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# Feature Template based 3D Model Retrieval

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**ABSTRACT**

*3D model retrieval has attracted more and more research interests. Lots of shape descriptors have been proposed till now. But during the process of constructing these shape descriptors, feature correlation among models is not considered. In this paper, we propose a simple but very effective method in improving retrieving accuracy by employing correlative information, namely feature template. Feature template is designed to remove such small variation while remaining discriminative features by performing meaning operation of feature vectors. As a result, it makes the feature vector be more robust for better retrieving accuracy. In addition, the feature template can be regarded as a post-processing of existing shape descriptors. Therefore, the proposed method can be used to improve retrieving accuracy for any shape descriptors in the form of feature vector. In experiments, we test the proposed method for several shape descriptors by using a public 3D model database. Comparing with original shape descriptors, our method can greatly improve the retrieval accuracy.*

Categories and Subject Descriptors (according to ACM CCS): IH3.1 [Information storage and retrieval]: Content Analysis and Indexing.

## 1. Introduction

3D models have been widely used in manufacturing, animation, entertainment etc. However, it is not easy to create a 3D model from scratch. Fortunately, the user's new design can often share high similiar characteristic with the existing models. Therefore, to efficiently generate new model, user has turned the concept of "How do they design 3D models?" to "How do they find them?" [FMK03].

To help user efficiently find the expected 3D model, we need define robust shape descriptor for 3D model retrieval. The defined shape descriptor should have a powerful discrimination for different kinds of 3D models. Meanwhile, it is should be stable under different transformations, including noise distortion, rotation, scaling, non-rigid transformation etc. Previous work is addressing the robustness problem by considering some preprocessing technology or affine invariance. For example, some works apply Principal Component Analysis(PCA) to keep the defined descriptors be robust under rotation. On the other hand, lots of affine invariance property, like rotation invariant spherical harmonics, pose insensitive shape diameter function etc, have been used in defining more robust shape descriptor. Section 2 will give a brief review about the previous research work. Undoubtedly, these excellent research works have made a great progress in improving retrieving accuracy. However, no method uses the correlation of features for defining more robust descriptor under different shape variations.



This paper fills the limitation, and proposes feature template to make the defined shape descriptor be more robust under shape variation. Feature template is not to define a new shape descriptor, but to remove small variation while remaining their discriminative information for shape descriptors by employing correlative information of feature vectors. Obviously, the feature template technology can be used for any shape descriptors in the form of feature vector. In addition, the process of generating feature template will not affect retrieving efficiency because it can be finished in an off-line process. That's to say, the feature template can greatly improve retrieving accuracy without losing any retrieving efficiency. To verify the improved retrieving accuracy by using the proposed method, we perform an experimental comparison on Generic 3D Warehouse from Shape Retrieval Contest'10 (SHREC'10). Results show that our method can greatly improve retrieving accuracy for different shape descriptors.

The remainder of the paper is organized as follows: Section 2 provides a brief review of the related work. Section 3 discusses how to construct feature template. Section 4 provides the experimental results for 3D model retrieval. Finally, Section 5 concludes the paper and recommends some future work.

## 2. Related work

In this section, we will briefly review previous research work related to our approach. To make a full survey about 3D model retrieval, user can refer to some



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excellent surveys[BKS*05][IKL05][TV04]. Taking the concept in pattern recogntion, we classify the existing shape descritpror into two groups, namely statistical descriptor and structural descriptor. Our algorithm is working on statistical descriptor. Therefore, this section only discusses existing researches about statistical descriptor.

