SHAPE-BASED 3D MODEL RETRIEVAL SYSTEM BASED ON ELEVATION DESCRIPTOR

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ABSTRACT

Recently, with the construction of digital libraries, the management of the large multimedia databases becomes an important issue. Unfortunately, traditional keyword searching techniques are not always effective for multimedia information. Thus, computer science has make incredible progress in retrieval of multimedia data based on image content. However, most of retrieval systems are focus on the 2D image databases. As the number of 3D models available on the digital libraries, the demand for a content-based 3D model retrieval system becomes urgent. Thus, in this paper, we propose two novel features for 3D model retrieval. One is adaptive D2, another is 3D model's six elevations including front elevation, plan, left side elevation, right side elevation, rear elevation and bottom elevation. Then, based on the rank of the feature distance, a similar measure is provided to do the similar 3D model retrieval. Finally, use a relevance feedback algorithm to better adapt to the preferences of users. Experiment results show that these proposed methods are superior to others.

1. INTRODUCTION

The recent emerging of multimedia as well as the availability of large image, video and 3D model archives have made computer-aided retrieval becomes a popular research topic. However, most of the current commercial multimedia retrieval systems search desired data based on the keywords. That is, the managers of database must define these keywords. If a database contains many multimedia data, it will be time consuming to define keywords for the entire database. Moreover, what are the proper keywords for an image is difficult to decide. Of course, the simplest approach is to find keywords in filenames, captions, or context (e.g., Google [1, 2]). However, this approach can fail when data are not annotated (e.g., "c0033.jpg") or data are annotated with unspecified filename (e.g., "jeffrey.gif" or "circle.bmp"). Thus, the demand for an automatic and user-friendly content-based/visual multimedia retrieval system become urgent. Most of the content-based retrieval and classification systems have been developed just for 2D data, including images [3-10] and video [11]. The 3D model retrieval system is still infancy. However, with the development of computer graphics, 3D models will be as ubiquitous as other multimedia data in the future. Thus, developing an automatic and fast content-based 3D retrieval system is necessary.

The major problem for such a system is how to extract proper features to represent the variable shape in a 3D model and query the similar 3D model by these features. The simplest way is to describe a 3D model by its 2D silhouettes from different views [12], users can search similar 3D models by those corresponding 2D shape features. Since, a 3D model could be rotated or deformed within the Cartesian coordinate system, the number of 2D silhouettes must be large enough to present a 3D model. On the other hand, if the number of silhouettes increases, the retrieval speed will be deceased. However, even many silhouettes are extracted, if a complex 3D model is rotated by small angle, these silhouettes don't guarantee to be invariant for the rotation of 3D model.

The better approach is to extract 3D features directly. Before extracting the 3D feature vectors, many methods [13-21] request to register the 3D models in a Cartesian coordinate system based on the principle component analysis (PCA). The moments [19, 20] have been popular used as the features for 3D model retrieval. The first two moments (the mass center and principal axes) are used to align the models and the moments up to the sixth order are compared using difference. Horn [21] proposes Extended Gaussian Image (EGI) to characterize a 3D model in terms of its distribution of surface normal vectors. EGI also have to be aligned based on object's principal axes. In our experience, we find that some similar 3D models have the different principal axes. Fig. 1 shows the principal axes of three similar mugs are different. The main reason is that these mugs have different type of handles. That is, if a 3D feature must rely upon the unstable PCA to align its 3D model, the retrieval result is not expected.

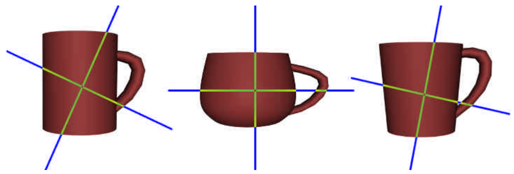

Fig. 1. The similar mugs with different principal axes.

Other approaches are based on comparing high-level representations of shape. Hilaga [22] presents a method for matching 3D topological models using Multi-resolution Reeb Graphs (MRG) which presents the skeleton structure defined by a continuous scalar function for a 3D model.

MRG can be used to measure distance among a set of pre-categorized 3D models and are robust for 3D shape deformation. However, methods of computing MRG are usually time consuming and sensitive to small features.

The 3D models also can be indexed based on the histograms of geometric statistics [24, 28-32]. For example, Ankerst et al. [33] proposes shape histograms to characterize the area of intersection with a collection of concentric spheres. Osada et al. [28] represents 3D objects with probability distributions of geometric properties computed for points randomly sampled on an object's surface. Five features, including A3, D1, D2, D3, and D4, are proposed in shape distribution. For instance, D2, the best feature among these five features, is the distribution of distances between two random points on the surface of 3D model. These features are invariant to tessellation of 3D polygonal model, since points are randomly selected from the object's surface. However, they are insensitive to small deformation due to noise, cracks, or insertion/removal of polygons, since sampling is area weighted. And, often these statistical methods are not discriminating enough to make slight differentiation between classes of shapes. Besides, MPEG-7 [23] uses shape spectrum descriptor (SSD) [24] as its 3D feature. The SSD represents the histogram of the curvature of all points on the 3D surface. The advantages of SSD are that it can represent the distribution of geometric statistics without align the objects and be robust to tessellation of 3D polygonal model.

Saupe et al. [17, 18] have used spherical harmonics to obtain multi-resolution representation of 3D models. However, their method requires a priori registration with principal axes. Recently, Funkhouser et al. [25] developed a 3D model search engine, which used adaptive spherical harmonics to compute discriminating similarity measures without repairing degenerate object or aligning object's orientation. The spherical harmonics decompose a 3D model into a collection of functions defined on concentric spheres and characterized it by a set of spherical functions which are the sum of different frequencies with specific spherical radius.

