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A database-adaptive distance measure for 3D model retrieval

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Abstract

The distance measure, in addition to the shape feature is a key factor in shape based 3D model retrieval. We employed a database adaptive distance measure for 3D model retrieval in the SHREC 2007 CAD track. The method described in this paper uses a feature dimension reduction based on an unsupervised learning of features to produce salient, lower dimensional feature from the original feature. Our method also combines a multiresolution shape comparison approach with the database adaptive distance measure. Our experiments the SHREC 2007 CAD track showed that both adaptive distance measure and multiresolution shape comparison approach added a few percent each to the original shape feature. Our method came in first in the SHREC 2007 CAD track despite the fact that the distance measure was trained by using a set of "generic" 3D models that are not CAD specific.

1. Introduction

Two of the most important components in a hape-based 3D model retrieval system [13] are the shape feature and the distance measure used. Intuitively, shape similarity decision would depend on shapes of models in the database to be compared, or a shape of the specific model to be queried. For example, a feature might excel at retrieving a class of models but not for the others classes. The shape similarity decision would also have inter-user variations as well intra-user variation depending on intention of the specific query. Despite these possible variations, most of the previous method uses a fixed feature and a fixed distance measure. Several researchers experimented with relevance feedback for on-line, interactive adaptation of distance measure [6] while the other tried query-adaptive combination of distances generated from multiple features [2].

Xhaofei He et al proposed, in the context of 2D image retrieval, a distance measure that *adapts to the database* of 2D images by using unsupervised learning. The method learns the non-linear subspace, or manifold, of features from large number of (unlabeled) 2D images. The dimension of an input feature is reduced by projecting the feature onto the manifold. A distance among a pair of dimension reduced and "salient" features corresponds to a geodesic distance on the manifold. He et al used the *Laplacian Eigenmaps* (LE) proposed by Belkin, et al [1] to learn the non-linear manifold. As the manifold generated by LE is defined only at the training samples, the manifold is smoothly approximated to handle queries not in the training set.

We adopted He's approach for 3D model retrieval in [9]. We applied the dimension reduction using the LE algorithm on two shape features. For both of the features, the dimension reduced feature overtook the original, untrained feature in retrieval performance when the number of training samples is more than about 1,500. For the unsupervised learning of feature manifold, we (quasi-) randomly sampled a set of models from the union of 1,814 model *Princeton Shape Benchmark* database [12] and 10,911 model *National Taiwan University* database [7].

Later, we further explored the approach by experimenting with six learning-based dimension reduction algorithms, both linear and non-linear [10]. These six dimension reduction algorithms are paired with eight shape features in a set of experiments. Of the dimension reduction methods we compared, the locally constrained, non-linear methods such as LE and *Locally Linear Embedding* (LLE) [11] performed the best. The best performing pair among those tested performed on a par with the top finisher in the SHREC 2006 contest, that is, Makadia's method.

To enter the SHREC 2007 CAD track, we used the same approach as described in [9, 10]. We used the set of "generic" 3D models as in [9, 10], not CAD specific 3D models, for learning the manifold. Our method came in first in every performance index for the contest even though the training samples are not CAD model specific.

This paper is organized as follows. We will describe in Section 2, the algorithm we employed. It is followed in Section 3 by the experimental results we have done using the SHREC 2007 CAD track benchmark. Section 3 will present the summary and future work.

2. The retrieval method

Our retrieval algorithm uses data-driven unsupervised learning to find a non-linear subspace of shape features for dimension reduction and then distance computation (See Figure 1);

Learning phase:

1. **Feature extraction:** Extract n-dimensional feature vectors from the K models in the training database (i.e., corpus).
2. **Sample selection:** If necessary, to reduce computational costs, sub-sample the training set down to L ($L \le K$) features.
3. **Manifold learning:** Perform unsupervised learning of the m-manifold ($m \le n$) from the n-dimensional training samples by using a manifold learning algorithm. Certain learning algorithm produces a manifold defined only at the set of training samples. In such a case, to handle queries outside of the training set, continuously approximate the manifold.

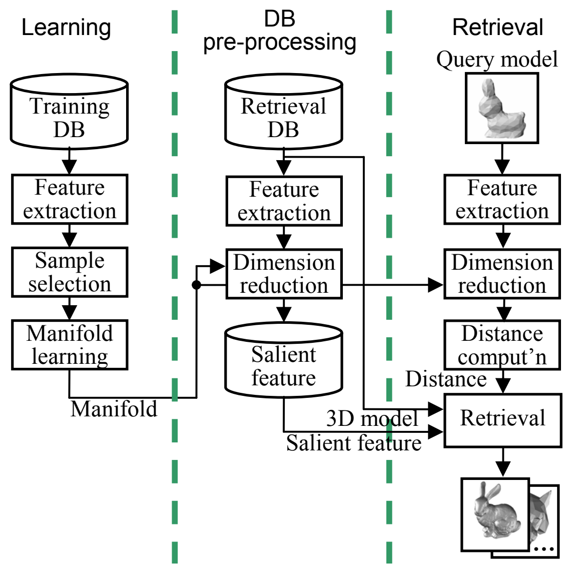

Figure 1. Our 3D model retrieval algorithm using database-adaptive distance measure.

