Ranking on Cross-Domain Manifold for Sketch-based 3D model Retrieval

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Introduction

- 3D models are widely used.
  - Mechanical CAD, Games,…
  - 3D range scanners, 3D printers,…
  - User generated.
    - Trimble 3D warehouse, ...

- 3D model retrieval is essential.
  - High retrieval accuracy.
  - Efficiency.
  - Ease of use.

Focuses of this research

accurate and easy to use

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Why sketch-based?

- **Keywords**
  - ✓ Accessible for most people.
  - ✗ 3D models lack textual tags.

- **3D model**
  - ✓ Sufficiently accurate for certain applications.
  - ✗ 3D models often unavailable.

- **2D hand-drawn sketch**
  - ✓ Accessible for most people.
  - ✓ Intuitively specify 2D shape.
  - ✗ Inaccurate.
    - • Even the best method yields MAP = 11% using SHREC 2013 benchmark.
Cross-domain matching problem

- How do we compare a 2D sketch and a 3D model?

Can’t be compared directly.

2D sketch 3D model
Cross-domain matching problem

- Approach 1: Image feature-based comparison.
  - Renders 3D models into lines.
    - e.g., Suggestive contour [DeCarlo03], …
  - Adopted by most.

😊 Can be compared.

2D sketch

2D sketch-like image
Cross-domain matching problem

- Approach 1: Image feature-based comparison.

⚠️ Can’t handle abstraction, semantic influence and noise.

_DISCONNECTED_

\[\text{2D sketch} \rightarrow \text{2D sketch-like image}\]

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Cross-domain matching problem

- Approach 2: Semantic label-based comparison.

2D sketch  $\rightarrow$ 3D model

"human"  $\rightarrow$  "human"

😊 Can be retrieved.
Cross-domain matching problem

- Approach 2: Semantic label-based comparison.

Learning sparse labels is difficult.

2D sketches

3D models
Our approach

- Combination of features and labels.
  - Matching by image features.
  - Matching by semantic labels.
Related work
- BF-GALIF [Eitz12]
  - Algorithm for sketch-based 3D model retrieval
- Manifold Ranking [Zhou03]
  - Algorithm for distance metric learning

Proposed method

Experiments and results

Conclusion and future work
Related work: Sketch-to-3D model matching algorithm
BF-GALIF [Eitz12]

- Efficiently compares sets of local features.
  1. Densely extracts Gabor filter-based local features.
  2. Integrates local features into a vector by Bag-of-Features.

2D sketch  *  gabor filter bank (4 orientations)  →  response images  →  a set of GALIF features

about 1,000 features per image
local feature
Related work: Sketch-to-3D model matching algorithm
BF-GALIF [Eitz12]

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<table>
<thead>
<tr>
<th>2D sketch</th>
<th>3D model</th>
<th>multi-view rendering</th>
<th>local feature extraction</th>
<th>BF integration</th>
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</thead>
<tbody>
<tr>
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<td>sketch-3D model feature distance</td>
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<td>distance computation</td>
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</tbody>
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Related work: Sketch-to-3D model matching algorithm

BF-GALIF [Eitz12]

- Efficiently compares sets of local features.

- Robust against articulation of 2D shape.

- Among the most accurate methods.

- Yet, insufficient …

Our approach
- better feature comparison.
- semantic labels.
Improving single-domain feature comparison

- Learns feature-adaptive distance metric on manifold.

Euclidean distance

feature space of 3D model

feature-adaptive distance

feature space of 3D model
Related work: Distance metric learning
Manifold Ranking [Zhou03]

- Diffusion distance on a feature manifold graph.

Our approach
  - extends Manifold Ranking to cross-domain.
Improving cross-domain feature comparison

- BF-GALIF [Eitz12]
  - 😞 Structure of feature manifold is ignored.

![Diagram showing 2D sketch domain and 3D model domain with sketch-3D model feature similarity](image-url)
Outline

- Related work

- Proposed method
  - Cross-Domain Manifold Ranking (CDMR) algorithm

- Experiments and results

- Conclusion and future work
Improving cross-domain feature comparison

- Ranking by diffusion distance on a Cross-Domain Manifold (CDM).
  - Structure of each feature manifold is kept.

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<table>
<thead>
<tr>
<th>2D sketch domain</th>
<th>3D model domain</th>
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</thead>
<tbody>
<tr>
<td>sketch-sketch feature similarity</td>
<td></td>
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<tr>
<td>sketch-3D model feature similarity</td>
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<tr>
<td>3D model-3D model feature similarity</td>
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</tbody>
</table>
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Improving cross-domain feature comparison

- Ranking by diffusion distance on a Cross-Domain Manifold (CDM).
  - 😊 Structure of each feature manifold is kept.

