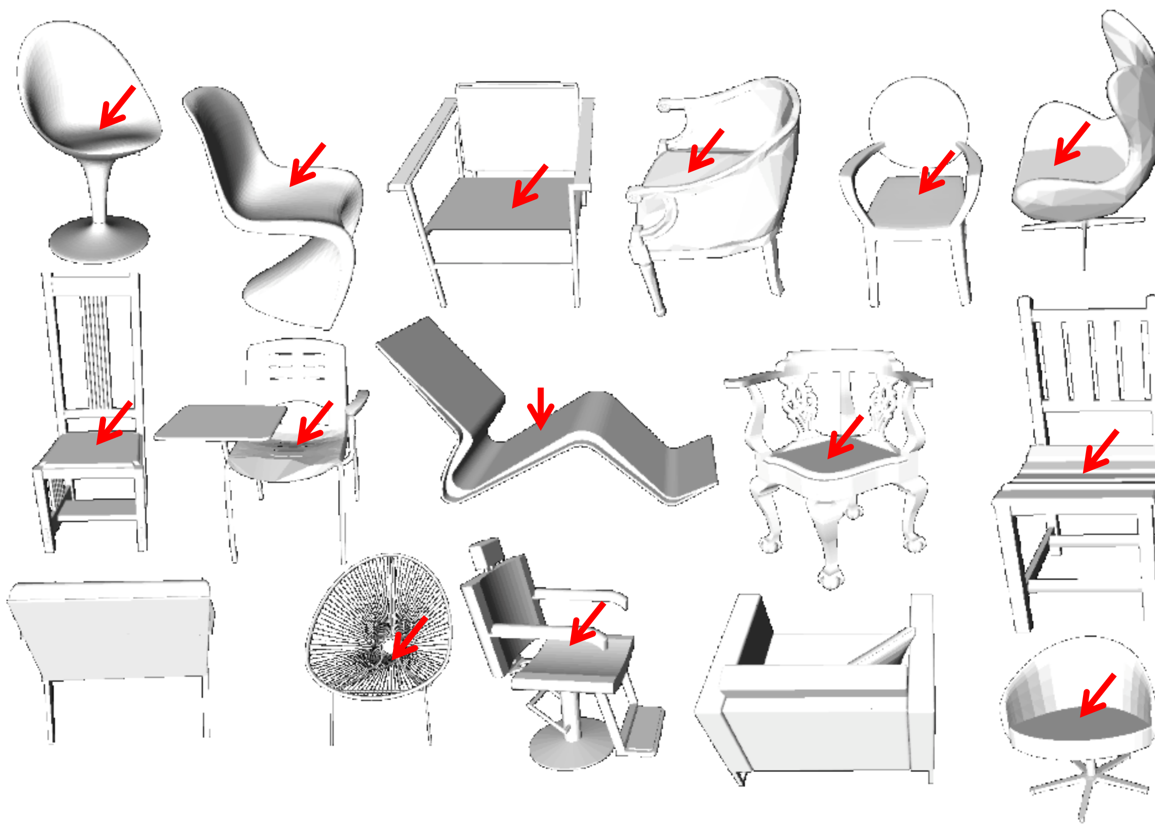
Consistent Segmentation [Golovisnkiy et al., SMI 2009]

Visualization of Shape Variations [Kim et al., SIGGRAPH 2012]

Goal

Develop algorithms to find point correspondences

- Suitable for collections of computer graphics models
- Robust to intra-class variations
- Align semantic features
- Automatic
- Efficient



Computer Graphics Models of Chairs Downloaded from SketchUp Warehouse

Previous Work

Classical methods:

- Local features
- Global maps

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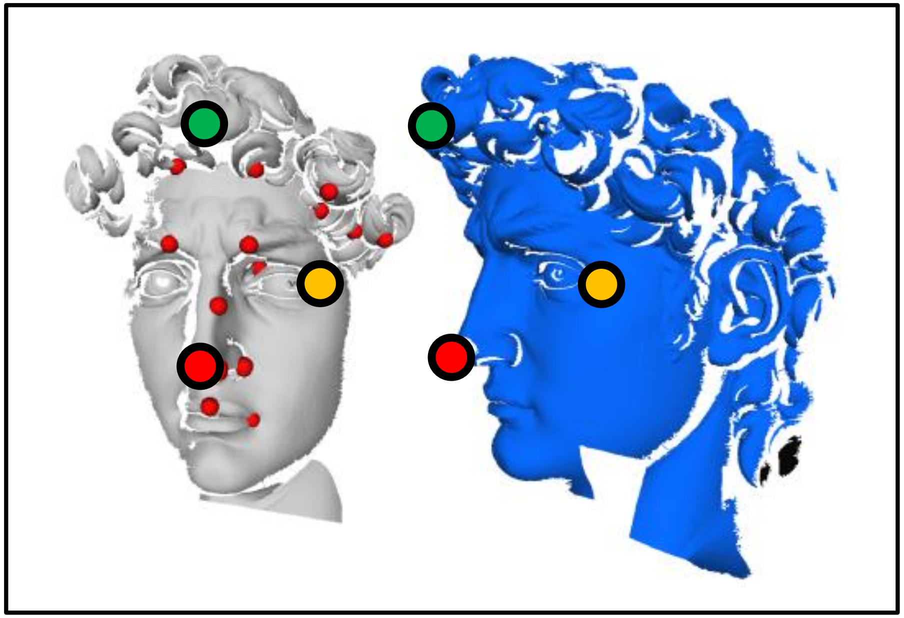
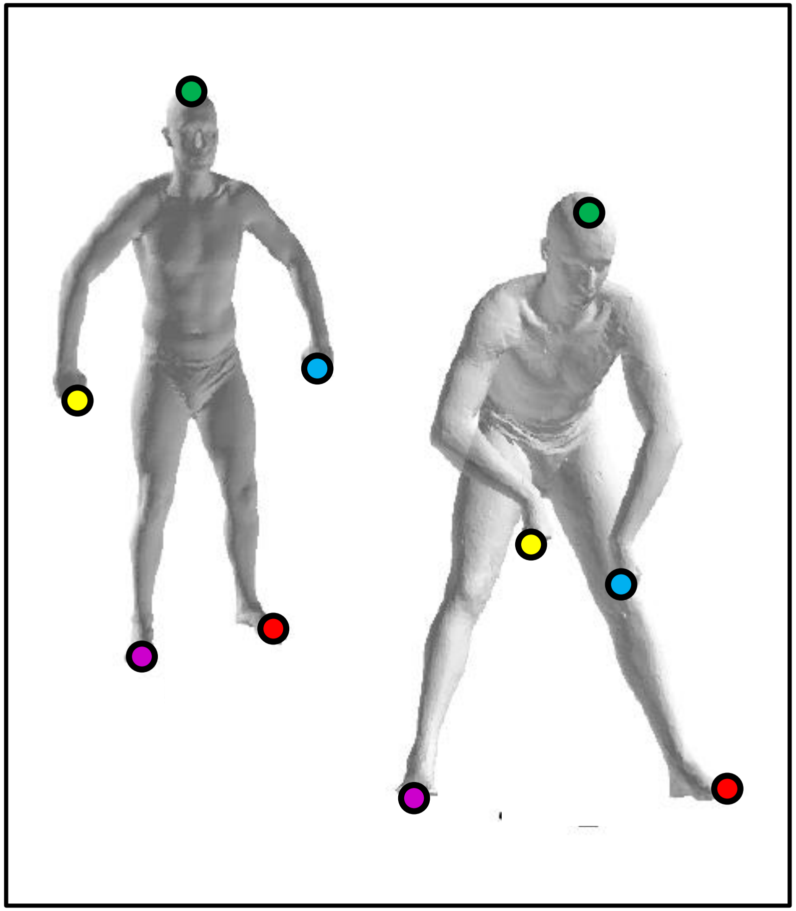
- ◦ Global maps

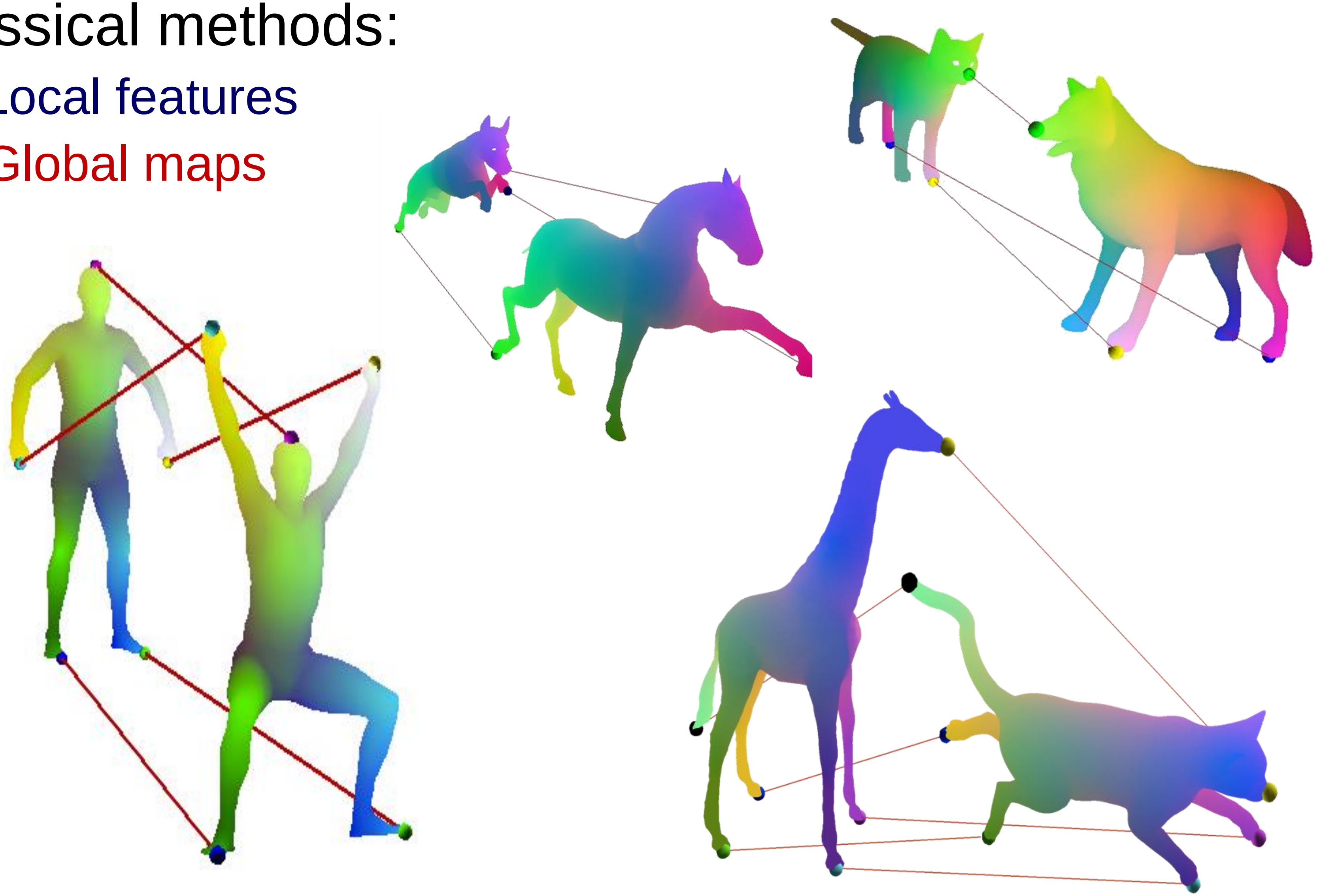




Previous Work

Classical methods:

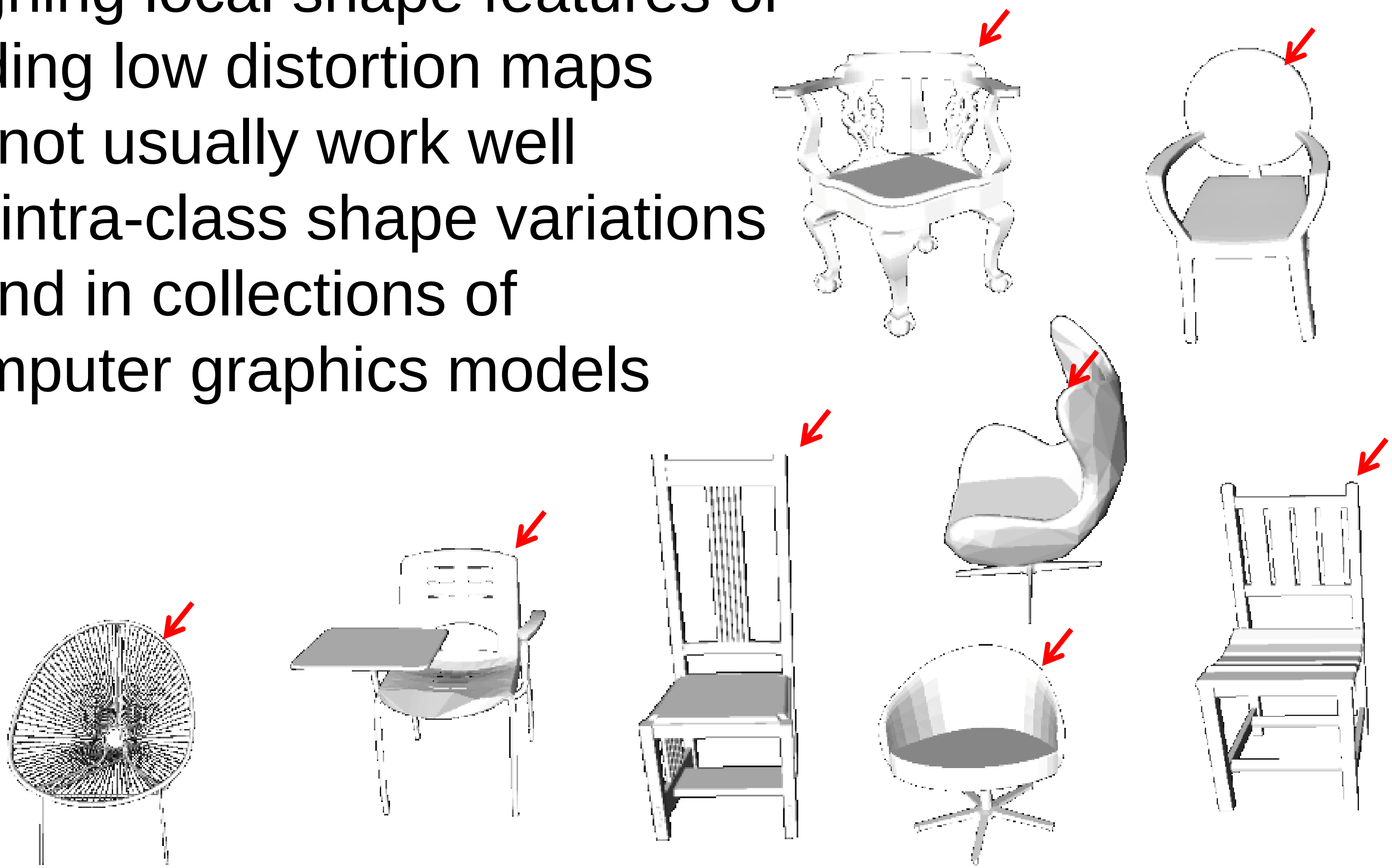
- Local features
- ➢Global maps



Blended Intrinsic Maps [Kim et al., SIGGRAPH 2011]

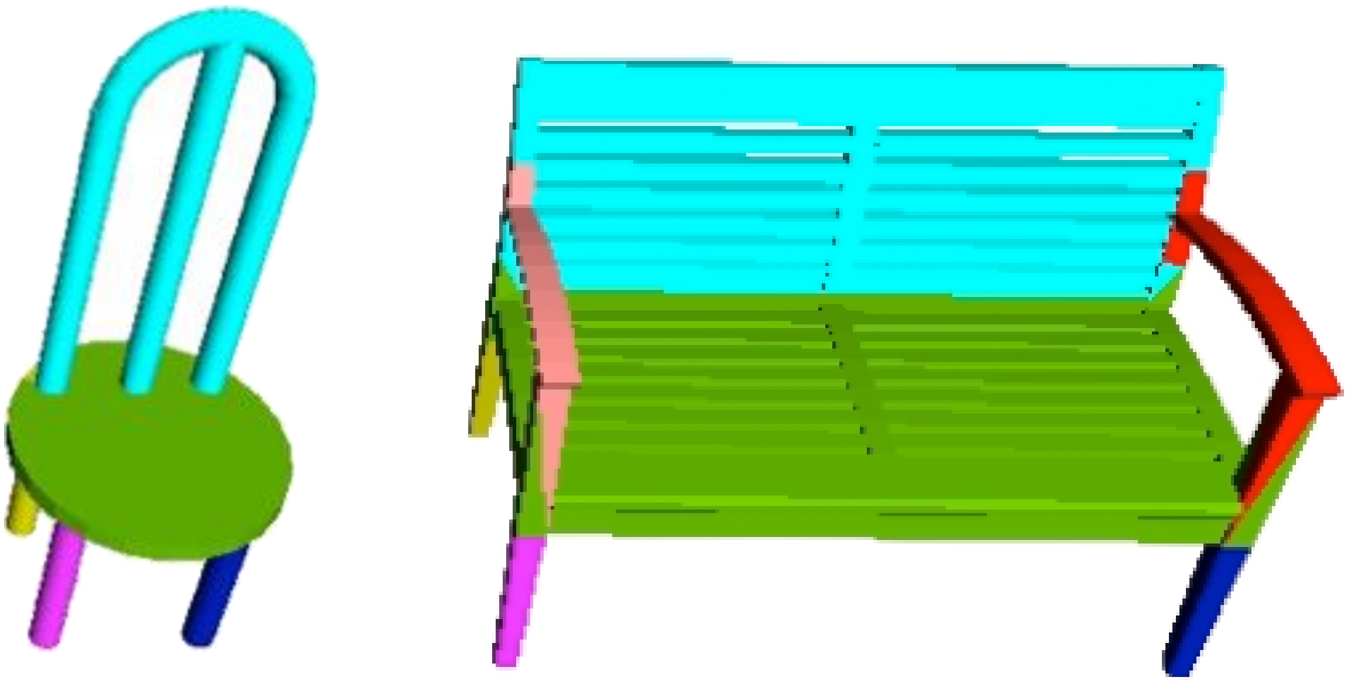
Challenge

Classical methods based on aligning local shape features or finding low distortion maps do not usually work well for intra-class shape variations found in collections of computer graphics models



Observation

Semantic correspondences are often coupled with symmetry, part segmentation, human contact, and other high-level features



This observation has also been made by many people, including Niloy Mitra, Michael Wand, Danny Cohen-Or, Hao (Richard) Zhang, Leo Guibas, etc.

