Non-linear Summarization of a Database for 3D Model Retrieval

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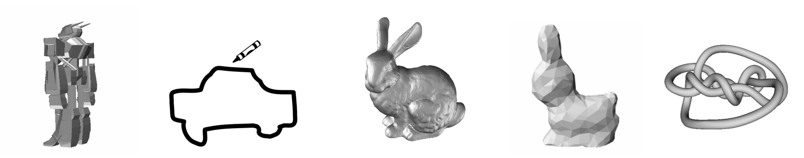
Shape similarity search of 3D models

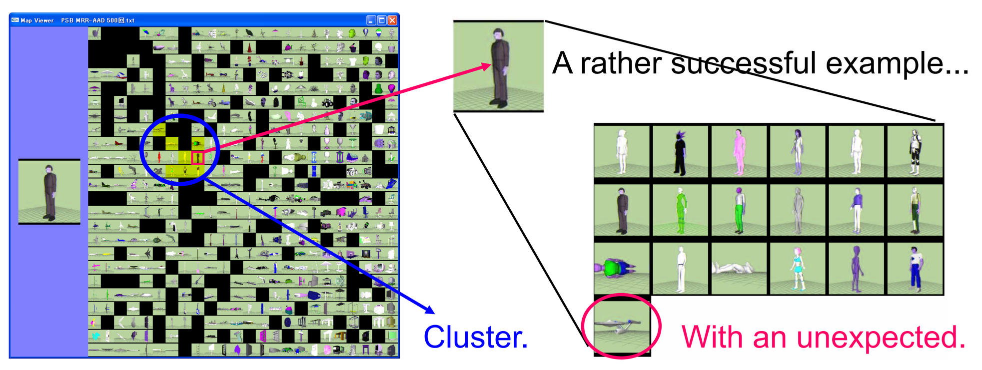
- How to query a shape?
  - text, (...can't name it.)
  - 3D example, (...don't have it.)
  - 2D sketch, (...can't draw.)
  - 3D sketch, (...no way.)
  - photographs (...doesn't exist.)



Retrieval by summarization

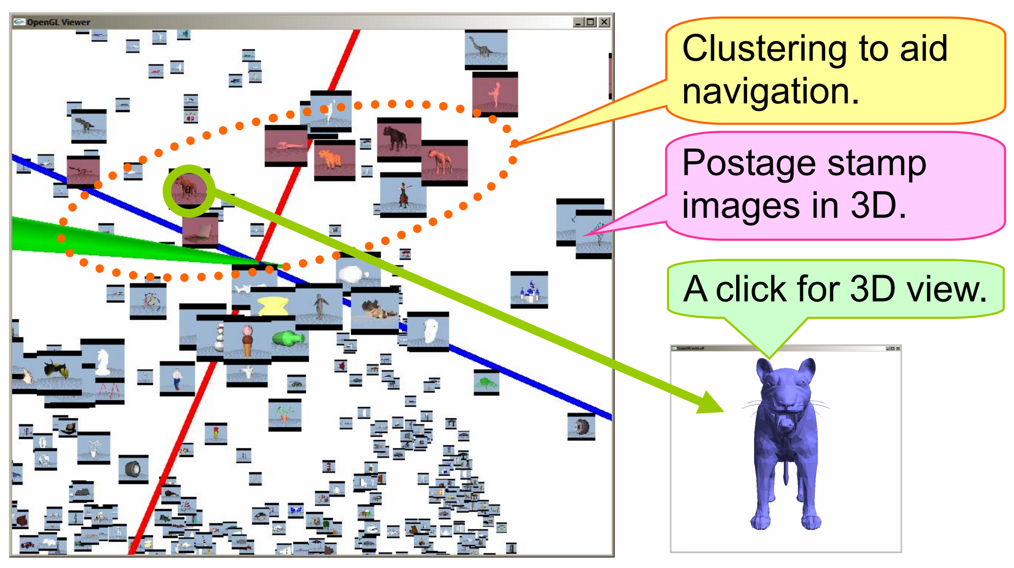
- Non-linear summarization of a database
  - Bustos 2004
    - Self Organized Map (SOM)
    - 2D array visualization
  - Kobayashi 2004
    - SOM, Learning Vector Quantizer
    - Clustering to aid navigation
    - 2D array visualization