Database pre-processing phase:

1. **Dimension reduction:** Project the feature of each 3D model in the database onto the (approximated) m-manifold to obtain an m-dimensional "*salient*" feature. Store each salient feature together with a corresponding 3D model.

Retrieval phase:

1. **Feature extraction:** Extract an n-dimensional feature from the query model.
2. **Dimension reduction:** Project the n-dimensional feature of the query onto the (approximated) m-manifold to obtain m-dimensional salient feature.
3. **Distance computation:** Compute distances from the query model to all the models in the database using their m-dimensional salient features using *cosine* distance.
4. **Retrieval:** Retrieve the models in the database having the p-smallest distances from the query.

To choose the combination of feature and dimension reduction method for the SHREC 2007 CAD track, we chose six dimension reduction algorithms including PCA, Kernel PCA, LE, and LLE [10]. We coupled these with the eight shape features including the SPRH and Spherical Harmonics (SH) [5]. Note that all the features we compared are purely geometric and applicable to polygon soup models as well as to watertight surface based models. Topological feature such as position and/or number of through holes is not used. The distance between a pair of salient features is computed by using Cosine distance. We chose the Cosine distance after comparing *L1*-norm, *L2*-norm, and Cosine distance for their retrieval performance.

For the training, we would have two major alternatives; (1) use CAD specific 3D models, e.g., that of the *Purdue University Engineering Shape Benchmark (PUESB)*, (2) use "generic" 3D models found, for example, the *National Taiwan University 3D Model Database* (NTUD) [7].

What we used for the SHREC 2007 CAD track is a set of "generic" 3D models, that is, the union of the training set of the *Princeton Shape Benchmark* (PSB) database containing 907 models and the *National Taiwan University 3D Model Database* (NTUD) ver. 1.0 containing 10,911 models. The NTU database does not have any labels. The labels in the PSB training set are simply ignored. By using a quasi-random sequence (*Niederreiter* sequence), we sub-sampled the union (12,775 models) down to 4,000, 5,000, or 10,000 models for the training.

Some of the learning algorithms have parameters, e.g., number of output dimensions, neighborhoods size k for manifold reconstruction, and spreads of RBF

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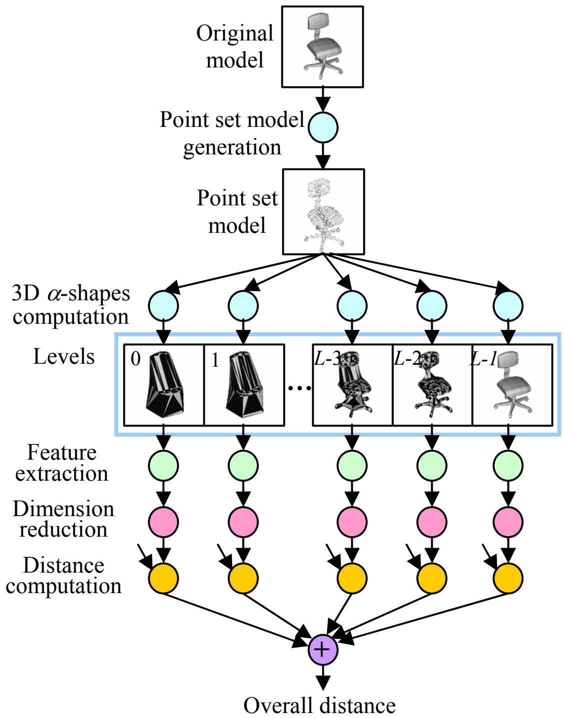

Figure 2. The multiresolution set of features is dimension reduced and distance computed separately at each resolution levels before integrated into an overall distance.

kernels for manifold approximation. We chose, through preliminary experiments using SHREC 2006 benchmark [14], a set of best-performing parameters.

We integrated the multiresolution 3D shape comparison approach we have previously proposed [8] with the learning based approach described above (See Figure 2.) The multiresolution shape comparison approach uses a mathematical morphology-like multiresolution (MR-) representation to obtain multiresolution set of shape features. We applied the manifold learning and dimension reduction separately at each resolution level. That is, if the MR representation has L resolution levels, a total of L manifolds are learned using features computed for each resolution level. Then, dimension reduction is performed independently at each level. To compare a pair of 3D models, a distance is calculated at each of the L levels of the MR representation. These L distance values are then combined into an overall distance between the pair of models by using a fixed-weight linear combination of the distances. We used the weight 1.0 for all the levels.