Outline of Talk

Introduction

“Structure-aware” correspondences

- Reflective symmetry
- Part segmentation
- Human pose

Conclusions

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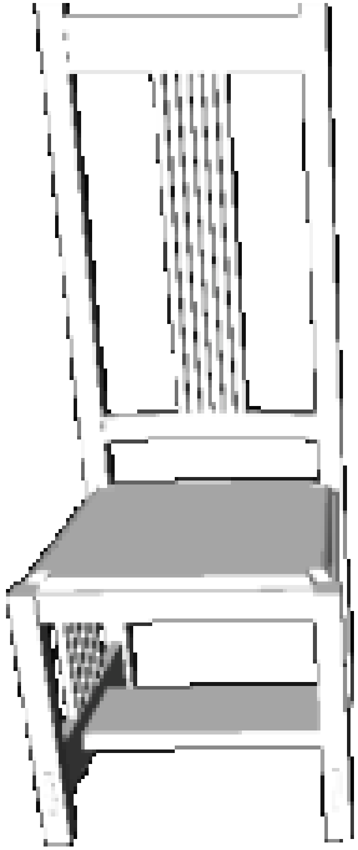
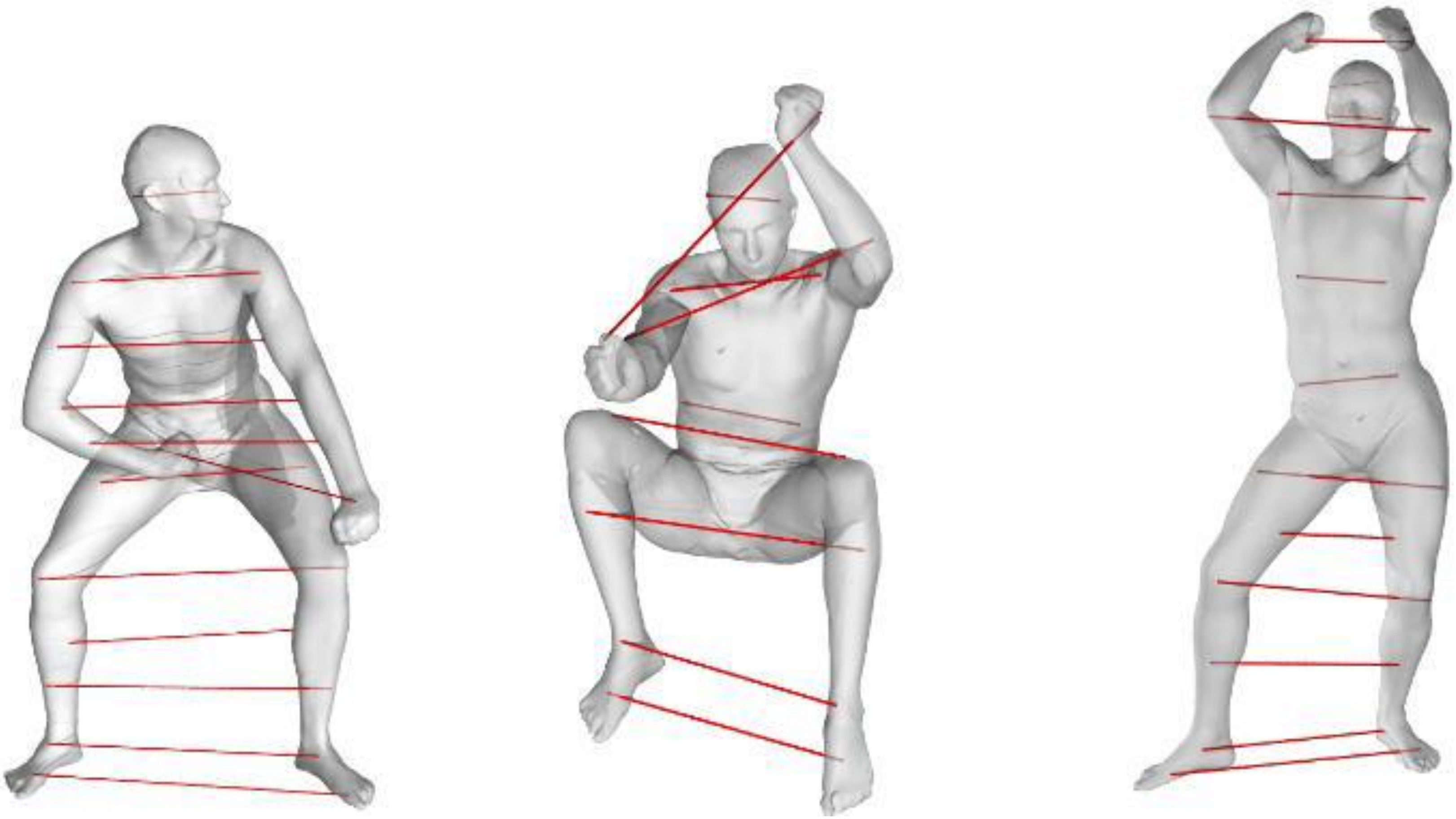
Symmetry-Aware Correspondences

Observation 1: reflective symmetry is ubiquitous in everyday objects



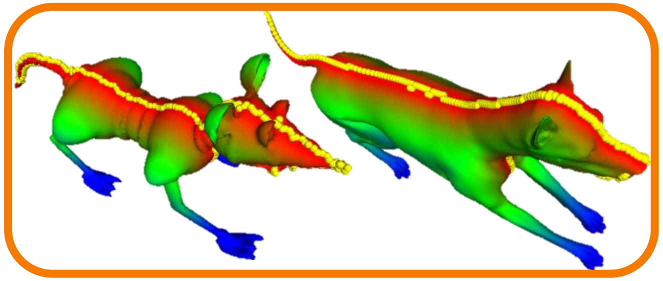
Symmetry-Aware Correspondences

Observation 2: detecting symmetries is easier than finding correspondences

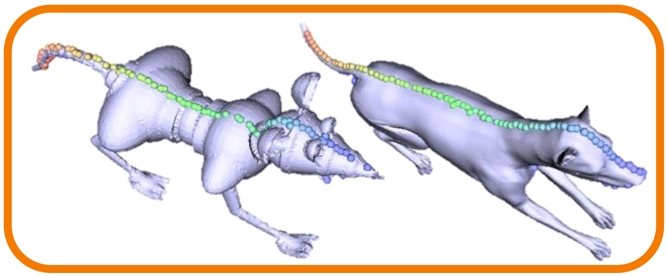


Symmetry-Aware Correspondence Algorithm

Symmetry Axis Detection



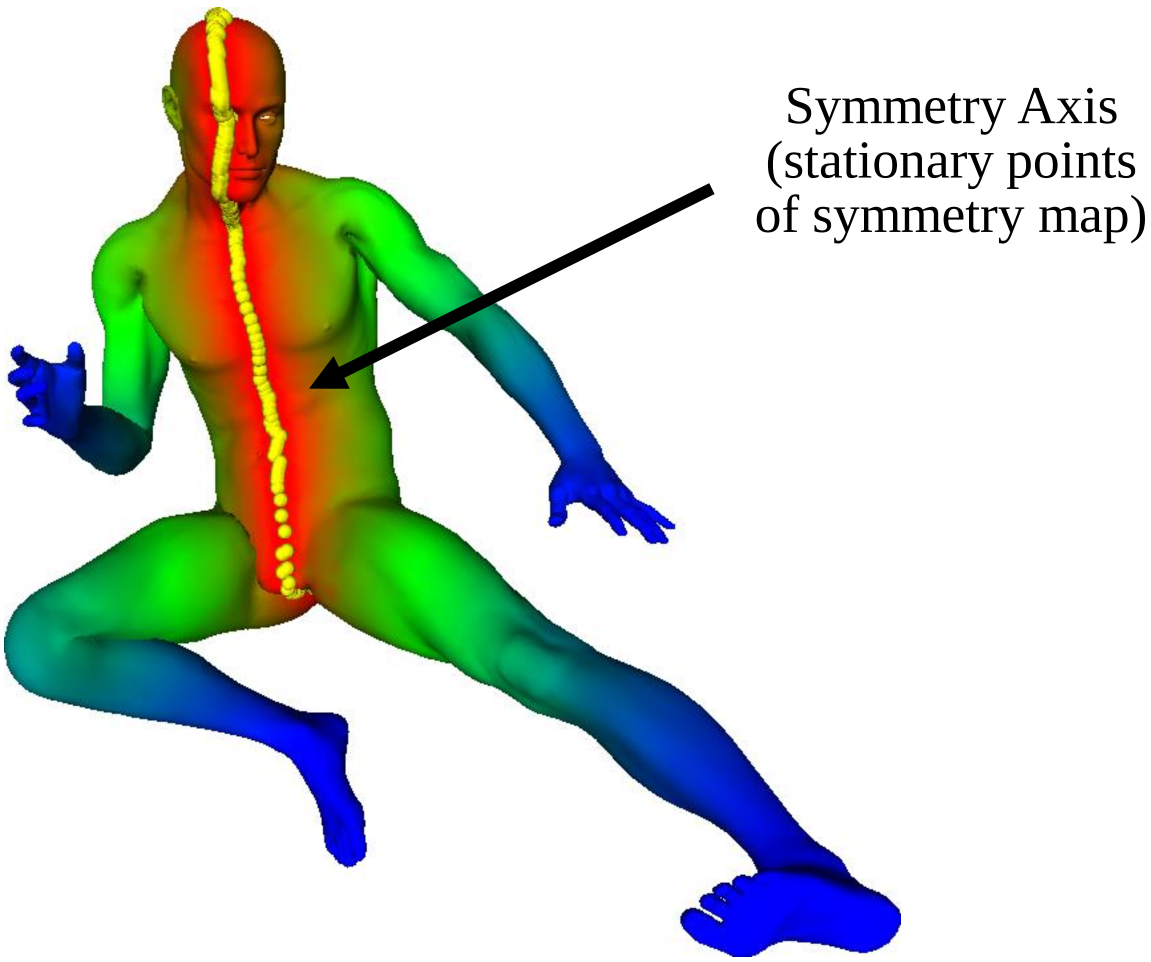
Symmetry Axis Alignment



Correspondence Extrapolation

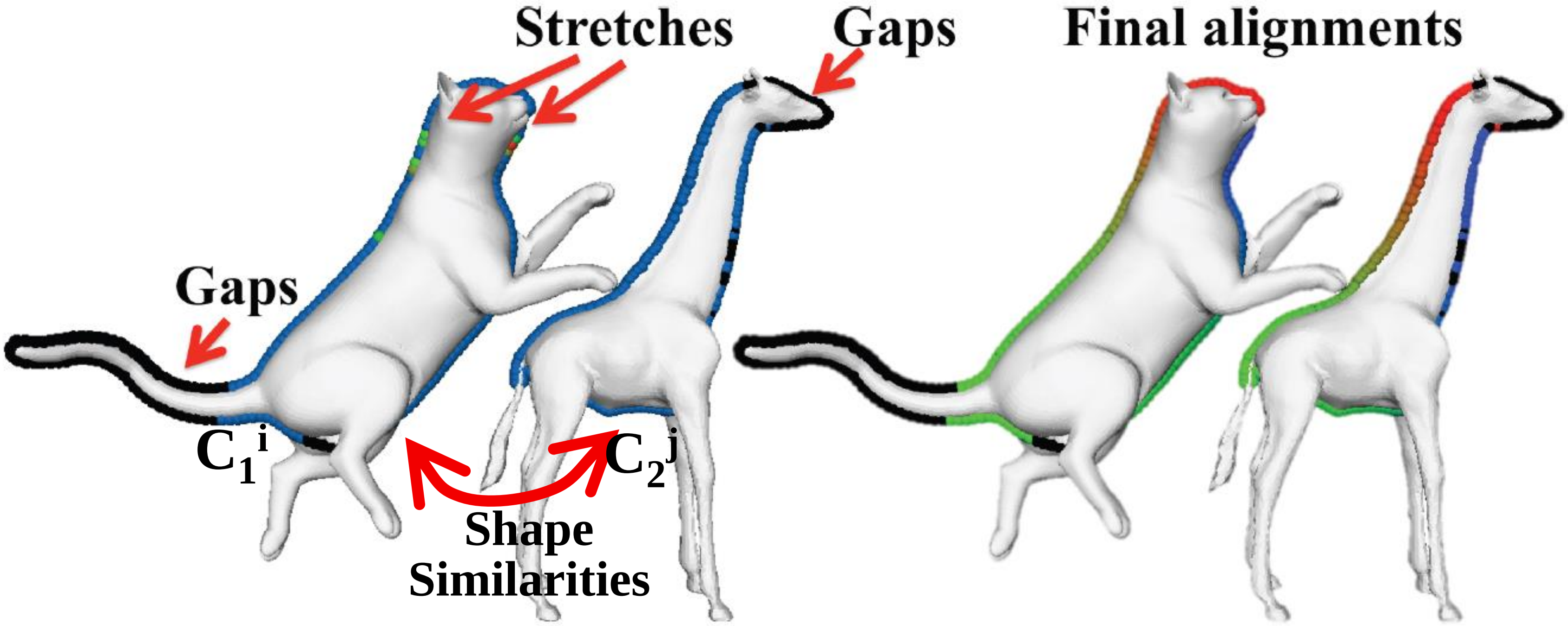
Symmetry Axis Detection

Given a mesh, extract potential symmetry axes



Symmetry Axis Alignment

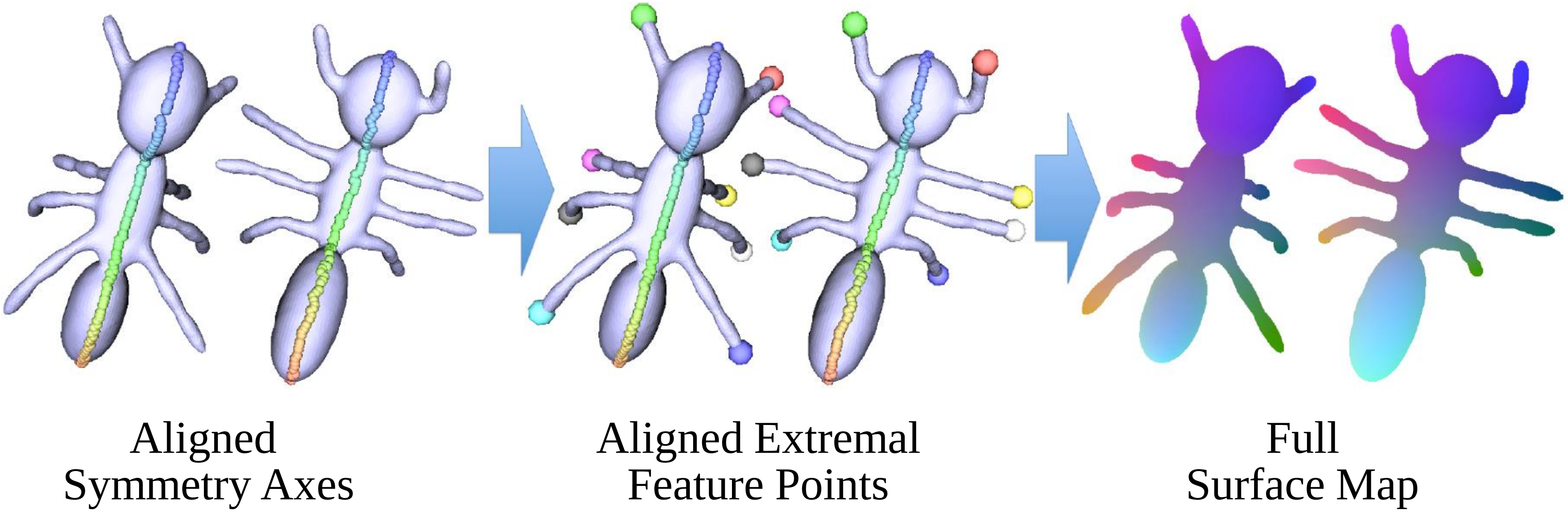
For every pair of symmetry axes, find optimal alignment for every pair of starting points



$$Q(C_1^i, C_2^j, c) = Q_{Axis}(C_1^i) \cdot Q_{Axis}(C_2^j) \cdot Q_{Align}(C_1^i, C_2^j, c)$$

