Exploring Collections of 3D Models using Fuzzy Correspondences

Vladimir G. Kim
Princeton University

Wilmot Li
Adobe

 Niloy J. Mitra
UCL

Stephen DiVerdi
Adobe

Thomas Funkhouser
Princeton University
Motivating Application

Exploring collections of 3D models

Google 3D Warehouse
Motivating Application

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Previous Work

Ovsjanikov et al., SIGGRAPH 2011
Goal

Exploration tool for understanding shape variations for arbitrary regions of models in collections
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- Find variations
- Sort by similarity
- Align viewpoints
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Approach

Compute correspondences between similar points on all models in the collection
Correspondences

Exploration Tool
Correspondences

Exploration Tool
Related Work

Previous Methods

- Pairwise alignment
- Map optimization
- Template fitting
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Nguyen et al., SGP 2011
Related Work

Previous Methods

- Pairwise alignment
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Allen et al., SIGGRAPH 2003.
Problem: Representing Correspondences

Point-to-point correspondences are not well-defined for all pairs of models.
Solution: Fuzzy Correspondences

Continuous function measuring "how well" two points correspond

\[ f(p_i, p_j) \in \mathbb{R} \]
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Concurrent work
Solomon et al., SGP’12
Ovsjanikov et al., SIGGRAPH’12
Problem: Matching Dissimilar Shapes

Geometric alignment algorithms work well only for similar pairs of shapes
Solution: Transitivity

Leverage correspondences between similar shapes to reason about correspondences in dissimilar shapes
Problem: Handling $N^2$ Complexity

Computing pairwise alignments for all pairs is too expensive for large collections: $O(N^2)$ alignments

Typical: $N=100$
Solution: Diffusion

Compute alignments for small number of pairs (M) and diffuse correspondences to other pairs: $O(MN)$.

A small amount of redundancy provides robustness to poor alignments.

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Computing Fuzzy Correspondences

1. Sample points on each model
2. Select pairs of models to align
3. Estimate correspondences for selected pairs
4. Diffuse point correspondences
5. Re-align pairs to improve consistency

Go to 4
Example Collection
Step 1: Sample Points

Input Model  $\rightarrow$  K Points
Step 2: Select Models To Align

Find pairs of models that can be aligned robustly and form a well-connected graph.
Step 2: Select Models To Align

Find pairs of models that can be aligned robustly and form a well-connected graph.

Compute minimum spanning tree based on shape similarity.
Step 2: Select Models To Align

Find pairs of models that can be aligned robustly and form a well-connected graph.

Augment graph to increase connectivity based on edge rank.
Step 2: Select Models To Align

Find pairs of models that can be aligned robustly and form a well-connected graph
Step 3: Estimate Correspondence

Align selected pairs of models to estimate correspondence $C(p_i, p_j)$ between points.

Rigid Alignment
PCA + ICP
Step 3: Estimate Correspondence

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Step 4: Diffuse Correspondence

Compute fuzzy correspondence $f(p_i,p_j)$ based on diffusion distance in graph represented by $C(p_i,p_j)$.
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Step 5: Improve Consistency

Sparse Correspondence Matrix $C(p_i, p_j)$
Step 5: Improve Consistency

Sparse Correspondence Matrix $C(p_i, p_j)$
Step 5: Improve Consistency

Sparse Correspondence Matrix $C(p_i, p_j)$

misalignment
Step 5: Improve Consistency

Iteratively adjust alignments in $C(p_i,p_j)$ to improve consistency with $f(p_i,p_j)$
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Pairwise Alignment

$C_0(p_i, \cdot)$

Diffusion

$C_0(p_i, \cdot) ightarrow f_0(p_i, \cdot)$

Re-align

$C_0(p_i, p_j) \rightarrow C_1(p_i, p_j)$
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Quantitative Evaluation – refer to paper

Experiments:
- Diffusion and optimization improve correspondences
- Far less than $N^2$ alignments are necessary
- Larger collections yield better correspondences
- Our method compare favorably on benchmarks

Chairs, Bikes, & Airplanes from Google 3D Warehouse [Kim et al. 2012]

Nonrigid Surface Alignment Benchmarks [Kim et al, 2011] [Nguyen et al., 2011]
Correspondences

Exploration Tool
Correspondences

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Key features enabled by fuzzy correspondences

- Find variations
- Align viewpoints
- Sort by similarity
Finding Variations
Finding Variations

Distance to Xth closest fuzzy correspondence can reveal amount of shape variation in data set
Finding Variations

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Finding Variations

Distance to Xth closest fuzzy correspondence can reveal amount of shape variation in data set

Collection 1:

Collection 2:
Aligning Models

Find best alignment weighted by fuzzy corrs.
Sorting by Similarity

Sort based on similarity in aligned regions
Sorting by Similarity: Intrinsic Matching

Sort based on similarity in aligned regions
Sorting with Multiple Facets

Provide several similarity objectives
Timing

Fuzzy Correspondences for 111 chairs

- Pairwise alignments $\approx 100s$ (602 / 6105 alignments)
- Iterative Optimization $\approx 800s$ (11 iterations)
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Fuzzy Correspondences for 71 SCAPE models
- Pairwise alignments $\approx 1775s$ (355 / 2485 alignments)
- Iterative Optimization $\approx 250s$ (5 iterations)
Timing

Fuzzy Correspondences for 111 chairs
  ◦ Pairwise alignments ≈ 100s  (602 / 6105 alignments)
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Fuzzy Correspondences for 71 SCAPE models
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Exploration tool
  ◦ Real time interaction
Summary

Fuzzy Correspondences via Diffusion

- Represent ambiguity in mapping
- More robust: easier to compare similar shapes
- Far less than $N^2$ pairwise alignments are required
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Fuzzy Correspondences via Diffusion
- Represent ambiguity in mapping
- More robust: easier to compare similar shapes
- Far less than $N^2$ pairwise alignments are required

Exploration with Fuzzy Correspondences
- Allows navigating in shape space by interactively selecting regions of interest
Future Work

Short-term

- Consistent bias in misalignments not always resolved by diffusion
- More diverse datasets (e.g. all classes jointly)
- Larger collections
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- More diverse datasets (e.g. all classes jointly)
- Larger collections

Long-term:
- Higher-level understanding of collections of shapes
- Data-driven Analysis: segmentation, labeling
- Data-driven Synthesis: assembly-based modeling
Acknowledgments + Our code

Data:
- Brown et al. (3D Warehouse), Giorgi et al. (SHREC Watertight), Anguelov et al. (SCAPE), Bronstein et al. (TOSCA)

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CODE AND DATA

http://www.cs.princeton.edu/~vk/CorrsFuzzy
Additional Slides
Results

A small subset of pairwise alignments suffices
Results

Diffusion & optimization improve correspondences
Results

Larger collections yield better correspondences
Results

Best results on examples in [Nguyen et al., 2011]
Results

Best results on benchmark in [Kim et al. 2011]
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- Larger collections
- (Near-)Symmetry
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