We conducted a set of preliminary experiments to compare retrieval performances of various combinations of the methods. To enter the SHREC 2007 CAD track, we chose the best performing combination, the multiresolution (MR) SPRH feature dimension reduced by using the LLE algorithm and 5,000 training models.

3. The experimental results

Table 1a shows the retrieval performance figures by using the SHREC 2006 benchmark. For example, the salient (6-level) multiresolution feature LLE-MR-SPRH-C trained using 5,000 models gained nearly 18% in First Tire Highly-Relevant (FT-HR) compared to the original SPRH (=SR-SPRH-K), that is, the single resolution SPRH without the learning-based adaptation of distance measure. The SR-SPRH-K used *Kullback-Leibler Divergence* (KLD) as the distance measure [15]. The table also lists the performance figures for the top finisher in the SHREC 2006 contest, the Makadia's method.

Table 1b shows the performance indices using the SHREC 2007 CAD track. The best performing is the LLE-MR-SPRH-C (Run6), which used a dimension reduced, 6-level multiresolution set of SPRH features. It has the FT-HR of 41.23%, which is 6.5% better than the original SPRH (=SR-SPRH-K) in the same benchmark. The LLE-MR-SPRH-C (Run5) used 5-level MR feature, omitting the level 0 (=convex hull). Overall performance of the 5-level version (Run 5) is slightly lower than that of the 6-level version (Run 6).

The performance gain due to learning appears to be more significant in the SHREC 2006 than in the SHREC 2007 CAD track. This may be due to the fact that we used the manifold trained by using the SHREC 2006-like 3D models for the SHREC 2007 CAD track.

It is interesting to note that the feature that uses only the convex-hulls of the models for feature computation, the MR-L0-SPRH-K, performed rather well. It would have placed at about 4th place in the SHREC 2007 CAD track. This might be an indication that the similarity decision of the SHREC 2007 CAD track depended heavily on the overall shape of the models.

4. Summary and future work

In this paper, we described the method we used for our entries in the SHREC 2007 CAD track. The method employs unsupervised learning to estimate a non-linear subspace, or manifold of features. Dimension reduction of the original feature using the manifold produces a salient feature that results in better retrieval performance. To enter the contest, we used the LLE algorithm [11] for the manifold learning, and used a set of 5,000 "generic" 3D models for the training samples. By combining the learning based adaptive distance measure with a multiresolution shape

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comparison approach we have previously proposed, we gained significant performance advantage to win the SHREC 2007 CAD track.

First in the list of items to do is to see if a training set consisting of CAD specific models would improve learning and thus retrieval performance. We are also interested in applying the database-adaptive approach to the other tracks, e.g., the face model retrieval track.

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Table 1a. Retrieval performance of our method measured using the SHREC 2006 [14].

Features	# training samples	# of MR levels	Distance	AP-HR	FT-HR [%]	DAR	NCG @25	NDCG @25
SR-SPRH-K	-	SR	KLD	0.2886	26.68	0.3990	0.3920	0.4384
MR-SPRH-K	-	6	KLD	0.3761	34.93	0.4631	0.4519	0.5101
LLE-MR-SPRH-C	5,000	6	Cosine	0.4614	44.46	0.5341	0.5604	0.5966
LLE-MR-SPRH-C	10,000	6	Cosine	0.4747	44.44	0.5382	0.5584	0.6013
Makadia (Run 2)	-	-	-	0.4364	44.77	0.5499	0.5498	0.5906

Table 1b. Retrieval performance of our method measured using the SHREC 2007 CAD track.

Features	# training samples	# of MR levels	Distance	AP-HR	FT-HR [%]	DAR	NCG @25	NDCG @25
SR-SPRH-K	-	SR	KLD	0.3721	34.76	0.4642	0.3916	0.4478
MR-SPRH-K	-	6	KLD	0.4055	36.38	0.5002	0.4369	0.4912
LLE-MR-SPRH-C (Run 6)	5,000	6	Cosine	0.4337	41.23	0.5357	0.5023	0.5341
LLE-MR-SPRH-C (Run 5)	5,000	5	Cosine	0.4319	40.25	0.5345	0.4850	0.5270
MR-L0-SPRH-K	-	1	Cosine	0.3437	30.97	0.4400	0.3896	0.4327

AP-HR: Mean Average Precision (highly relevant)
AP-R: Mean Average Precision (relevant)
FT_HR: Mean First Tier (Highly Relevant)
FT_R: Mean First Tier (Relevant)
ST_R: Second Tier (Relevant)
DAR: Mean Dynamic Average Recall
NCG @25: Mean Normalized Cumulated Gain @25
NDCG @25: Mean Normlized Discounted Cumulated Gain @25

- "MR" denotes a multiresolution feature, while "SR" denotes a single resolution feature.
- Suffix "-K" denotes distance computed by using Kullback-Leibler Divergence, while "-C" denotes Cosine distance.