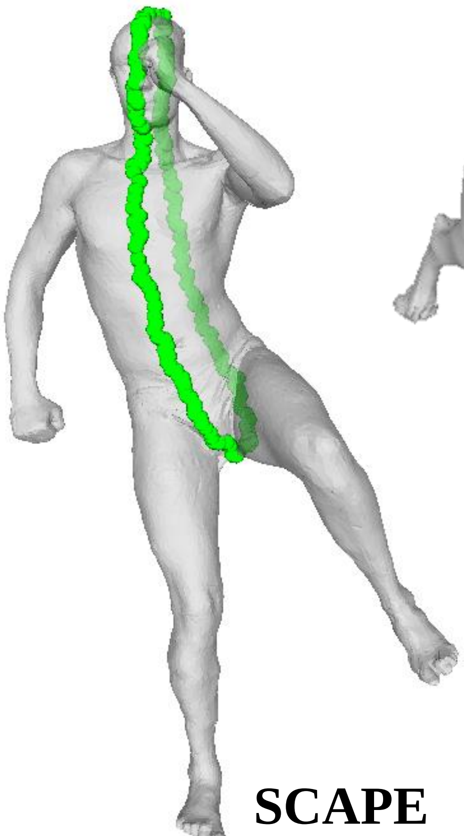
Correspondence Extrapolation

Given an alignment between symmetry axes, extrapolate correspondences to rest of surfaces

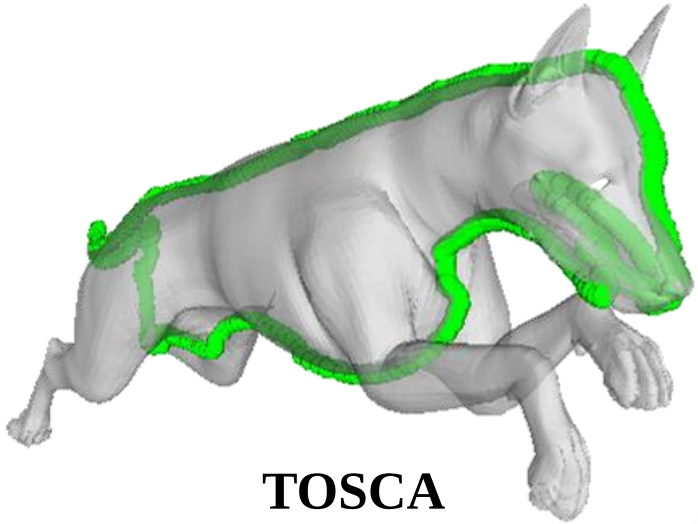


Symmetry-Aware Correspondence Evaluation

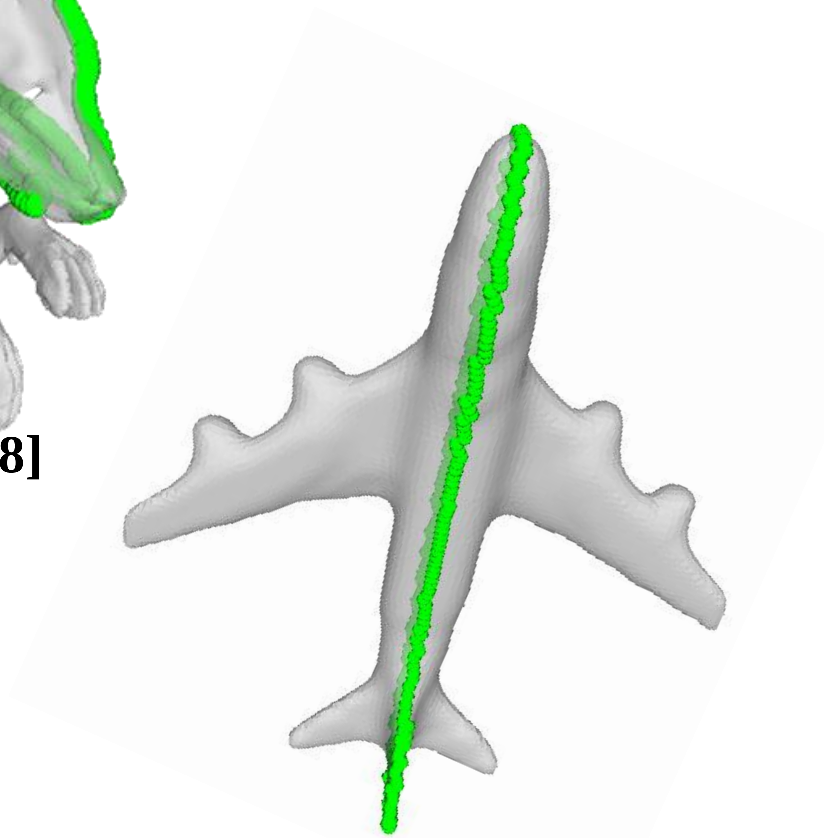
Surface Correspondence Benchmark [Kim 2011]



SCAPE
[Anguelov et al., 2004]



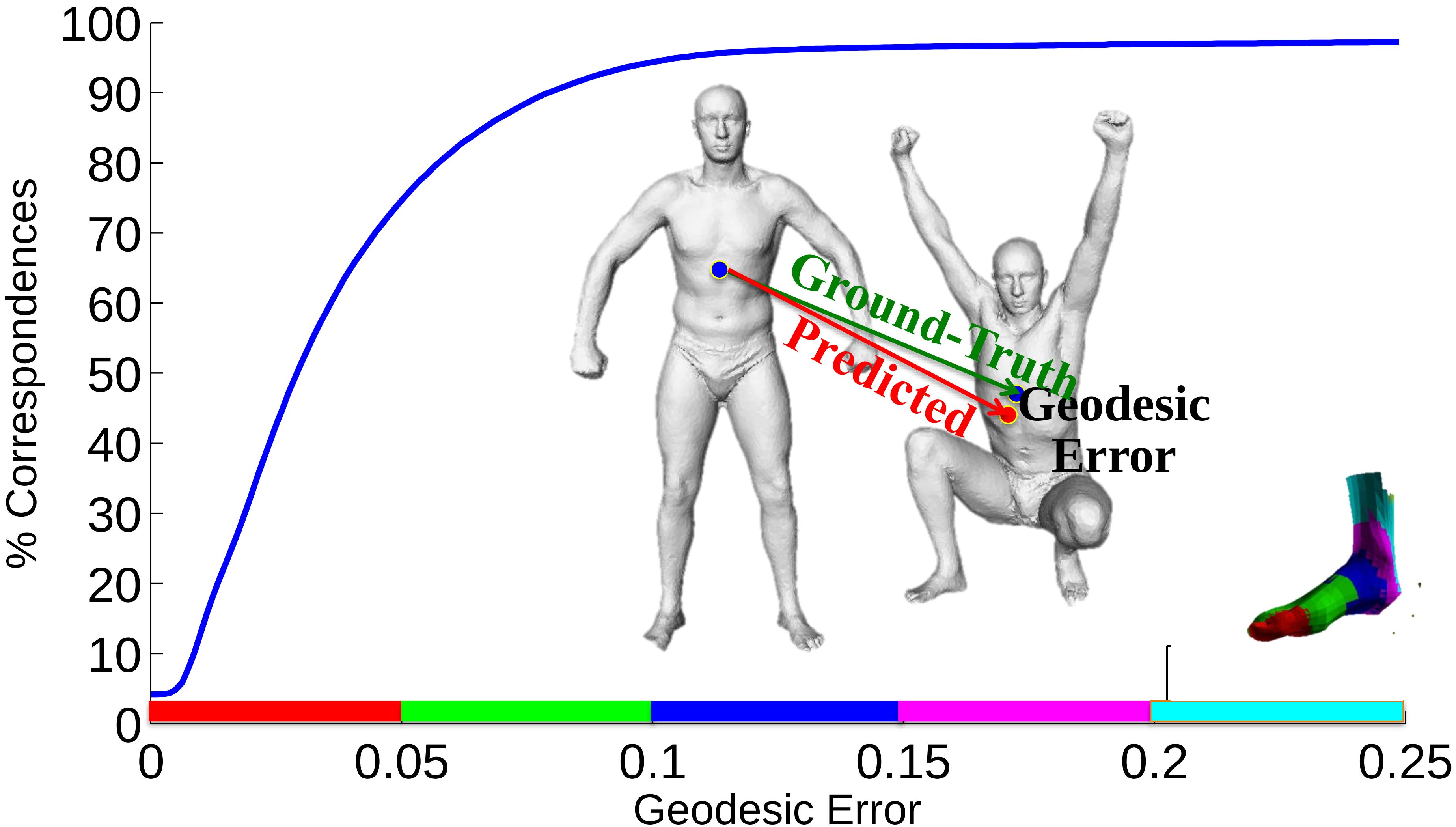
TOSCA
[Bronstein et al., 2008]



SHREC Watertight 2007
[Giorgi et al., 2007]

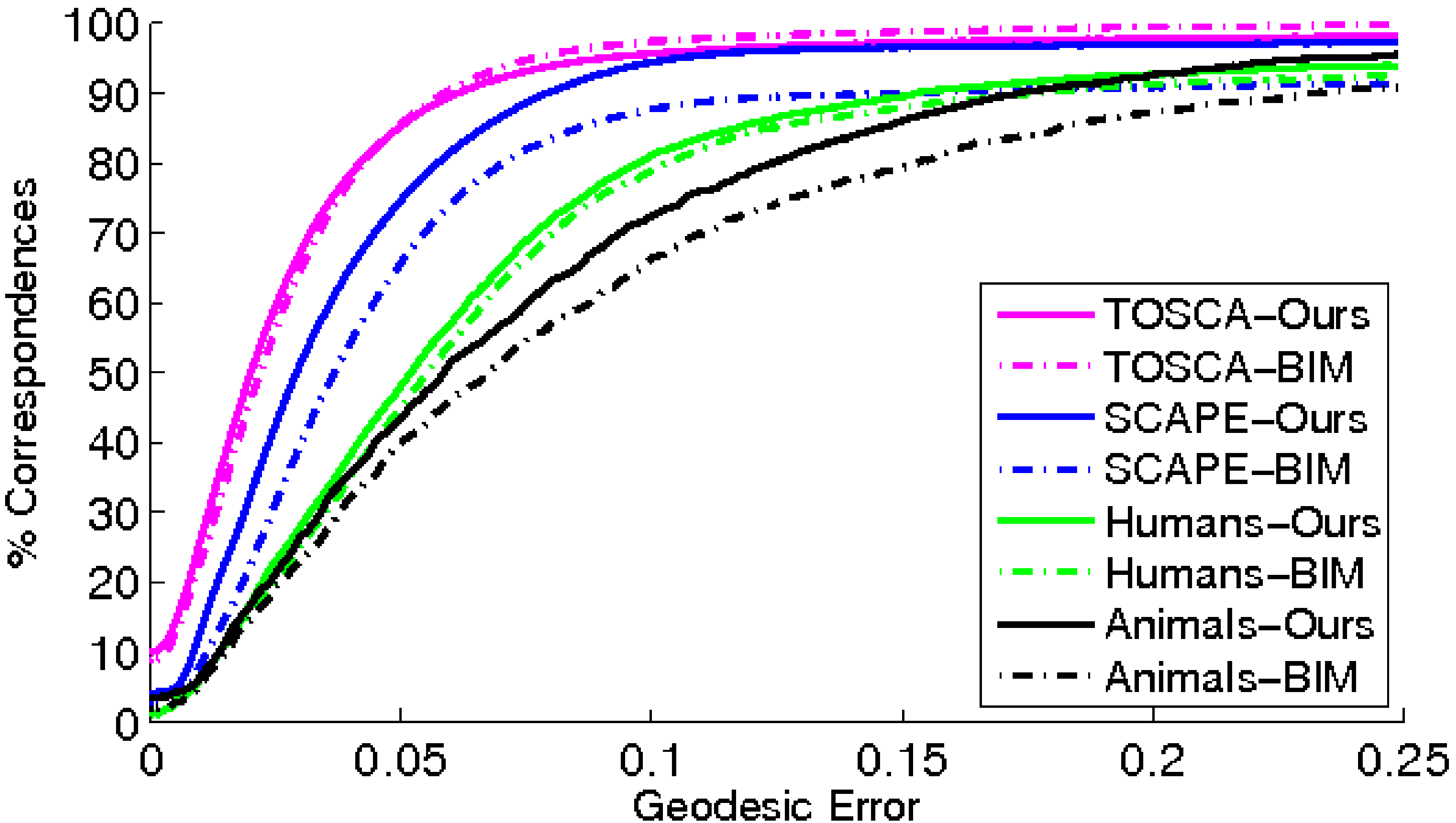
Symmetry-Aware Correspondence Results

Evaluation methodology

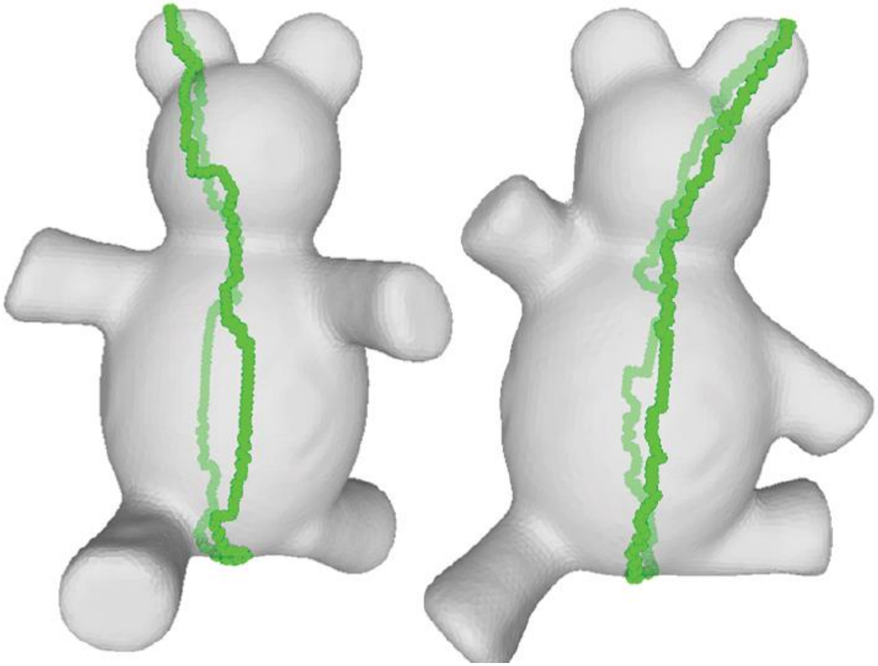


Symmetry-Aware Correspondence Results

Comparison to Blended Intrinsic Maps [Kim 2011]



Symmetry-Aware Correspondence Failures



Poor Symmetry
Axis Extraction

Non-descriptive
Symmetry Axes

Outline of Talk

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"Structure-aware" correspondences

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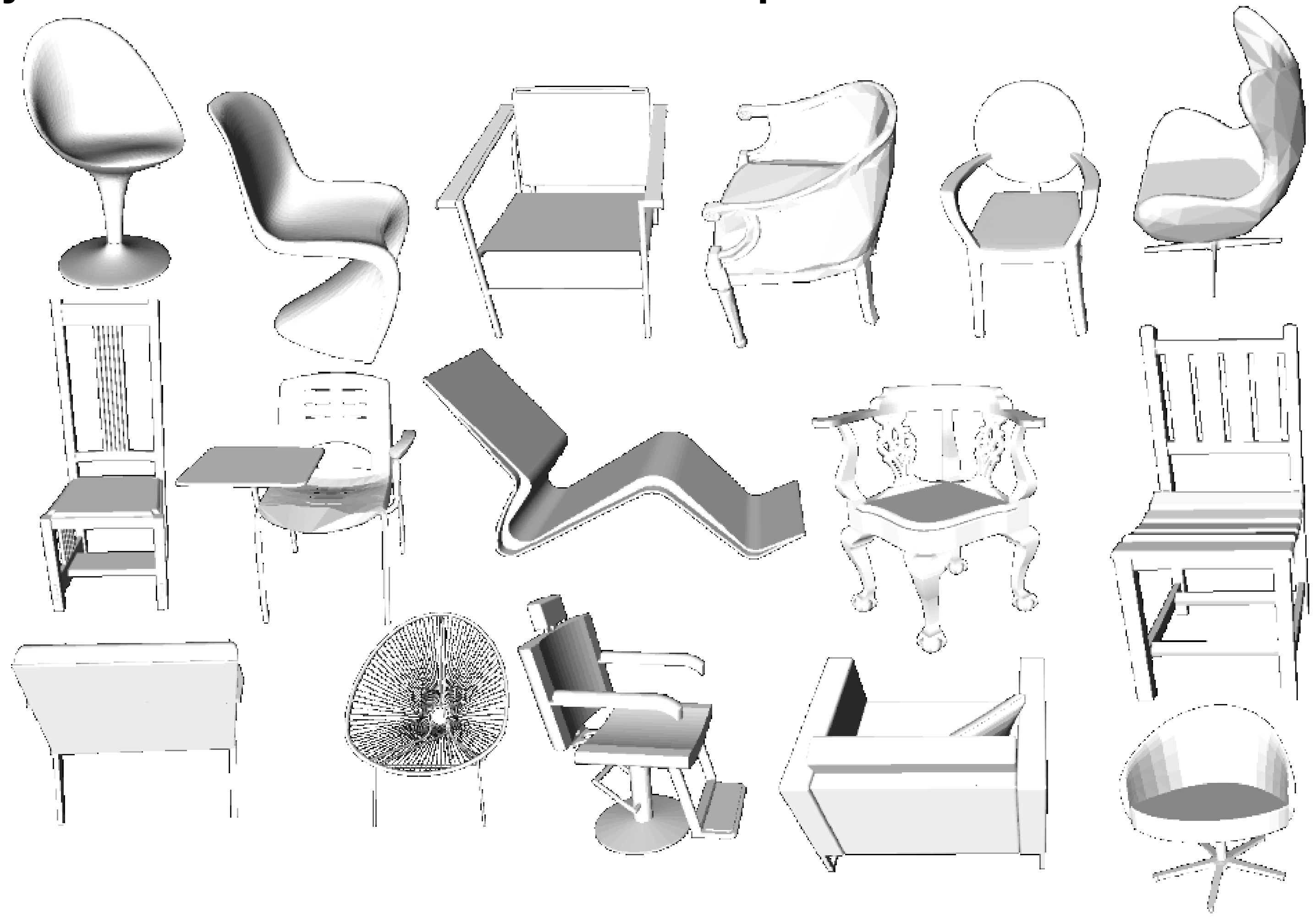
- Part segmentation
- Human pose