![Diagram showing 2D sketch domain and 3D model domain with feature similarity connections.]
Improving cross-domain feature comparison

- Ranking by diffusion distance on a Cross-Domain Manifold (CDM).
  - 😊 Structure of each feature manifold is kept.
Proposed method
Cross-Domain Manifold Ranking (CDMR)

- Ranking by diffusion distance on the CDM.
  1. Generates a feature manifold on each domain.
  2. Links the two manifolds by feature and label similarity.
  3. Diffuses relevance from the query.

2D sketch domain

3D model domain

feature similarity (weight [0, 1])
Proposed method
Cross-Domain Manifold Ranking (CDMR)

- Ranking by diffusion distance on the CDM.
  1. Generates a feature manifold on each domain.
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- 2D sketch domain
- 3D model domain

feature similarity (weight [0, 1])
Proposed method
Cross-Domain Manifold Ranking (CDMR)

- Ranking by diffusion distance on the CDM.
  1. Generates a feature manifold on each domain.
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![Diagram showing feature and label similarity with diffusion distance]
Proposed method
Cross-Domain Manifold Ranking (CDMR)

- Ranking by diffusion distance on the CDM.
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Proposed method
Cross-Domain Manifold Ranking (CDMR)

- Example 1: Ranking by label similarity.
Proposed method
Cross-Domain Manifold Ranking (CDMR)

- Example 1: Ranking by label similarity.

Incorrect results.
Proposed method
Cross-Domain Manifold Ranking (CDMR)

- Example 1: Ranking by label similarity.
Proposed method
Cross-Domain Manifold Ranking (CDMR)

- Example 1: Ranking by label similarity.

Correct results thanks to semantic labels.
Proposed method
Cross-Domain Manifold Ranking (CDMR)

- Example 2: Ranking by feature similarity.
Proposed method
Cross-Domain Manifold Ranking (CDMR)

- Example 2: Ranking by feature similarity. Correct results.
Proposed method
Cross-Domain Manifold Ranking (CDMR)

CDMR embodies an automatic query expansion.
Proposed method
Cross-Domain Manifold Ranking (CDMR)

- Feature comparison methods.

- sketch-to-sketch
  BF-fGALIF
  (based on [Eitz12])

- sketch-to-3D model
  BF-fGALIF
  (based on [Eitz12])

- 3D model-to-3D model
  BF-DSIFT
  [Furuya09]
3D model-to-3D model comparison
BF-DSIFT [Furuya09]

- Dense and random extraction of local visual features.
- Per-model BF integration.

SIFT [Lowe04]
- invariant for rotation.
- robust against affine transformation.
- multi-scale.
Outline

- Related work
  - BF-GALIF [Eitz12]
    • Algorithm for sketch-based 3D model retrieval
  - Manifold Ranking [Zhou03]
    • Algorithm for distance metric learning

- Proposed method
  - Cross-Domain Manifold Ranking (CDMR) algorithm

- Experiments and results

- Conclusion and future work
Experiments

- Evaluate retrieval accuracy.
  - BF-fGALIF ($\cong$[Eitz12])
    - No distance metric learning.
    - Baseline
  - CDMR-BF-fGALIF (F)
    - Unsupervised learning.
  - CDMR-BF-fGALIF (L)
    - Supervised learning.
  - CDMR-BF-fGALIF (F+L)
    - Semi-supervised learning.
Experiments
Benchmark databases

- S-PSB [Eitz12]

- Test set (90 categories)
  - 907 sketches
  - 907 models

- Training set (92 categories)
  - 907 sketches
  - 907 models

Difficult to learn labels.
- 21 shared categories.
- As few as 4 labels per category.
Experiments
Benchmark databases

- S-PSB [Eitz12]

- Test set (90 categories)
  - Difficult to learn labels.

- 21 shared categories

- As few as 4 labels per category.

2D sketch domain

3D model domain

feature similarity

label similarity
Experiments

Benchmark databases

- SHREC2013 sketch-based 3D shape retrieval (SH13) [Li13]

- Test set (90 categories)
  - 2,700 sketches
  - 1,258 models

- Training set (90 categories)
  - 4,500 sketches
  - “ant”
  - “duck”

Easy to learn labels.

- share all categories.
- 50 labels per category.
Experiments

Benchmark databases

- SHREC2013 sketch-based 3D shape retrieval (SH13) [Li13]

Easy to learn labels.

- Test set (90 categories)
  - Easy to learn labels
  - 2,700 sketches
  - 1,258 models

- Training set (90 categories)
  - 50 labels per category
  - 4,500 sketches

2D sketch domain

feature similarity

label similarity

3D model domain
Experimental results
Effectiveness of CDMR for S-PSB

- CDMR is effective.

![Graph showing MAP (%)]

- BF-fGALIF: 17.5
- CDMR-BF-fGALIF (F): 27.5
- CDMR-BF-fGALIF (L): 27.7
- CDMR-BF-fGALIF (F+L): 31.9

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Experimental results
Effectiveness of CDMR for S-PSB

- CDMR is effective.