Statistical descriptor can be further classified into two groups, including histogram and transformation based methods. Histogram is the most popular method in defining shape descriptor. Any geometric signature, like curvature, normal surface distance etc, can be used in constructing a histogram based shape descriptor. The shape diameter function compute the distance between surface point and medial axis[GSC07]. Multivariate probability density function is also used to define shape descriptor[ASY*09]. Atmosukartoa et al proposed a 2D histogram by longitude–latitude transformation[AWH*10]. Unlike the histogram based methods, transformation based methods first perform transformations for the 3D shape or their 2D views. Then, the obtained transformation coefficients can be used for shape retrieval. In 3D space, Spherical harmonics is the most typical transformation, and has a wide application in 3D model retrieval[KFR03]. Further extension of spherical harmonics is performed by Papadakis et al[PPP*07]. Besides spherical harmonics, spectral information of 3D model is also considered in constructing descriptor. Zhang et al construct a bending-invariant 3D shape representation by using spectral embeddings[JZ07]. All the above methods perform transformations in the 3D space, but the transformations can also be performed in 2D space for view-based 3D shape matching. As a result, lots of transformation-based 2D shape descriptors can be used for 3D model retrieval. The most effective view-based descriptor is the Light Field Descriptor (LFD), which is developed by Chen et al. LFD gets 100 2D silhouette image rendered from a 2D array of cameras distributed uniformly on a sphere[CTS03]. For each image, its Zernike moments and Fourier coefficients are extracted for 3D model matching. BF-DSIFT-E(Bag-of Densely-Sampled Local Visual Features), the best shape descriptor in SHape REtrieval Contest (SHREC 2010), is another descriptor defined by view based transformation[OSF08]. However, BF-DSIFT-E has a very high computation cost, which can not be accepted by retrieving efficiency.

In conclusion, lots of stastical descriptors have been proposed before. However, no correlative information is considered in the process of constructing shape descriptor. Therefore, we consider how to employ correlative information among models.

## 3. Feature template for 3D model

This section discusses how to construct feature template. Firstly, we provide an overview about the flowchart of constructing feature templates. Then we discuss how to construct feature template in details.

### 3.1 Overview the proposed method

Here, the feature templates are the post-processing of shape descriptors. Therefore, we assume that each model in database has been represented by the form of feature vector. The feature template is designed to analyze the relationship of these feature vectors. The whole flowchart of constructing feature templates is shown in Figure 1.

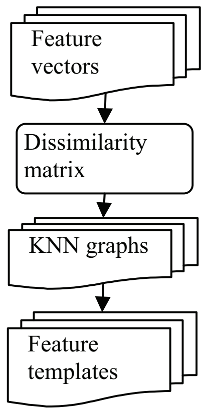


**Figure 1:** *The flowchart of constructing feature templates*

Firstly, for any two feature vectors, their dissimilarity is calculated by using L1 metric. As a result, we can get a dissimialrity matrix of models in database. Secondly, from the dissimarity matrix, we can generate KNN graph to get adjacent models of each model. Finally, the feature template of each model can be defined as the mean of its adjacent models. Notice the whole process is performed in an off-line process. Therefore, the process has few effect on the retrieving efficiency.

### 3.2 Construction of feature templates

This subsection gives some details about the above flowchart. Supposing that the model database can be represented as a set

$$ST = \{S_1, S_2, \cdots S_i \cdots S_N\}\ .$$

here, the symbol $N$ denotes the number of model count in database. For each model $S_i \in ST$ , it has a feature vector

$$F_i = \{f_{i,1}, f_{i,2}, \cdots f_{i,k} \cdots f_{i,M}\}$$

here the symbol $M$ denotes the dimension of feature vector. For any two feature vectors $F_i$ and $F_j$ , their dissimilarity $dis_{i,j}$ can be calculated by using the following equation:

$$dis_{i,j} = \left|F_i - F_j\right| \qquad (1)$$

The above equation means the dissimilarity of two vectors. If the value is small, it means that two models share the high similarity. Therefore, we can get dissimilarity matrix $D$ of all models in database. Based on dissimilarity matrix, we can construct KNN graph(K-nearest neighbor



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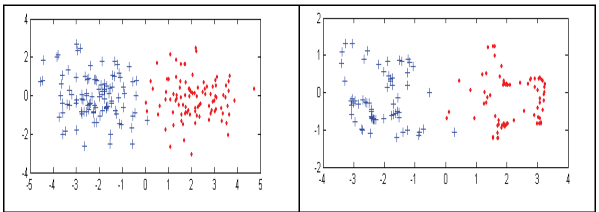
graph) and find K closest models for each model. Here K is the number of adjacent nodes. we set K to 6 in our implementation. That's to say, for each model $S_i \in ST$ , it has adjcant models $Neig(S_i)$ . With the defined KNN graph, we can easily get the feature template by the following equation:

$$F_i' = \frac{\sum F_j}{K}, S_j \in Neig(S_i) \qquad (2)$$

The idea of vector template is taken from the unsupervised clustering. That means the data can move along the direction of its clustering center while be far away from other clustering center. This is very important for retrieving task. In retrieving task, there are some models near the boundary of different classes due to shape variation. Generally, these models have a high risk to be retrieved wrongly. Fortunately, these points have the following propeteries: its adjacent datas often contains more models belonging to the same class. Therefore, we can perform an meaning operation for its adjacent points to remove small variations while improving their clustering. Figure 2 gives such an example. As shown in Figure 2(a), there are many data near the seperating boudary in the original distrubtion. However, the separability of these fuzzy points have been greatly improved after performing feature template. In this way, the clustering of feature templates will be more obivious than that of feature vectors.