Conclusions

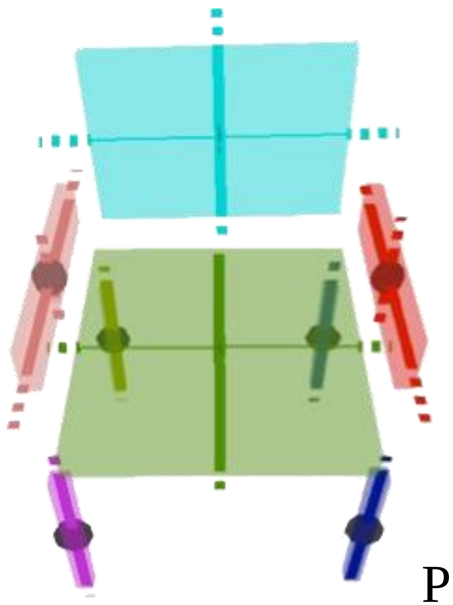
Goal

Observation: semantic relationships between objects are often based on parts



Part-Aware Correspondences

Approach: learn part-based template for object class, and then use it to segment, correspond, and align surfaces



Part-Based Template

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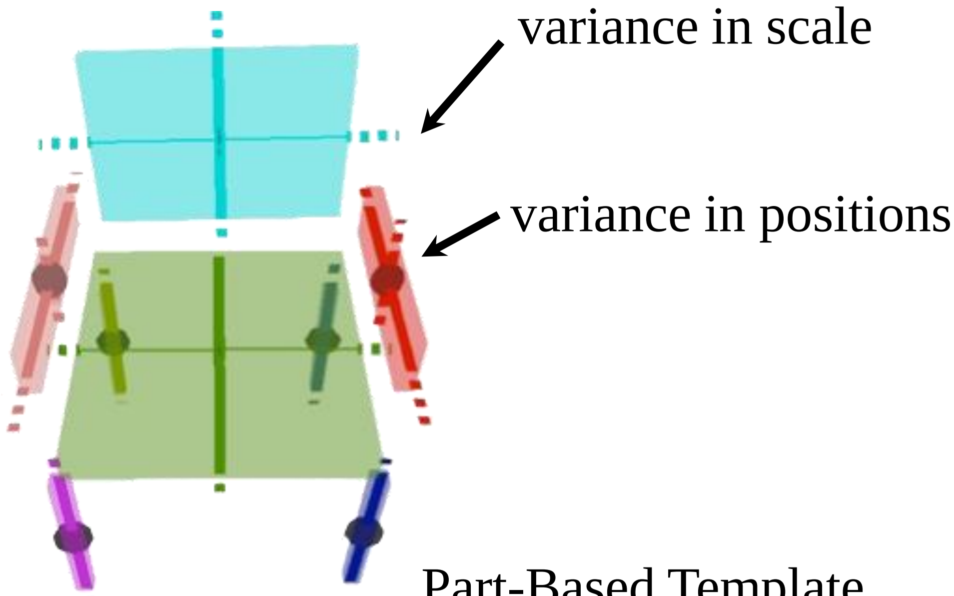

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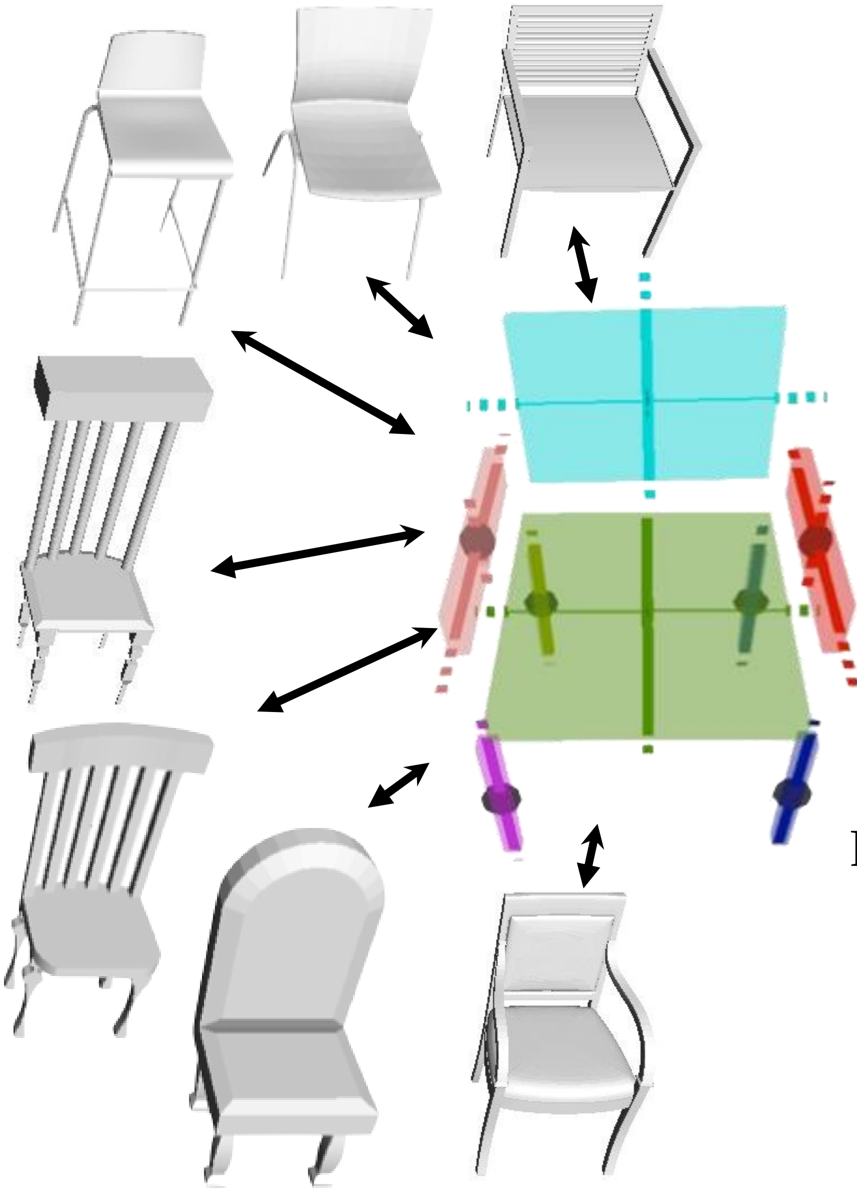

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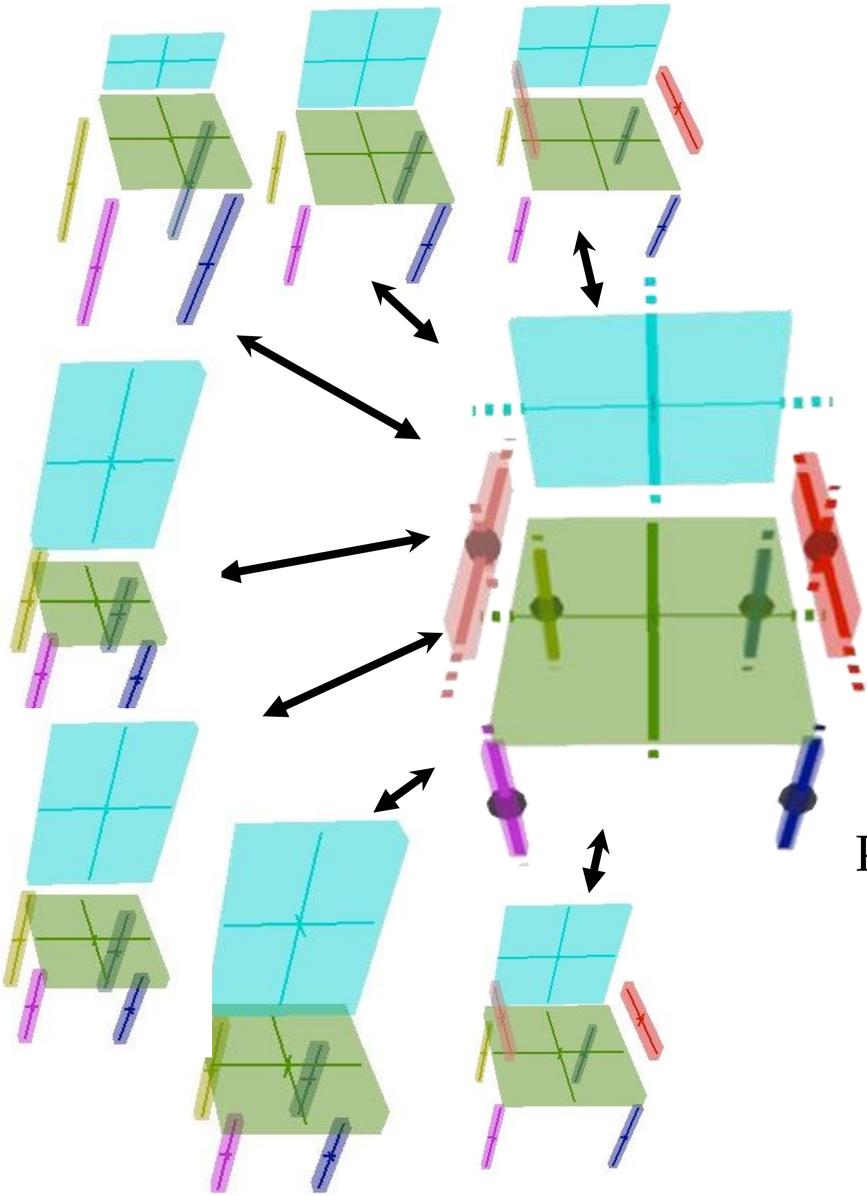

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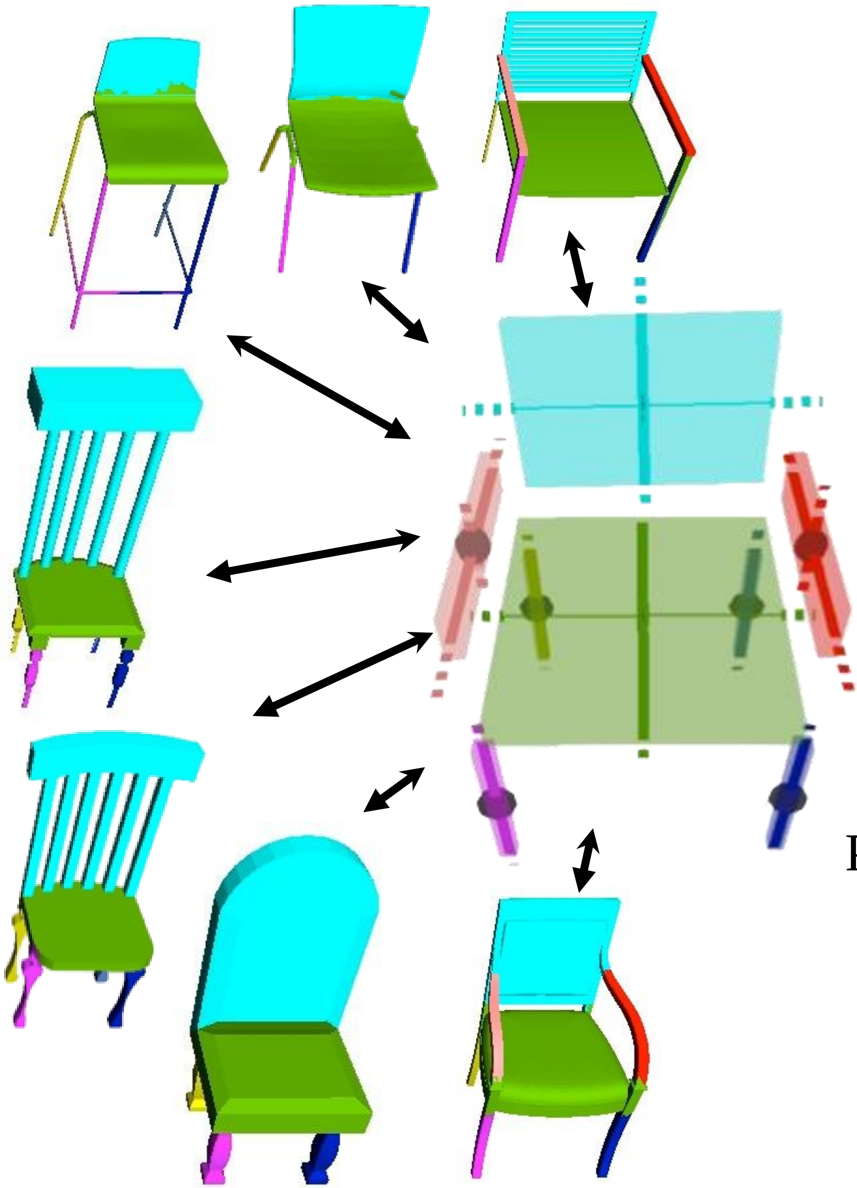

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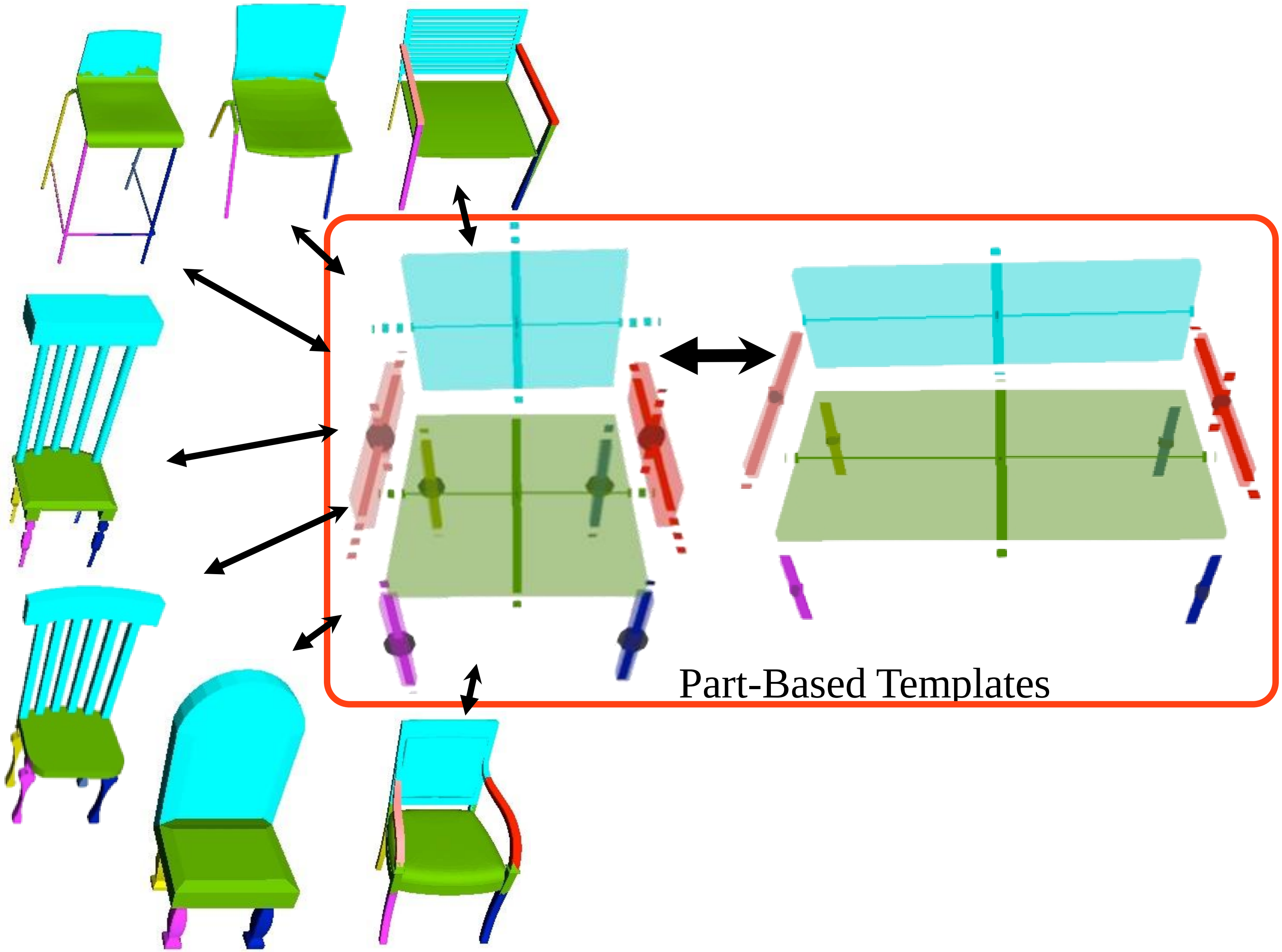
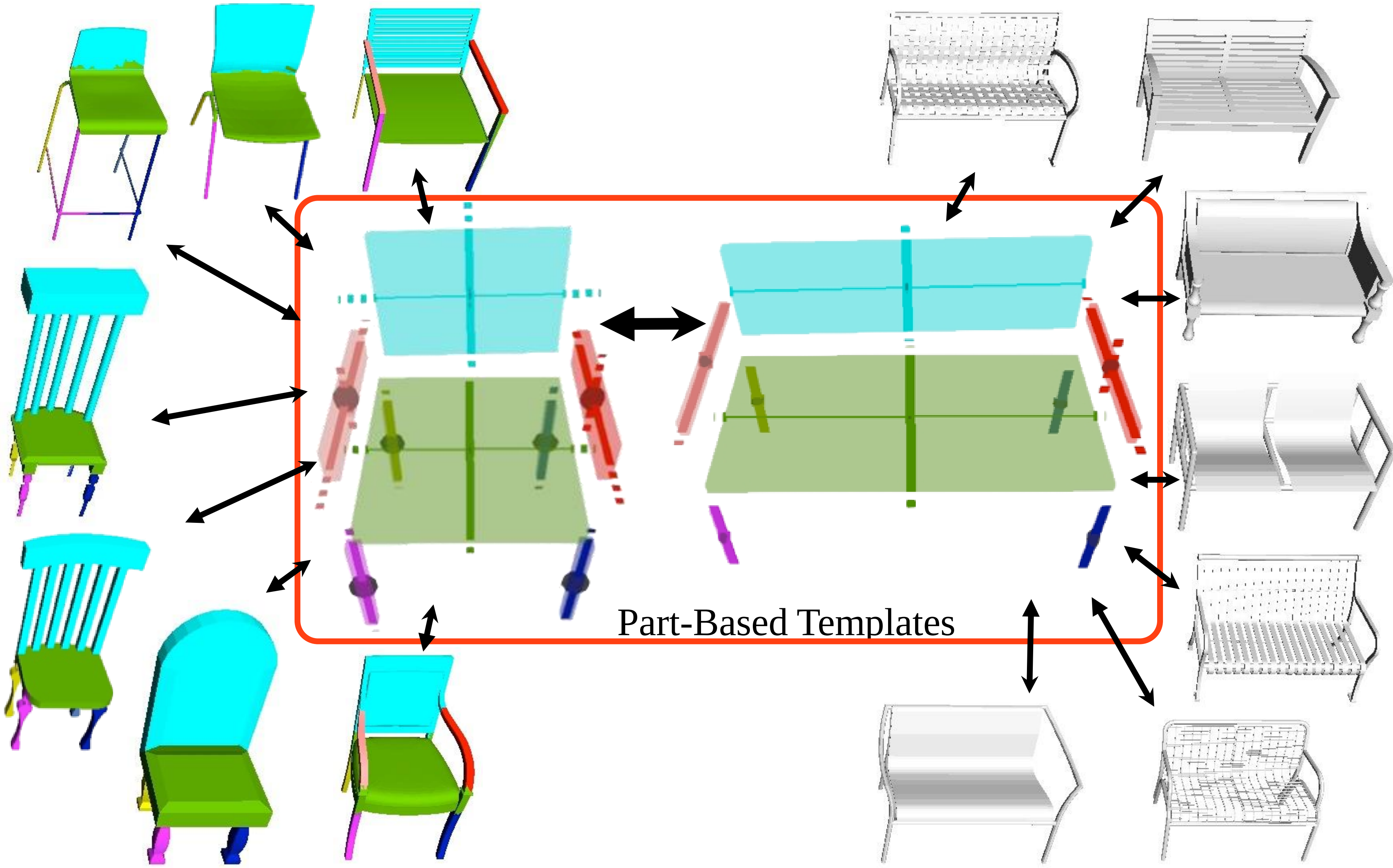