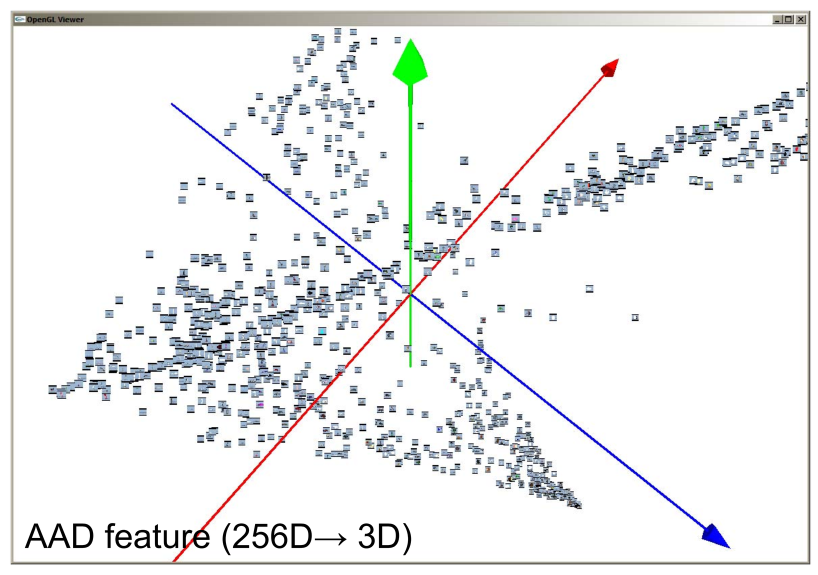
- SOM + 2D cell visualization [Kobayashi 2004]
  - Dimension reduction by SOM or LVQ
    - Models behind a cell not apparent.
    - Distance among cell not apparent.



Proposed method

- Overview
  - Compute n-dimensional feature vectors.
    - Eg., n=21, 30, 256, 625, …
  - Reduce dimension.
    - n-dimensional feature vector → 3D coordinate
  - Visualize in 3D space.
    - Postage-stamp sized images in 3D space.
    - Clustering of similar models to aid navigation.



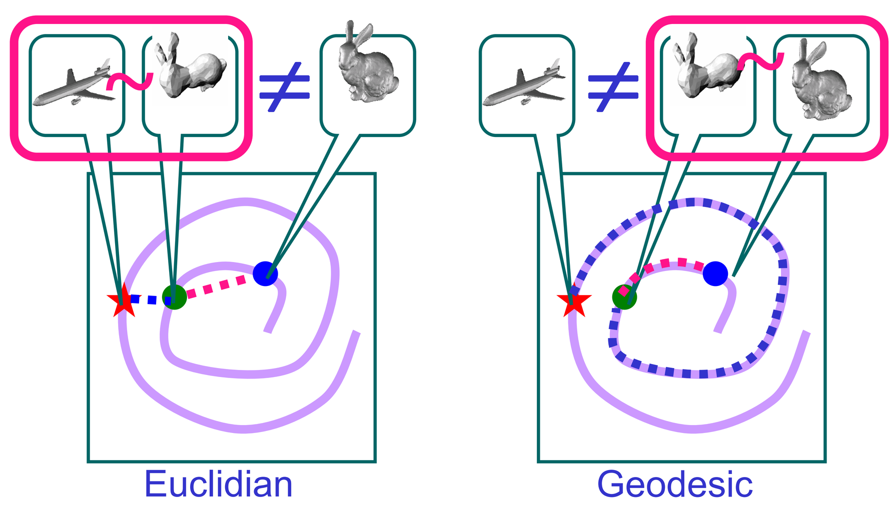


Dimension reduction

- Dimension reduction
  - Linear methods
    - PCA, MDS, ICA, …
  - Non-linear methods
    - SOM, LVQ, ...
    - Kernel-PCA, ...
    - Locally Liner Embedding, Isomap, Laplacian Eigenmaps, ...
- On 3D model retrieval [Ohbuchi, MIR2006]
  - Linear methods (PCA and ICA) didn't work.
  - A non-linear method (LE) did work.