![Bar chart showing MAP percentages for different conditions:]
- BF-fGALIF: 17.5%
- CDMR-BF-fGALIF (F): 27.5% (+10%)
- CDMR-BF-fGALIF (L): 27.7%
- CDMR-BF-fGALIF (F+L): 31.9% (+14%)

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Experimental results
Effectiveness of CDMR for S-PSB

- CDMR (F+L) effectively learns sparse labeling.

![Graph showing MAP (%) for different categories and methods]

- BF-fGALIF: 17.5 all classes, 13.6 unlabeled classes, 23.1 labeled classes
- CDMR-BF-fGALIF (F): 27.5 all classes, 20.0 unlabeled classes, 38.5 labeled classes
- CDMR-BF-fGALIF (L): 6.6 all classes, 27.7 unlabeled classes, 58.4 labeled classes
- CDMR-BF-fGALIF (F+L): 20.6 all classes, 20.6 unlabeled classes, 48.3 labeled classes

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Experimental results
Effectiveness of CDMR for S-PSB

- CDMR (F+L) effectively learns sparse labeling.

![Graph showing MAP [%] for different categories and CDMR variants.]

- CDMR-BF-fGALIF (F) over-fits to labels.
- CDMR-BF-fGALIF (L) over-fits to labels.
- CDMR-BF-fGALIF (F+L) improves performance without over-fitting.
Experimental results
Effectiveness of CDMR for S-PSB

- CDMR (F+L) effectively learns sparse labeling.

![Graph showing MAP% for different categories and methods, with a note indicating that CDMR-BF-fGALIF (F+L) avoids over-fitting.](image-url)
Experimental results
Effectiveness of CDMR for SH13

- Large improvement of MAP due to dense labeling.

![Bar chart showing MAP improvement](chart.png)

- BF-fGALIF: 11.3%
- CDMR-BF-fGALIF (F): 19.4%
- CDMR-BF-fGALIF (L): 66.1%
- CDMR-BF-fGALIF (F+L): 65.7%

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Experimental results
Effectiveness of CDMR for SH13

- Large improvement of MAP due to dense labeling.

| Method               | MAP [%] | Improvement
<table>
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<tr>
<td>BF-fGALIF</td>
<td>11.3</td>
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<tr>
<td>CDMR-BF-fGALIF (F)</td>
<td>19.4</td>
<td>+ 55%</td>
</tr>
<tr>
<td>CDMR-BF-fGALIF (L)</td>
<td>66.1</td>
<td>+ 54%</td>
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<tr>
<td>CDMR-BF-fGALIF (F+L)</td>
<td>65.7</td>
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</table>
Experimental results
Comparison with other algorithms

S-PSB

SH13

Proposed
Experimental results

Retrieval results (S-PSB)

- “human” (labeled category)

BF-GALIF [Eitz12]

<table>
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<tr>
<th>Query</th>
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CDMR-BF-GALIF (L) ÷ CMCP [Zhai12]

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CDMR-BF-GALIF (F+L)

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<tr>
<th>Query</th>
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</tbody>
</table>
Experimental results
Retrieval results (S-PSB)

- “glass_with_stem” (unlabeled category)

<table>
<thead>
<tr>
<th>BF-GALIF [Eitz12]</th>
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<tbody>
<tr>
<td>✓</td>
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</table>
### Experimental results

**Computation time per query**

**Computation time per query for S-PSB [s]**

<table>
<thead>
<tr>
<th>methods</th>
<th>extract BF-GALIF</th>
<th>compute distance</th>
<th>CDMR (matrix size : 3,628 x 3,628)</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>BF-GALIF</td>
<td>0.11</td>
<td>1.59</td>
<td></td>
<td>1.70</td>
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<tr>
<td>CDMR-BF-GALIF</td>
<td>0.11</td>
<td>1.59</td>
<td>36.86</td>
<td>38.56</td>
</tr>
</tbody>
</table>

**Computation time per query for SH13 [s]**

<table>
<thead>
<tr>
<th>methods</th>
<th>extract BF-GALIF</th>
<th>compute Distance</th>
<th>CDMR (matrix size : 8,458 x 8,458)</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>BF-GALIF</td>
<td>0.11</td>
<td>1.13</td>
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<td>1.24</td>
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<tr>
<td>CDMR-BF-GALIF</td>
<td>0.11</td>
<td>1.17</td>
<td>659.93</td>
<td>661.21</td>
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</tbody>
</table>

measured by using: Intel Xeon E3-1245 @ 3.30 GHz, 32 GB of memory
Conclusion and Future work

**Conclusion**
- More accurate sketch-based 3D model retrieval.
  - Cross-Domain Manifold Ranking (CDMR)
    - Combines feature similarity and semantic similarity.
    - Outperforms previous methods.

**Future work**
- Faster computation (e.g., approximation of diffusion).
- More accurate feature comparison.