Part-Aware Correspondences



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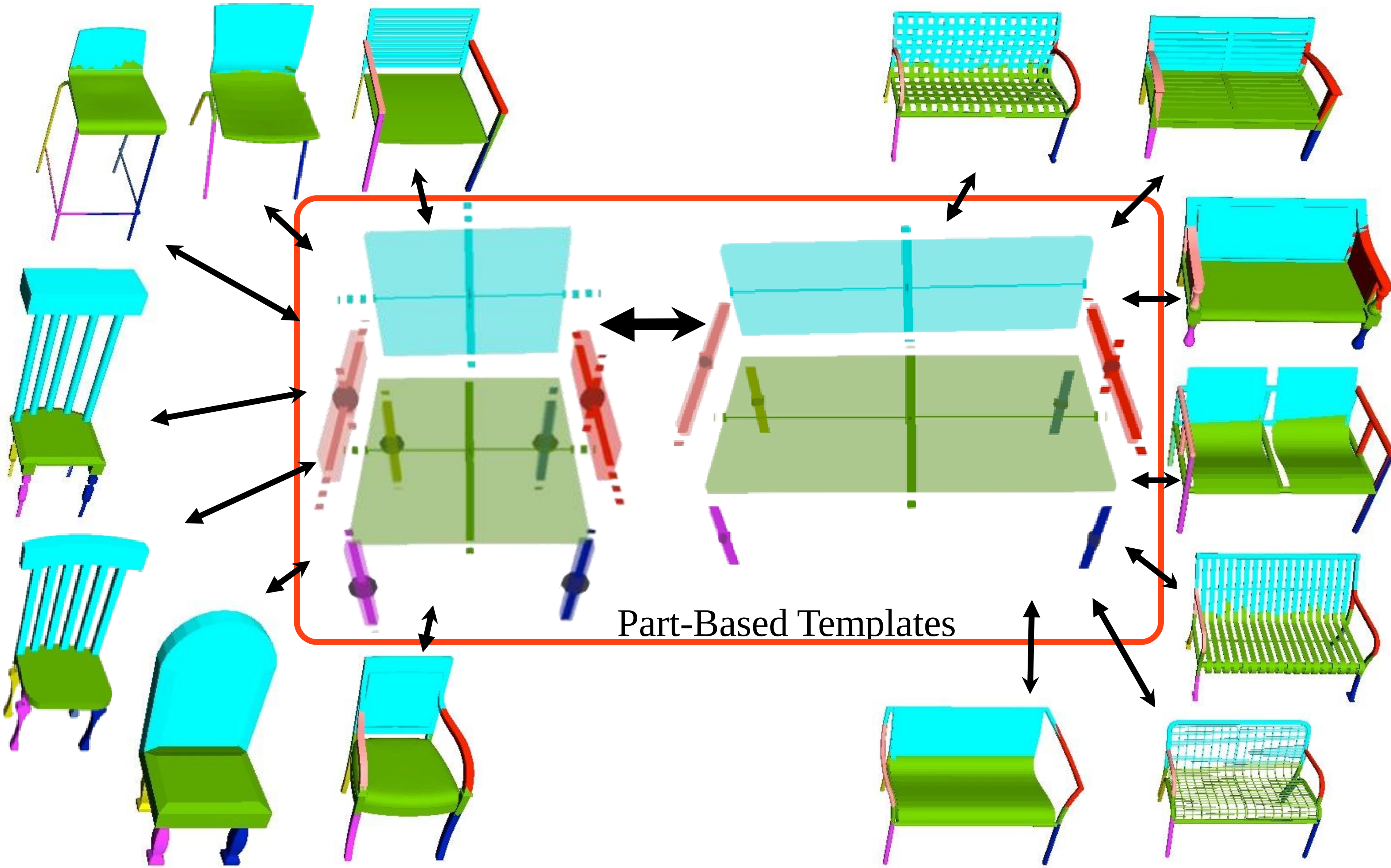
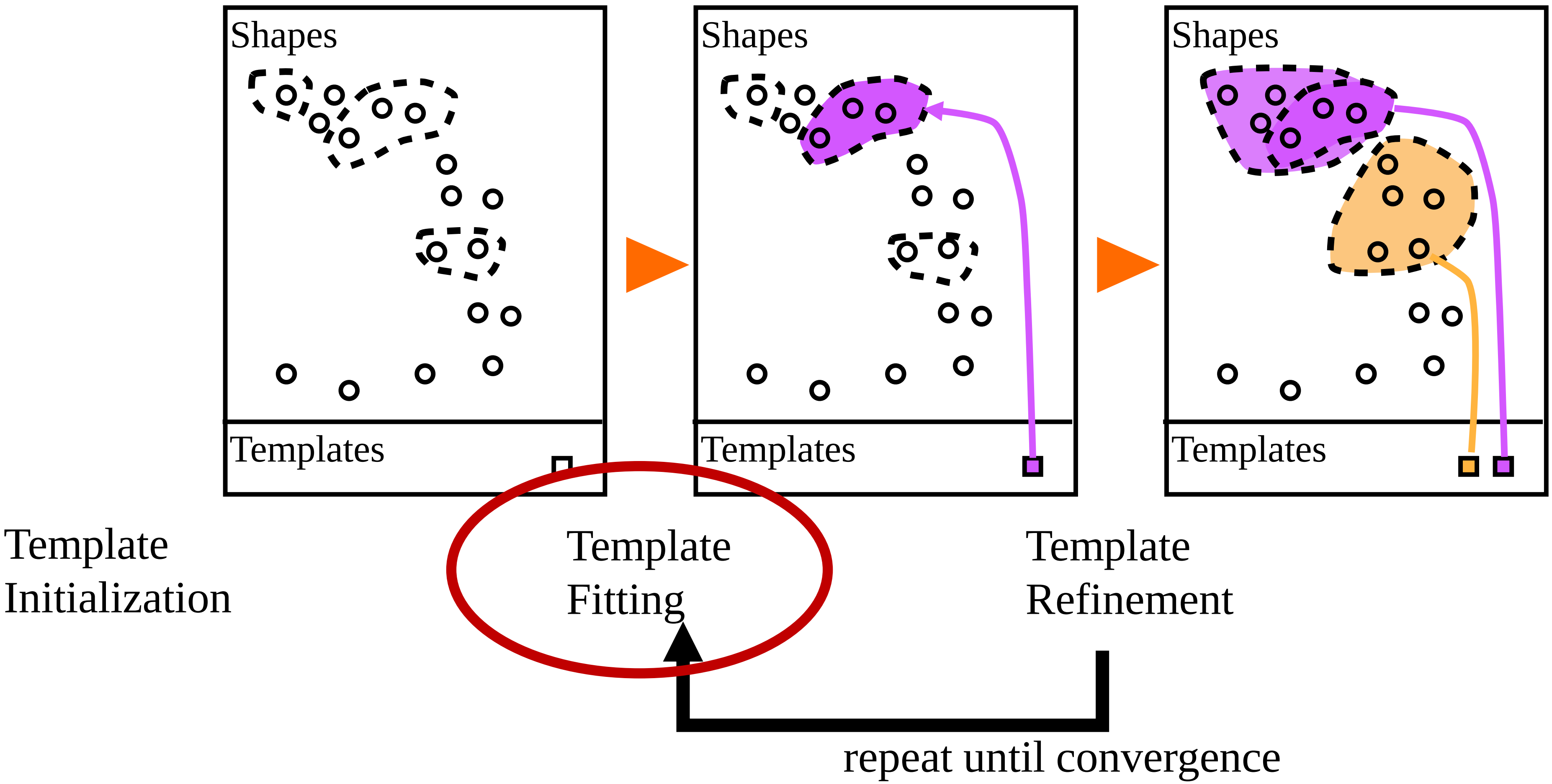


Part-Aware Correspondence Algorithm

Search for a set of templates that best explains a collection of models



Part-Aware Fitting Algorithm

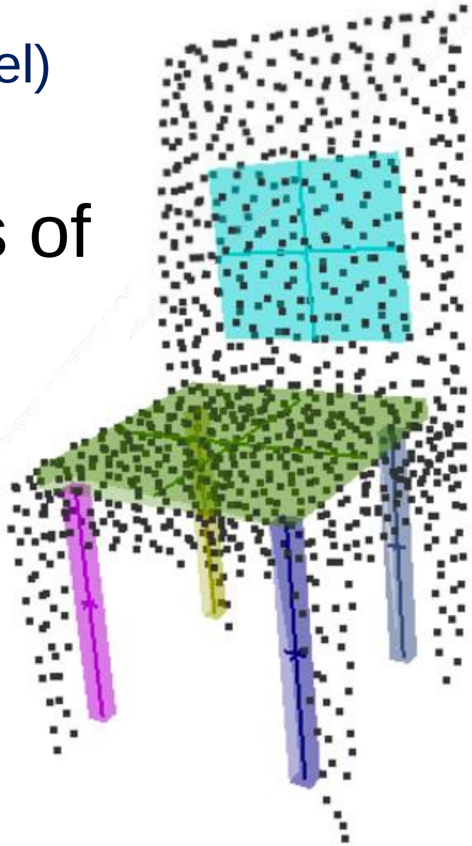
Objective function for each template-model fit:

$$E = E_{\text{data}} + \gamma E_{\text{deform}} + \beta E_{\text{smooth}}$$

- E_{data} (template ↔ shape distance + local shape features)
- E_{deform} (plausibility of template deformation)
- E_{smooth} (close & similar regions get same label)

Algorithm iterates solutions to subsets of objective function until convergence:

- Segmentation
- Correspondence
- Part-aware deformation



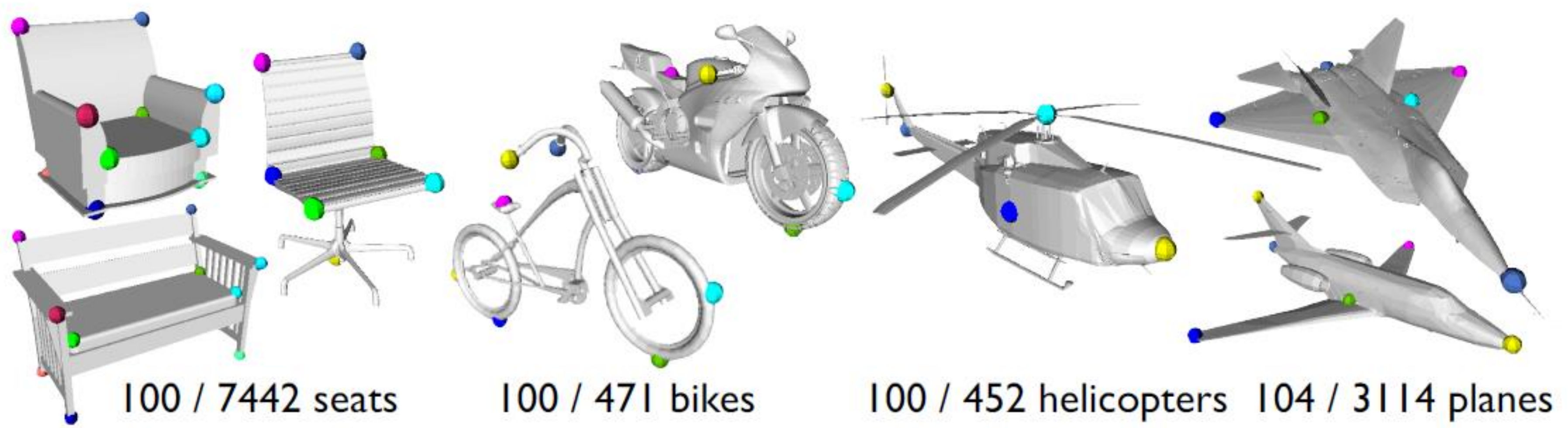
Part-Aware Correspondence Evaluation

Data sets:

- Crawl SketchUp Warehouse for collections by keyword
- Eliminate outliers with Mechanical Turk
- Specify manual correspondences for subset of models

Experiments:

- Solve for part-based template for collection
- Evaluate correspondences & segmentations



Part-Aware Correspondence Results

2 Templates

3113 Airplanes

Part-Aware Correspondence Results

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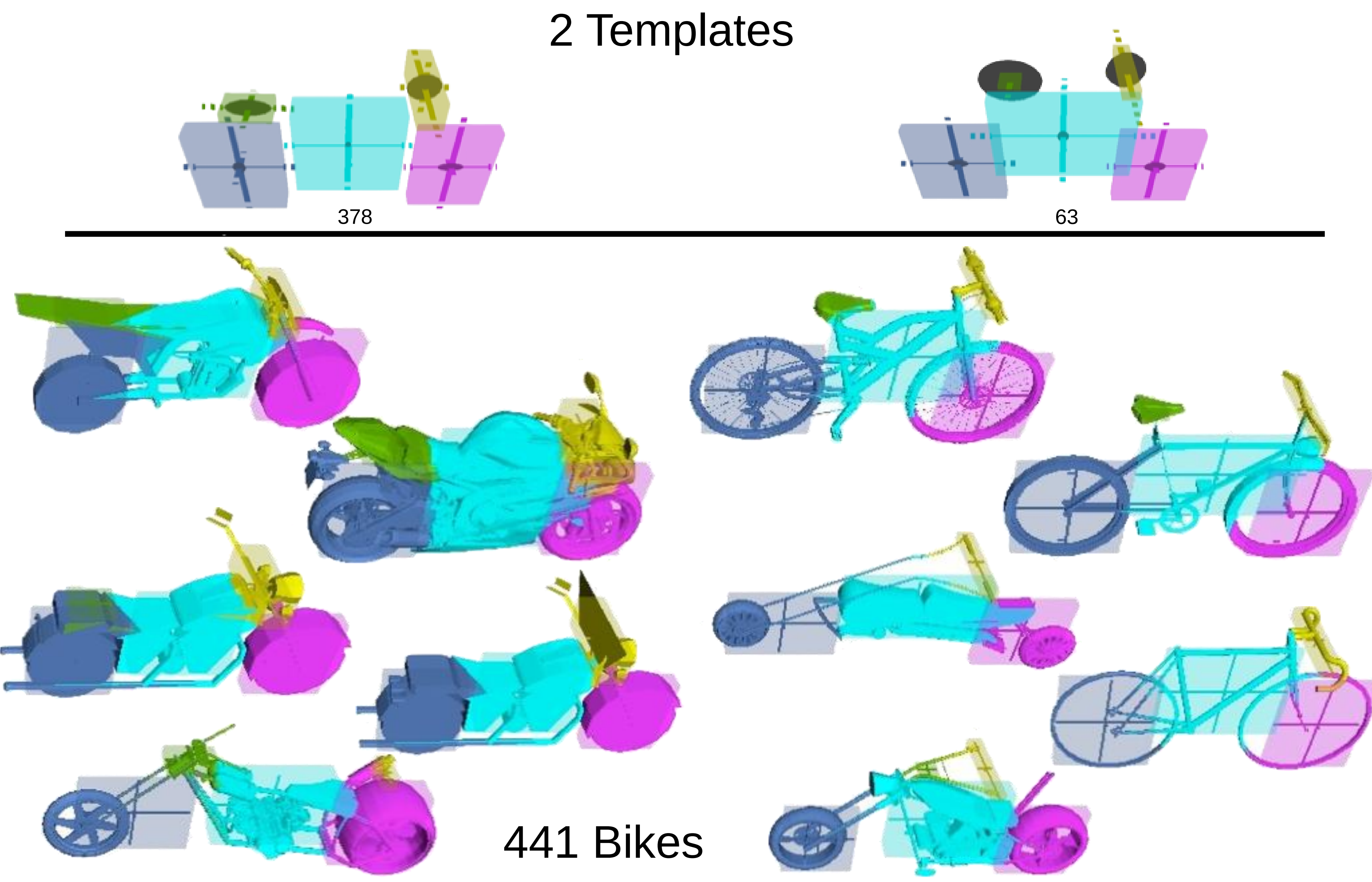
3113 Airplanes