➡ Try LE for the visualization-based retrieval.

- Dimension reduction by using ***manifold learning***
  - Learn a non-linear subspace, i.e., *manifold*.
  - Unsupervised learning.
  - Better distance on the learned manifold.
    - *Geodesic* distance.



Laplacian Eigenmaps [Belkin02]

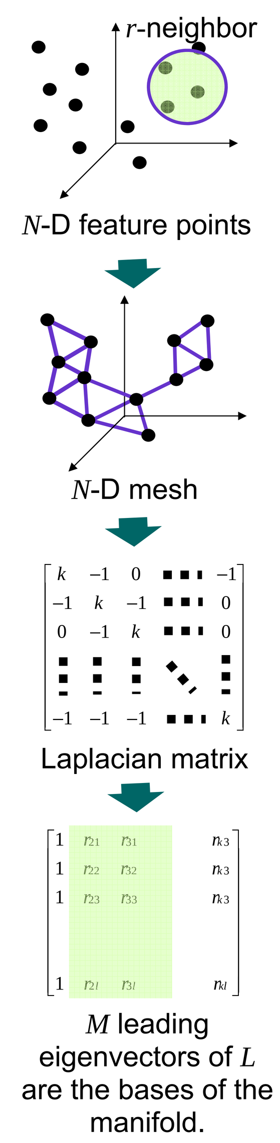
- Reconstruct an N-dimensional mesh G from the input points.
  - Using Euclidian neighborhood of radius r.
- Generate a mesh-Laplacian matrix L.
  - $L = D - W$
  - W: adjacency matrix where

$$w_{ij} = \begin{cases} 1, & \text{if vertices } i \text{ and } j \text{ are adjacent;} \\ 0, & \text{otherwise.} \end{cases}$$

  - D: diagonal matrix where

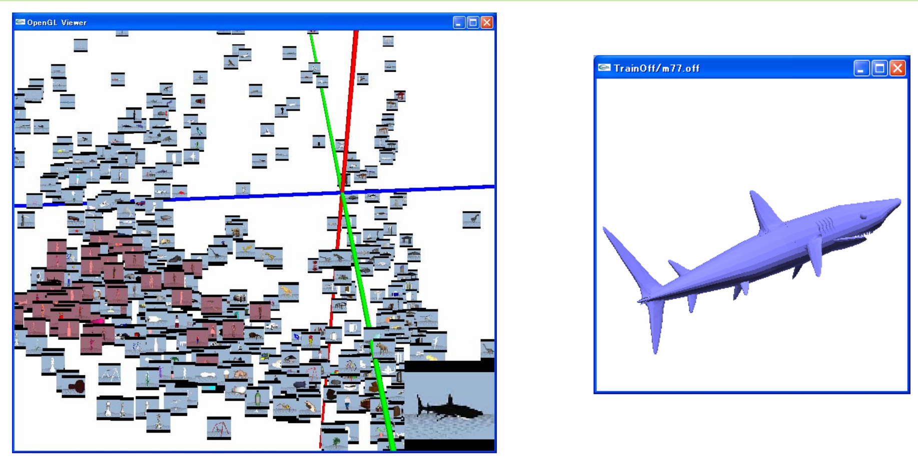
$$D_{ii} = \sum_j w_{ji}$$

- Eigen-analyze the matrix.
  - M dominant eigenvectors
    - ~ bases for the M-dim. subspace, i.e., *manifold*.
- Project the input vectors onto the M-dimensional bases.
  - M=3 for 3D visualization.



Visualization

- Simple 3D visualization
  - Postage-stamp sized images in 3D.
    - 3D coordinates given on the 3D manifold.
  - A click for a 3D-view window.
  - Cluster of "similar" models shown on demand.
    - k-means clustering (k=30).