(a) The distrubtion of feature vectors

(b) The distrubtion of feature templates

**Figure 2** *The distribution of feature vectors and feature templates(The clustering of feature templates will be more obvious)*

## 4. Experimental analysis

In this section, we show that the feature template can improve the retrieving accuracy regardless of using any existing shape descriptors. Firstly, this section describes the experiment data, including testing database and shape descriptors. Secondly, we show the used measures for quantitative evaluation. Finally, we provide some comparison results.

### 4.1 Experimental data

There are many benchmark databases released for retrieving performance comparison. In our experiments, we prefer to the dataset used in SHREC 2010 for Generic 3D Warehouse[VGD10].About the 3D shape descriptors, we use ray-based using spherical harmonics(RSH) and Depth Buffer-Based Feature Vector(DBD). The implementation of two shape descriptors has been released and can be downloaded from the Author's website.

### 4.2 Evaluation measures

In our comparison analysis, we use some most common evaluation measures for retrieving accuracy. These measures include Precision-Recall plot, first tier(FT), second tier(ST). And their detailed definition can be found in reference[Vra04].

### 4.3 Comparison of retrieving performance

In comparison experiments, we verify that the proposed approach can improve the retrieving accuracy for different kinds of shape descriptors. Firstly, we analyze the FT and ST measures. As shown in Table 1, both them have a great improvement for testing database. In addition, we notice the feature template for RSH has a higher retrieving accuracy than the DBD. It is very important for retrieving efficiency because the DBD and RSH have a vector with 484 and 136 dimensions, respectively. It means that the feature template of RSH can get similar retrieving accuracy with that of DBD, while remaining a relatively low feature dimension. In other words, feature template can improve the retrieving accuracy without losing any retrieving efficiency.

Table 1 Comparison between feature vector and feature template

| Shape descriptor | FT | ST |
|---|---|---|
| RSH | 39.7 | 52.8 |
| Feature template for RSH | 44.0 | 57.6 |
| DBD | 43.1 | 56.0 |
| Feature template for DBD | 46.5 | 58.7 |

To further verify the improved retrieving accuracy, we give the standard Precision-Recall plots(Figure 3). The curves with different colors correspond to the different descriptors we have tested. Remember that curves shifts upwards and right indicates better retrieval accuracy. Results show the retrieving accuracy by using feature template is improved obviously.

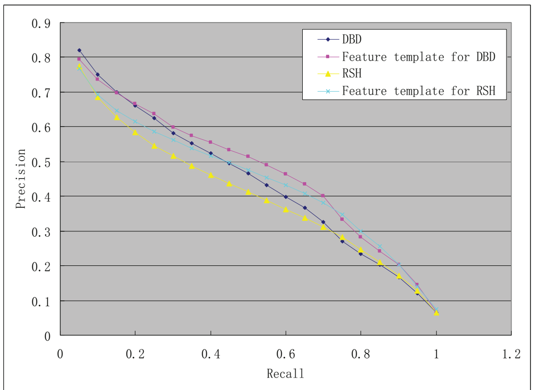



**Figure 3** *Precision–Recall plot*

## 5. Conclusion

This paper proposed a novel idea for improving 3D retrieving accuracy, namely feature template. The proposed method is to remove small variation by employing correlation information in model database. The implementation of feature template is very simple. The improved retrieving accuracy, however, is very obvious.

There are lots of shape descriptors proposed before. Generally, it is difficult to propose a new shape descriptor both better in retrieving accuracy and efficiency. For instance, the shape descriptor BF-DSIFT-E can get best retrieving accuracy in SHREC2010 while has a very high computation cost. Therefore, we can get clustering information by using BF-DSIFT-E descriptor, and then the clustering information can be used in constructing a more compact descriptor. On the other hand, this paper only considers correlation among the models by using single shape descriptor. However, the correlation among different shape descriptors is not considered. Maybe, we can analyze correlation among different shape descriptors to make their good complementation. It will be an interesting topic in the future.

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