Part-Aware Correspondence Results



Part-Aware Correspondence Results

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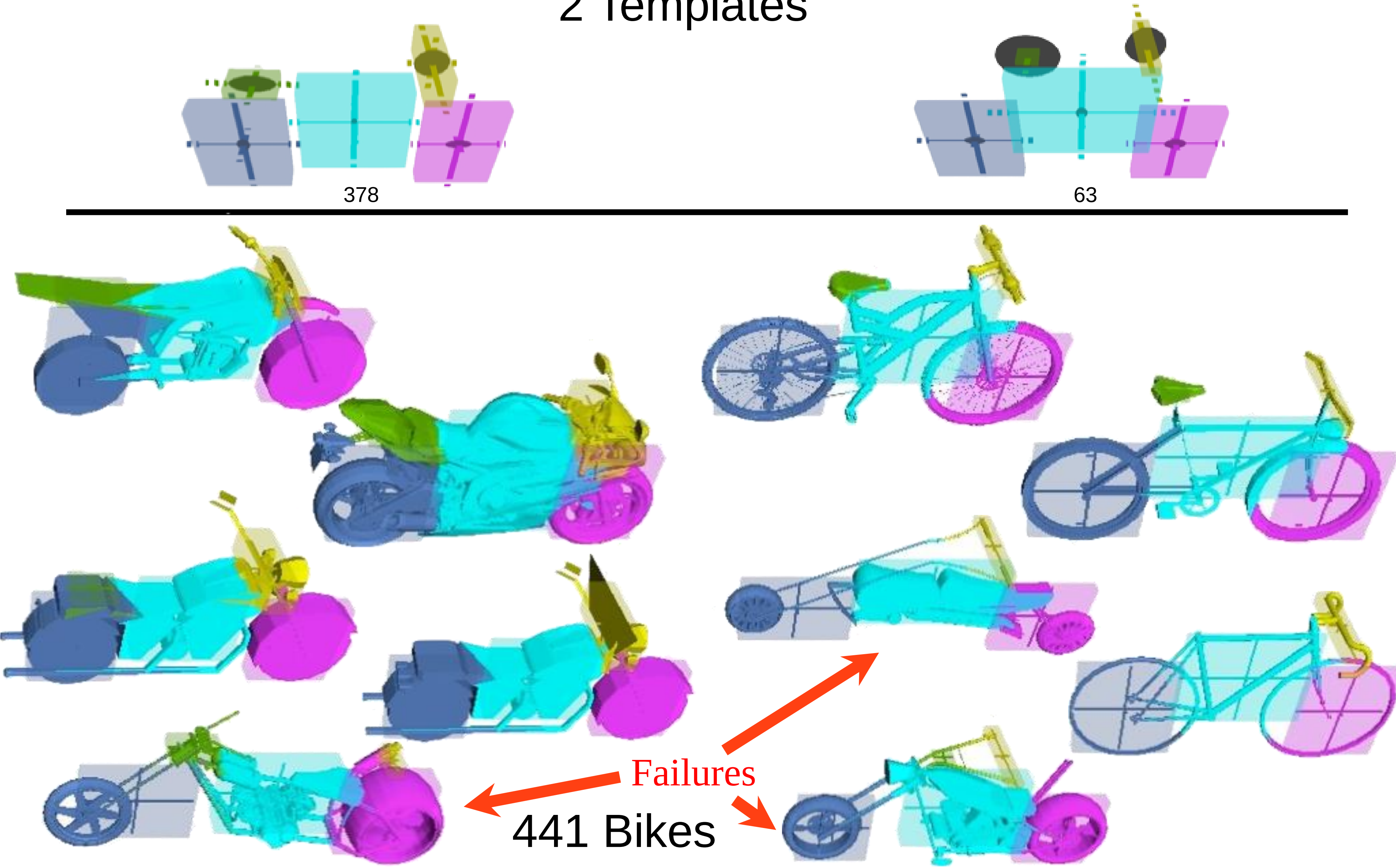
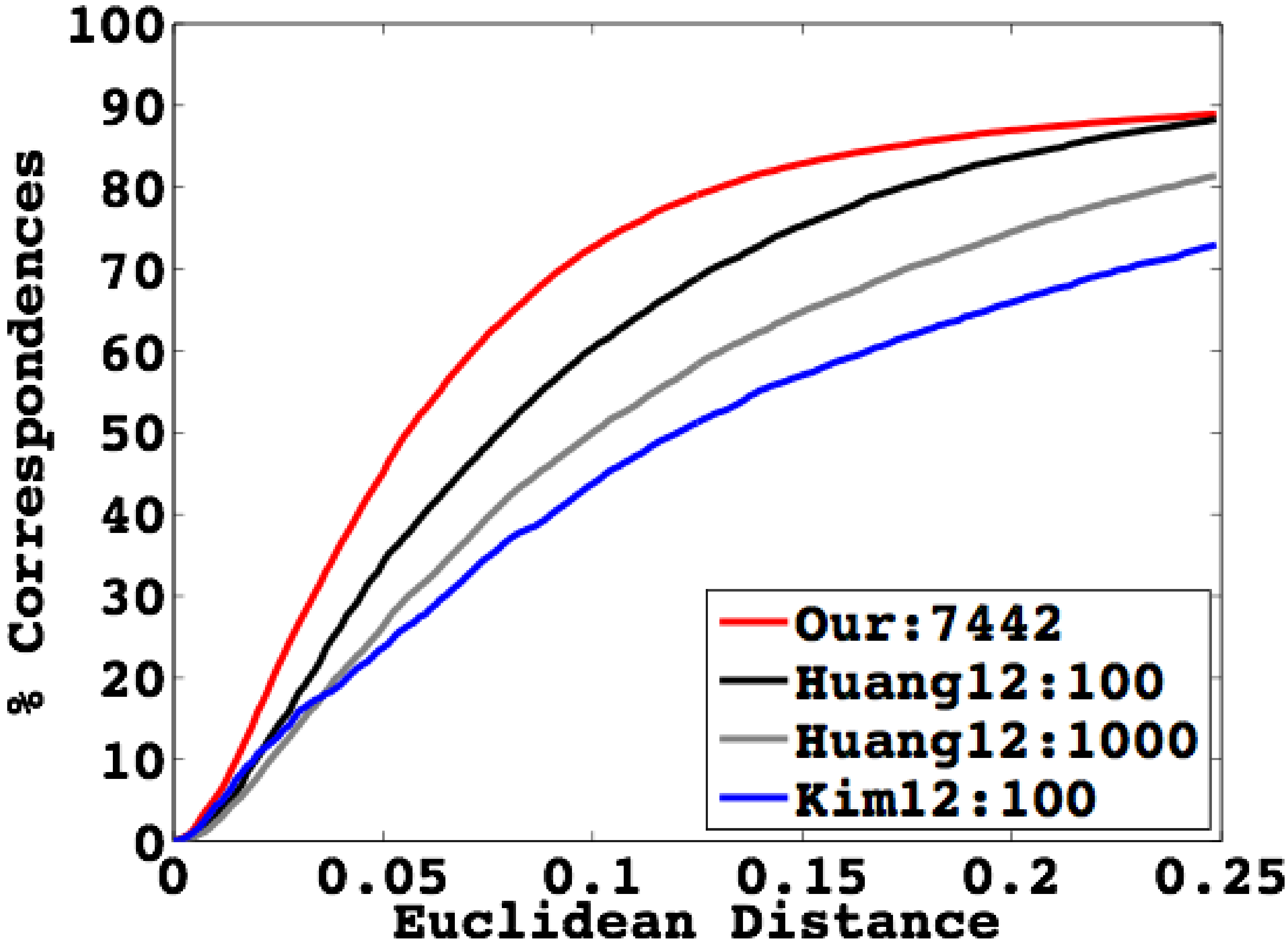


Part-Aware Correspondence Results

Correspondence benchmark (7442 seats)



Part-Aware Segmentation Results

Co-segmentation benchmark [Sidi et al, 2011]

Class	Hu	Our
Chairs	89.6	$\boxed{97.6}$
Lamps	90.7	$\boxed{95.2}$
FourLegged	88.7	86.9
Goblets	99.2	97.6
Vase	80.2	81.3
Guitars	98.0	88.5
Candelabra	93.9	82.4

within 2%
or ours
is better

Outline of Talk

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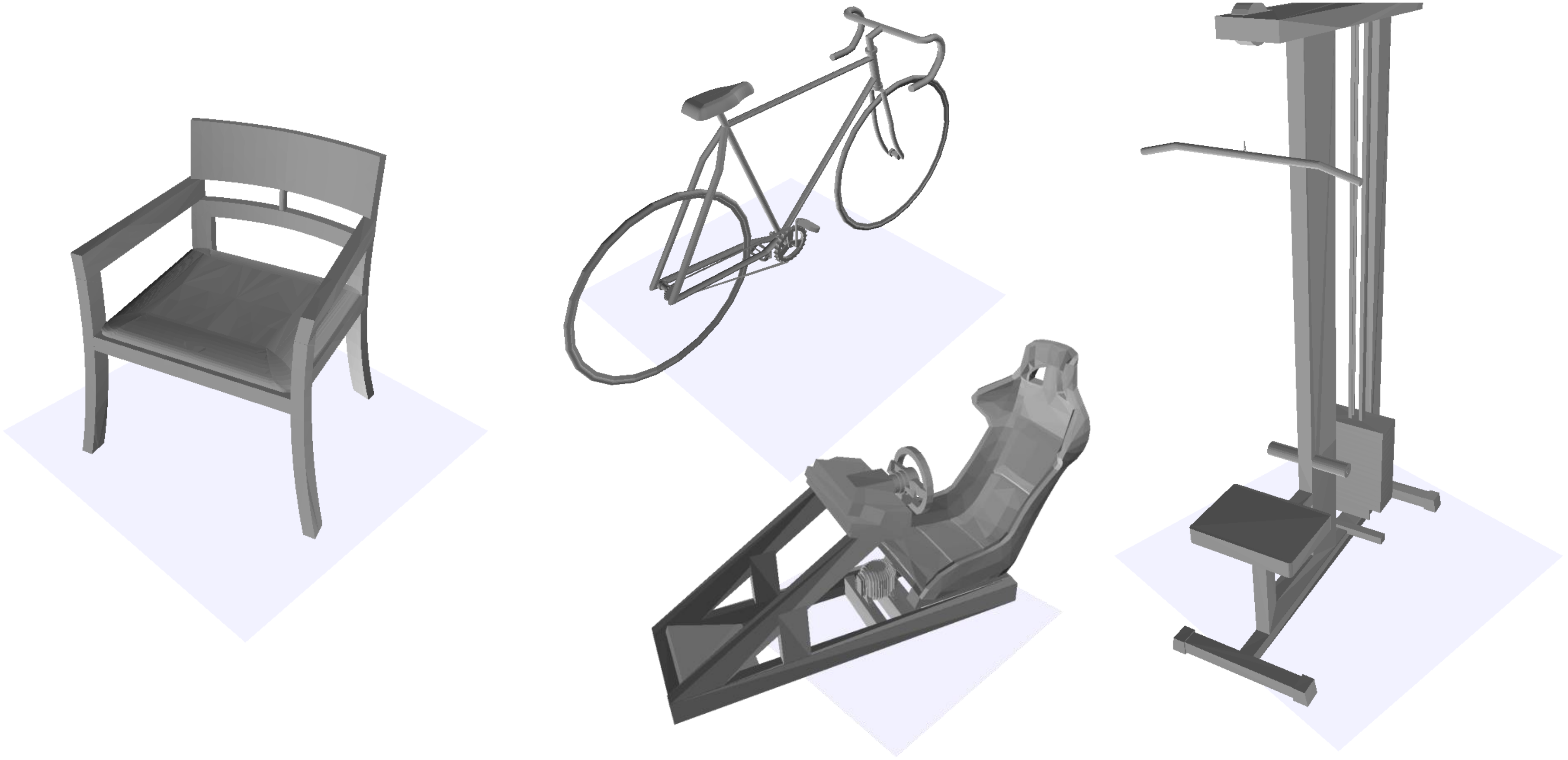
"Structure-aware" correspondences