Experiments and results

- Shape feature vectors
  - AAD [Ohbuchi05]: 256 dimensional.
  - SPRH [Wahl03]: 625 dimensional.
- Database
  - Princeton Shape Benchmark [Shilane04]
    - "Training set" 907 models.
- Shape feature vectors
  - AAD [Ohbuchi05]: 256 dimensional.
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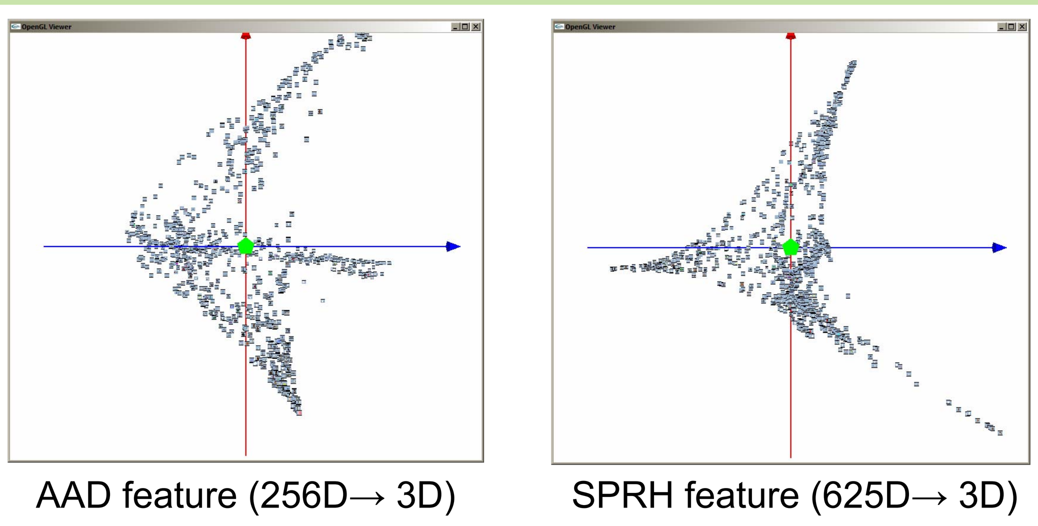
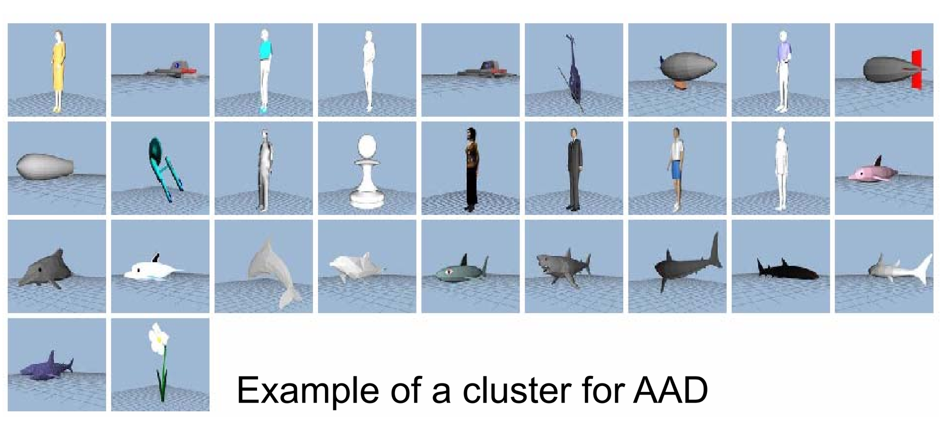


Results

- OK for 907 models.
  - Easier to navigate than the SOM 2D cell.
- Fixed number of clusters not good.


Example of a cluster for AAD

Summary

- 3D model retrieval via visual search
  - Non-linear summarization
    - Unsupervised learning of the feature subspace.
  - 3D visualization using postage stamp images.
    - Clustering to aid navigation.
  - Useful for about 1000 models.

Future work

- Scalability.
  - E.g., for 10k, or 100k models.
- Better dimension reduction.
  - Manifold learning algorithm (LLE, Isomap, etc.)
  - Others.
- Better clustering algorithm.

IEEE InfoVis 2006 poster , Baltimore, M.D., U.S.A.