- Reflective symmetry
- Part segmentation
- Human pose

Conclusions

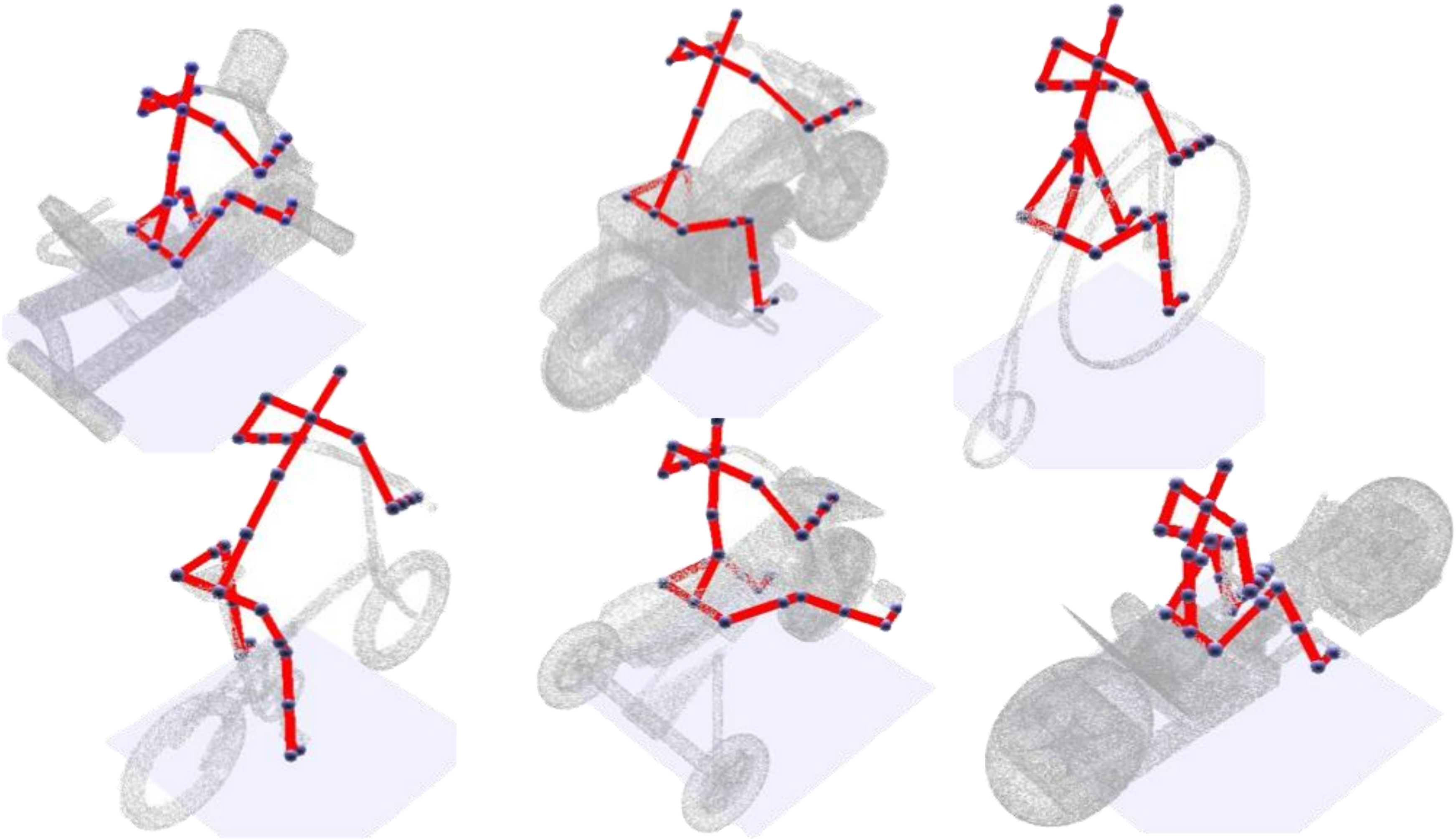
Pose-Aware Correspondences

Observation 1: almost all 3D models represent objects used by people



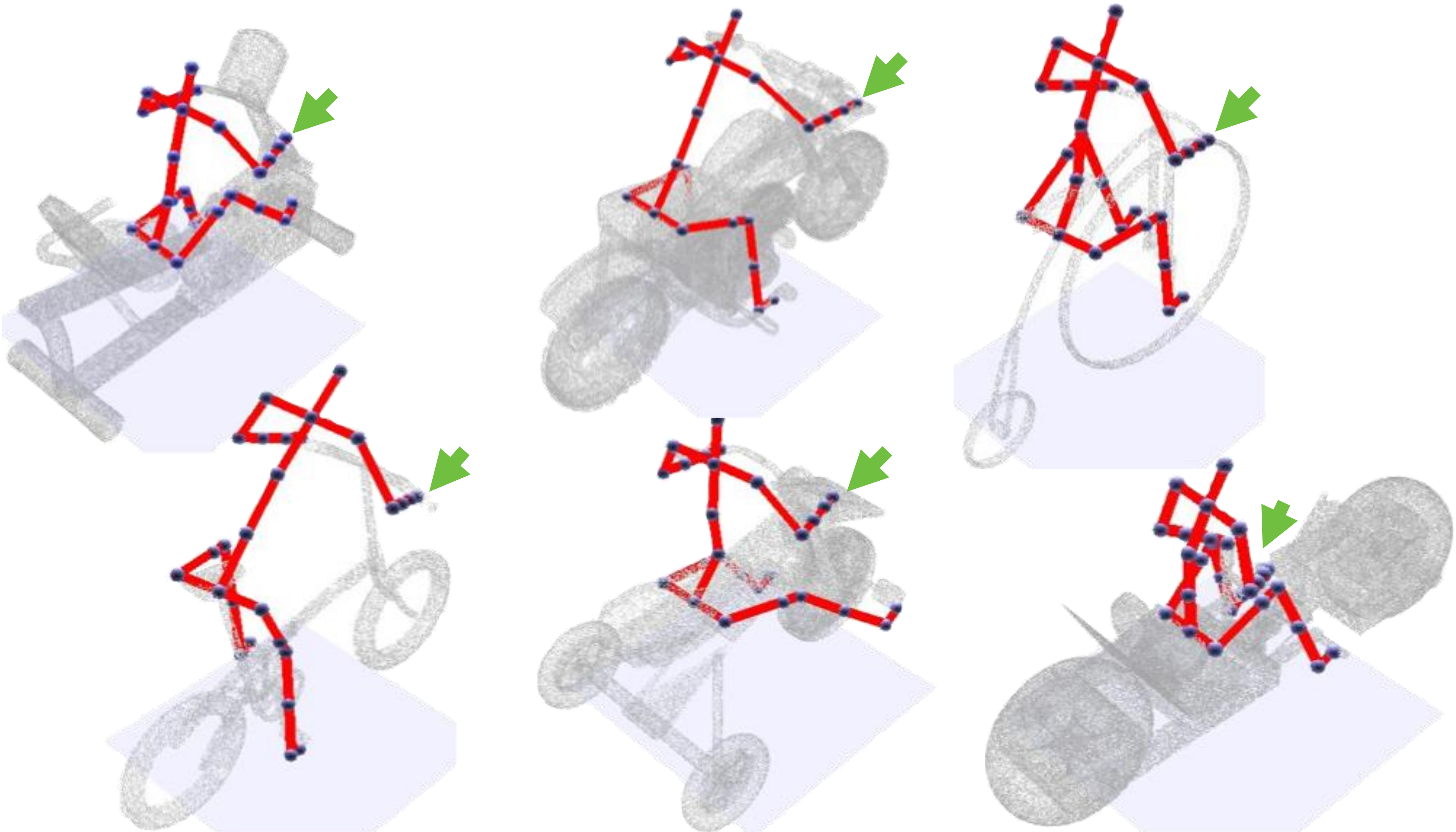
Pose-Aware Correspondences

Observation 2: the poses people take when interacting with objects reveal functional correspondences



Pose-Aware Correspondences

Approach: predict poses of people interacting with 3D models and use them to predict correspondences



Pose Prediction Algorithm

Pose Parameters

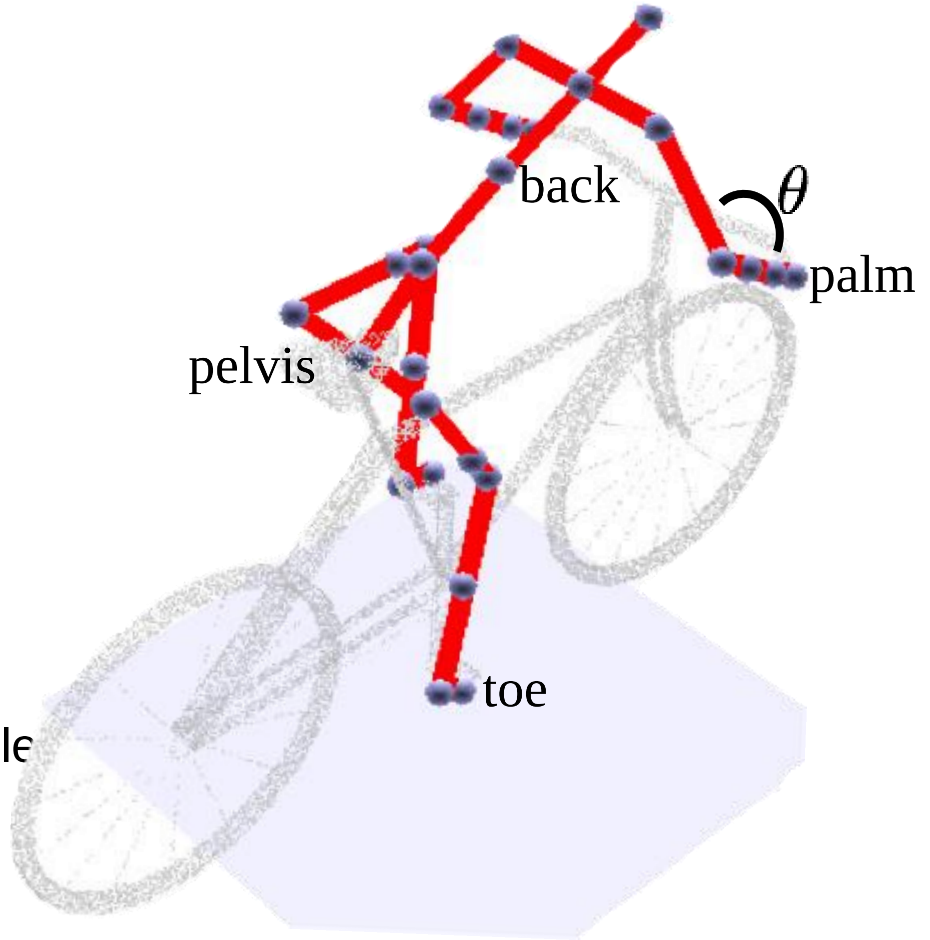
- Contact points
- Joint Angles

Energy Function

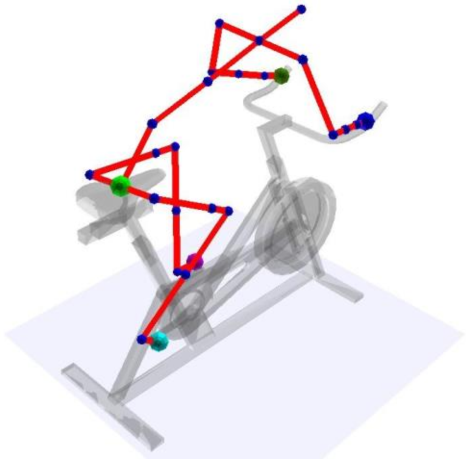
- Contact Distance
- Feature Compatibility
- Pose Prior
- Symmetry
- Surface intersections

Search Procedure

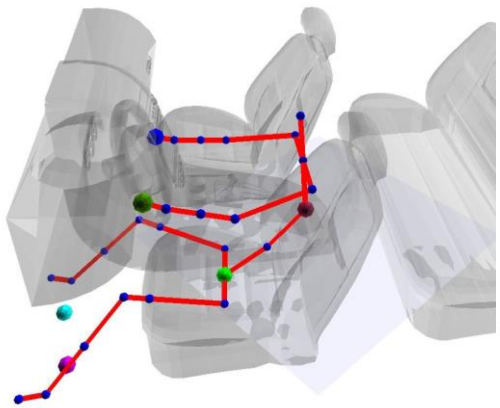
- Sample pose parameters
- Solve contact points or joint angle
  (inverse kinematics)
- Evaluate energy function



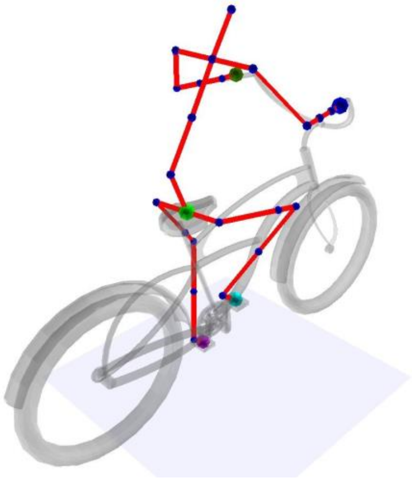
Pose Prediction Experiment



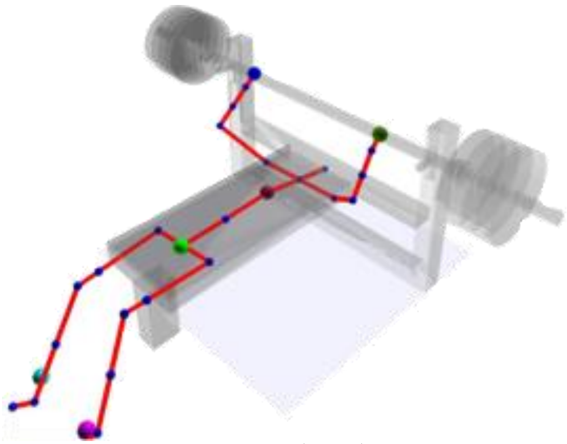
Bipedals (30)



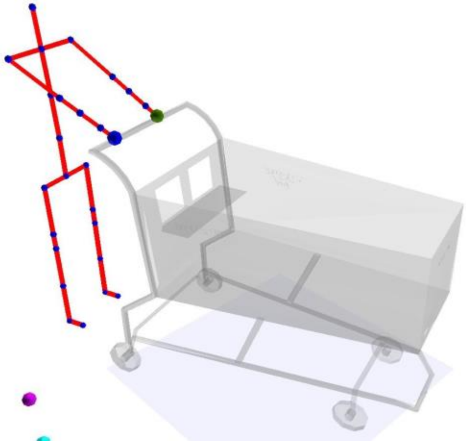
Cockpits (21)



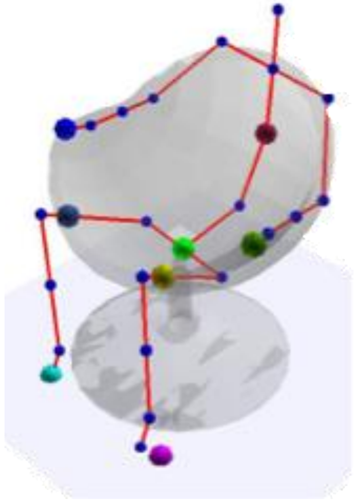
Bicycles (30)



Gym (25)



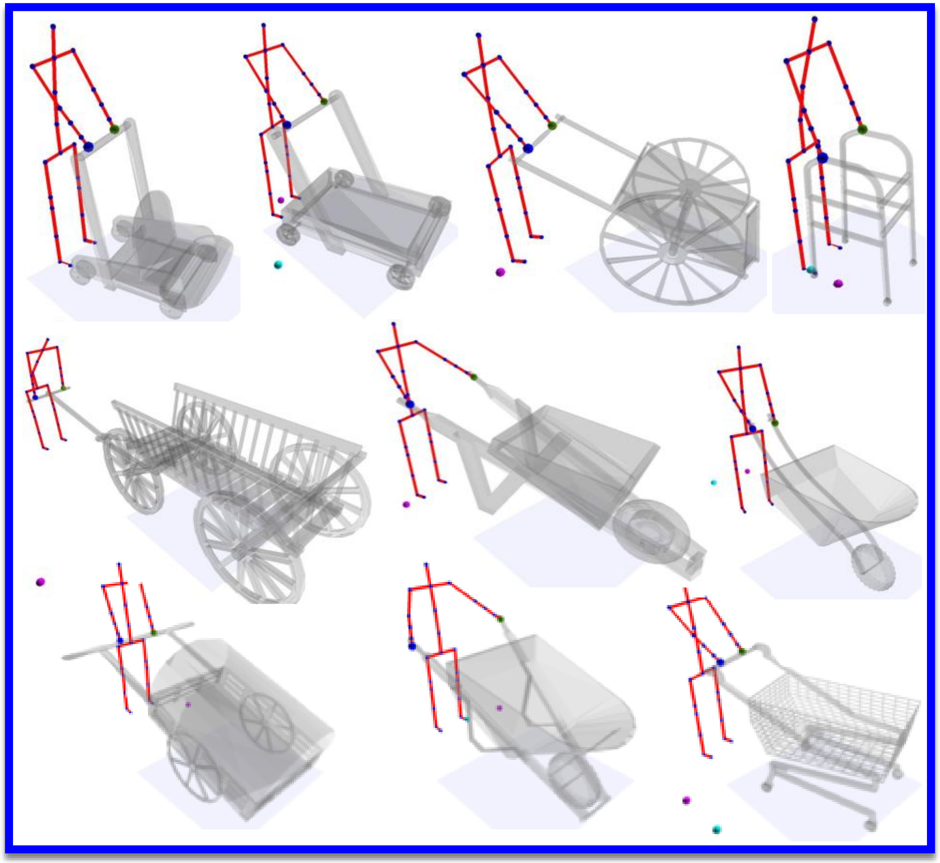
Carts (11)



Chairs (30)

Pose Prediction Experiment

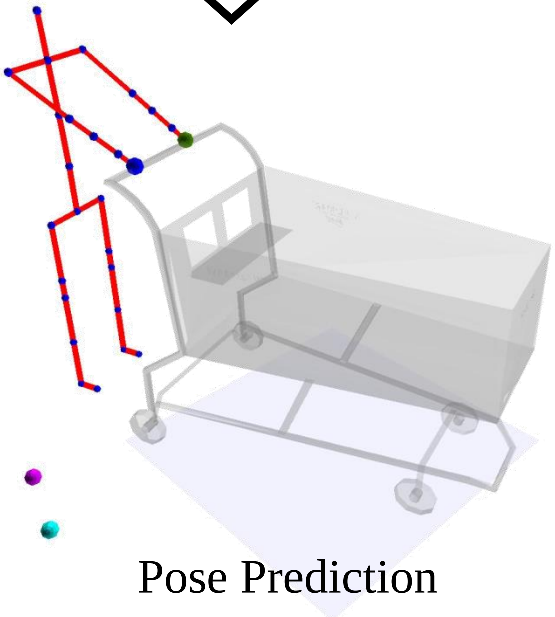
Leave-one-out test



Training Data (10)

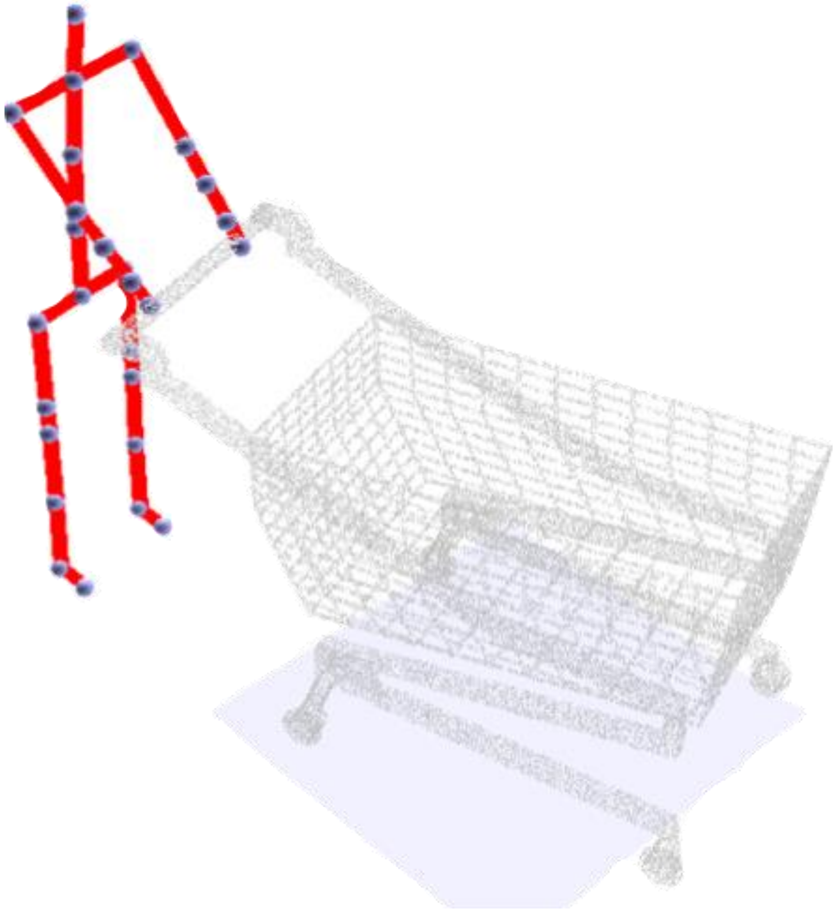
Test Data (1)

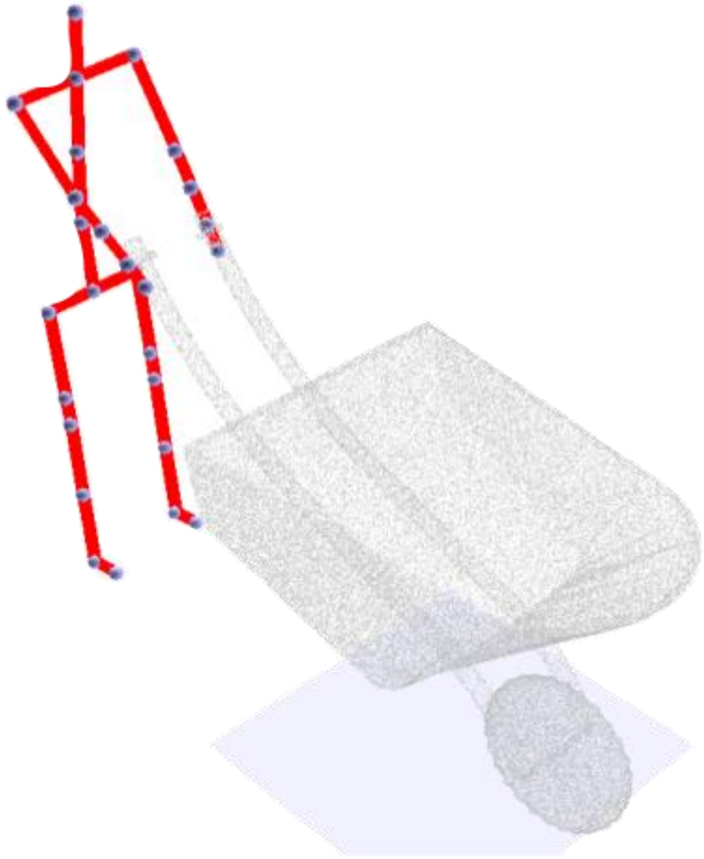
Learned Energy Function



Pose Prediction

Pose Prediction Results





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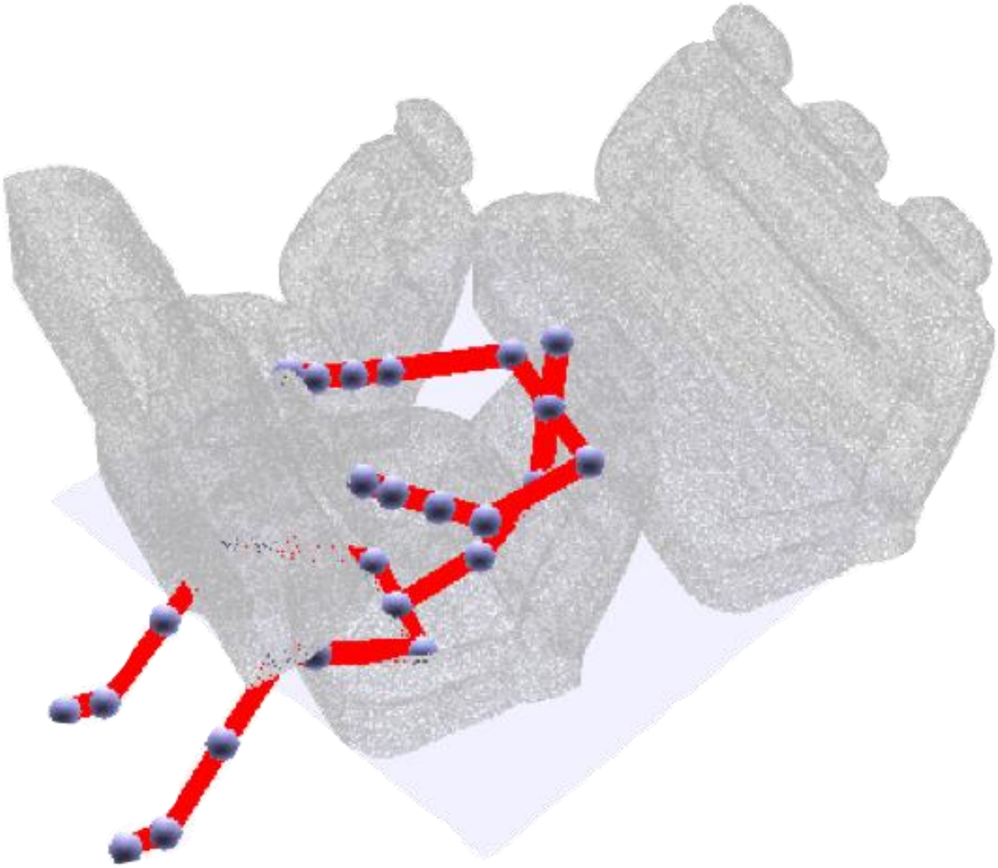
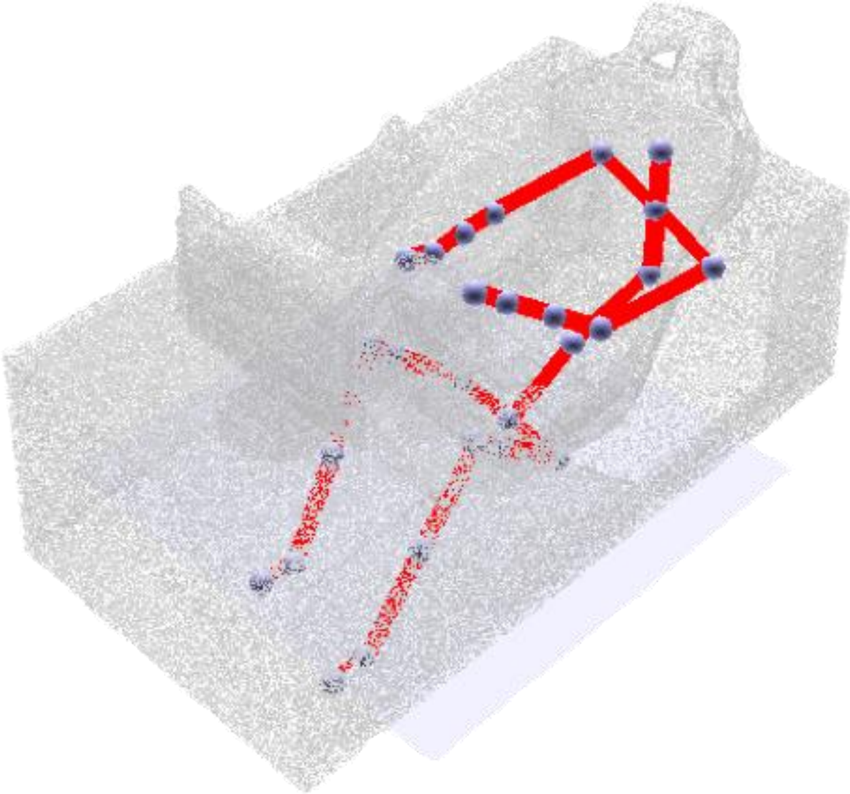
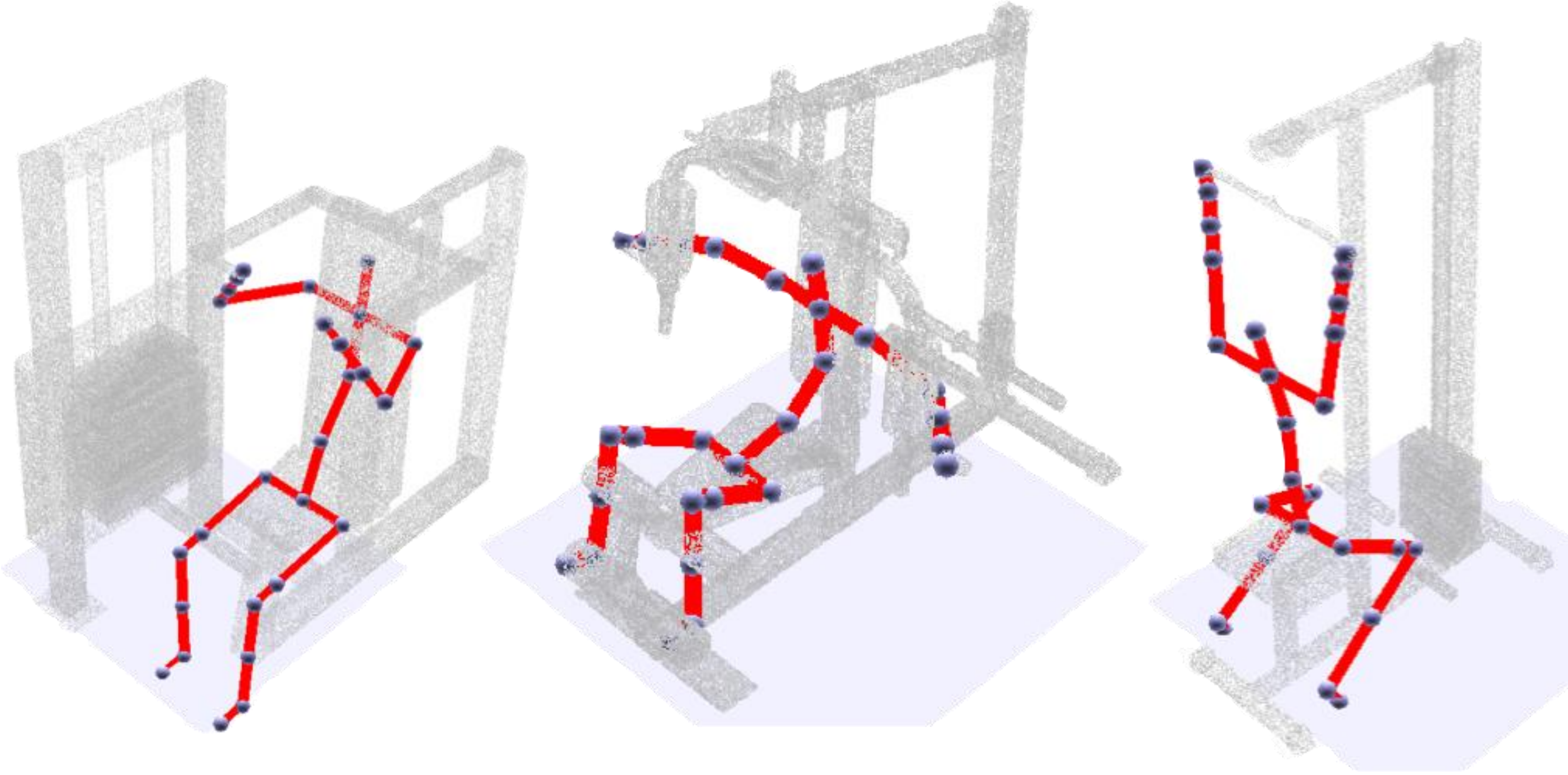
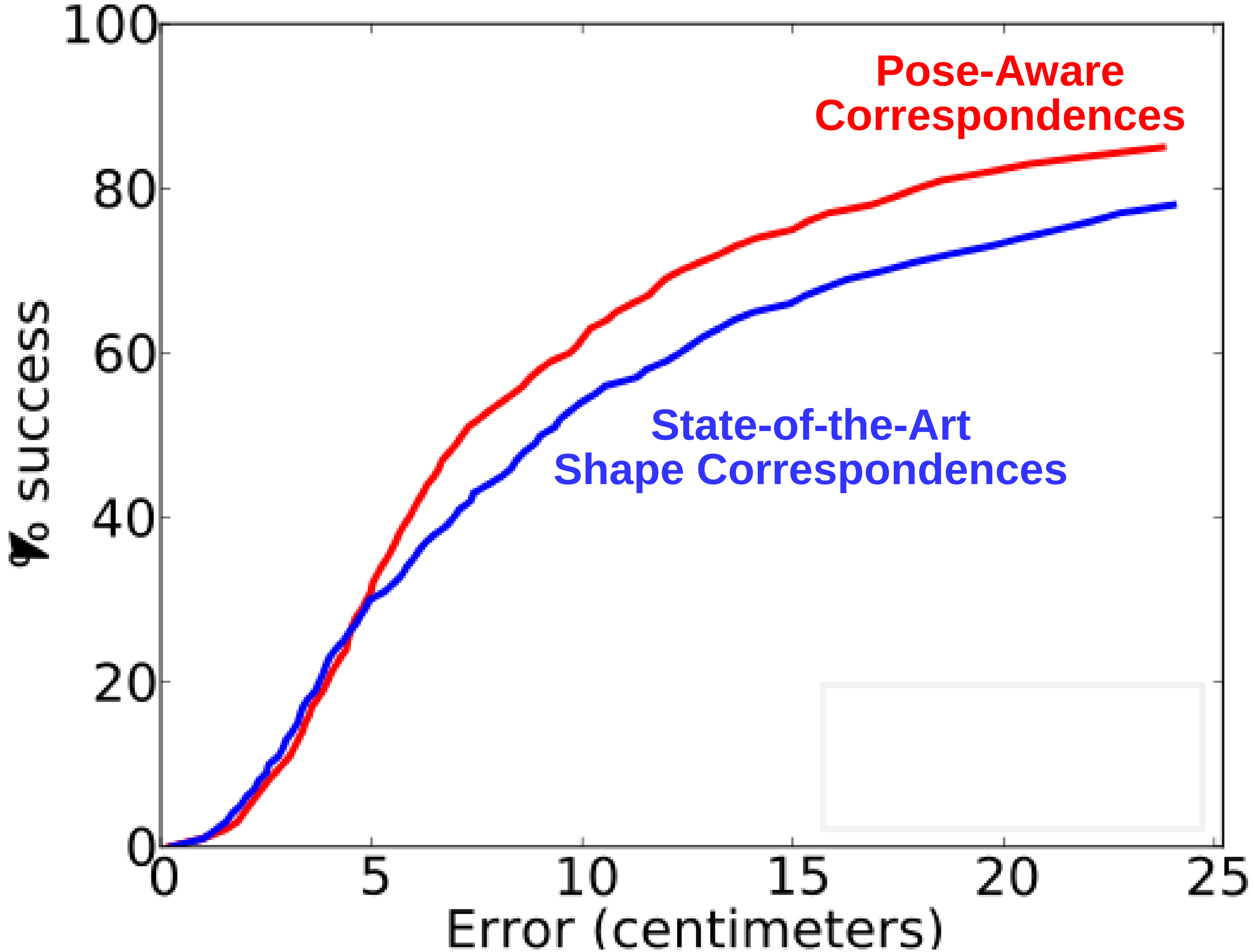




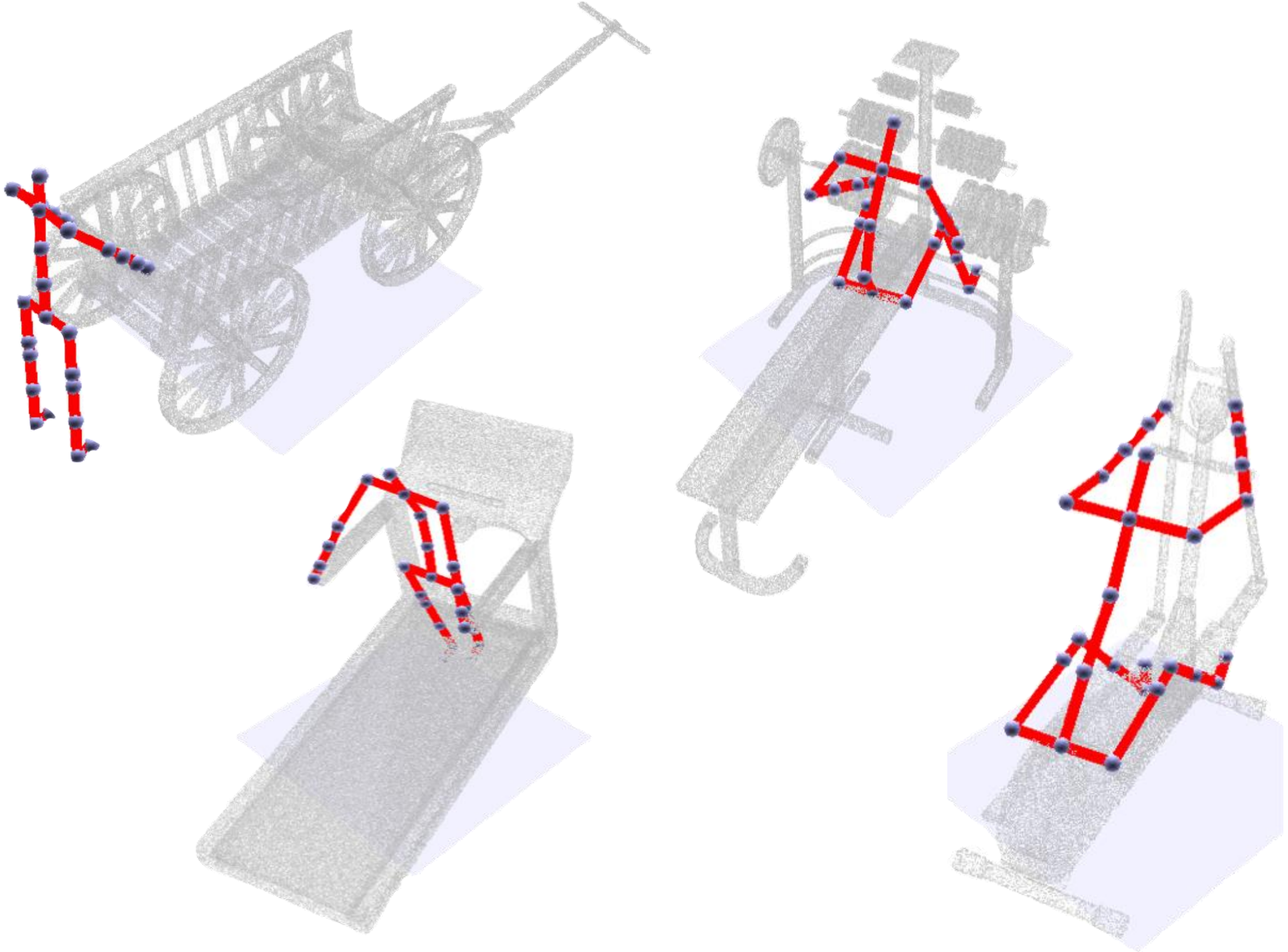
Pose Prediction Results



Pose-Aware Correspondence Results



Pose Prediction Failures



Conclusions

Surface correspondence is an important problem

- Finding geometric correspondences between 3D surfaces can yield insights into functional relationships

Matching large-scale structural features is useful for finding correspondences in diverse collections

- Symmetries, part decompositions, human poses

Future research should focus on high-level features

- Hierarchies, context, generative probabilistic models, etc.

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Thank You!