In this paper, we investigate a novel method for automatic shape-based 3D model retrieval. The main idea is to observe 3D model's six elevations including front elevation, plan, left side elevation, right side elevation, rear elevation and bottom elevation. These elevations express different altitude of six different visual angles from 3D model. We use these six elevations to represent a 3D model. Then, the new method of extract feature from 3D models is proposed in this paper.

In summary, many kinds of features have been commonly used for searching a similar 3D object. However, most of the current 3D model retrieval systems only use one feature to search the similar objects. And, in the above-mentioned features, no one can appropriate for all kinds of 3D models. To treat this problem, in this paper, a composite feature set that is robust for object deformation and don't request to register an object in a Cartesian coordinate system will be used for 3D model retrieval. Moreover, to get the better retrieval result, in this paper, a relevance feedback algorithm is proposed. It has been used in many content-based image retrieval systems [3-5, 8, 26]. The main concept of relevance feedback algorithm is to automatically determine the best method among the feature set according to the user's response.

The rest of the paper is organized as follows. In Section 2, feature extraction methods will be described. In Section 3, the similarity measure and the relevance feedback algorithm are described. The experimental results are described in Section 4. Finally, conclusions will be given in Section 5.

2. FEATURE EXTRACTION

We propose two novel shape-descriptors for 3D models, including adaptive D2 and elevation descriptor for 3D models.

2.1 Adaptive D2

Osada et al. [28] represents 3D objects with probability distributions of geometric properties computed for points randomly sampled on an object's surface. Five features, including A3, D1, D2, D3, and D4, are proposed in shape distribution. For instance, D2, the best feature among these five features, is the distribution of distances between two random points on the surface of 3D model. These features are invariant to tessellation of 3D polygonal model, since points are randomly selected from the object's surface.

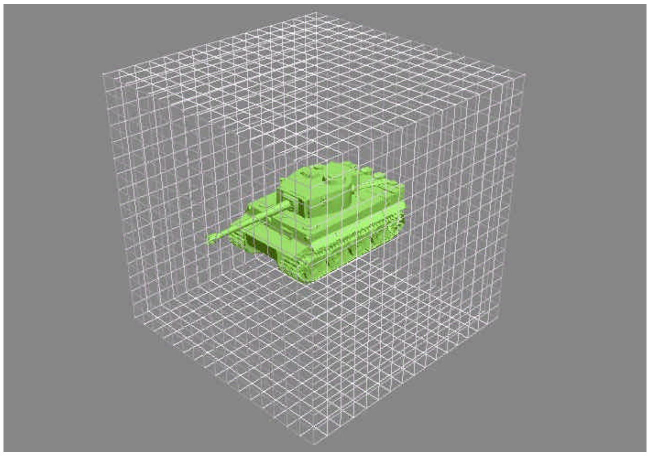

Fig. 2. Diagram of voxel grid for 3D model.

However, they are insensitive to small deformation due to noise, cracks, or insertion/removal of polygons, since sampling is area weighted.

For this reason, we propose adaptive D2 to improve D2. First, the 3D model is quantized by a voxel grid. Then the distribution of distances between two random points can be calculated. The main steps for computing the adaptive D2 are computed by the following steps:

(1) The polygonal surfaces are segmented into a $2R \times 2R \times 2R$ voxel grid (see Fig. 2). The voxel is assigned 1 if it is within one voxel width of a polygonal surface and 0 otherwise. To normalize for translation and scale, the object's mass center is moved to the point (R, R, R) and the average distance from non-zero voxels to the mass center is scaled to $R/2$. R is set as 32, which provides adequate granularity for discriminating objects while filtering out high-frequency noise in the original data.

(2) D2 can measure the distance between two random points in the voxel grid. We evaluate S samples from the D2 shape distribution and construct a histogram by counting how many samples fall into each of 256 bins. In order to normalize the distribution , we define adaptive D2 as:

$$AD2 = \left\{ \frac{V_1}{S}, \frac{V_2}{S}, \frac{V_3}{S}, \ldots, \frac{V_{256}}{S} \right\}$$

where V_i is the count of i-th bins for i=1, 2, …, 256.

2.2 Elevation Descriptor For 3D Models

Elevation descriptor is to observe 3D model's six elevations including front elevation, plan, left side elevation, right side elevation, rear elevation and bottom elevation. These elevations express different altitude of six different visual angles from 3D model. We use these six elevations to represent a 3D model.

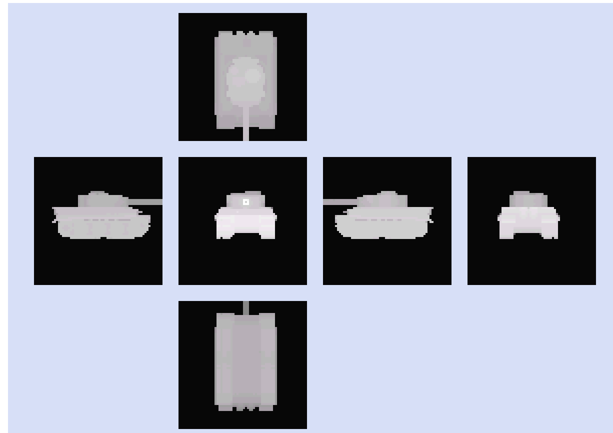

Fig. 3. Six elevations of a 3D military tank model: front elevation, plan, left side elevation, right side elevation, rear elevation and bottom elevation.

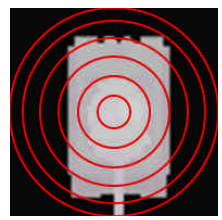

Fig. 4. The different radius of concentric circles for a elevation.

The main steps for computing the elevation descriptor for 3D models are described as follows:

(1) First, the 3D models are quantized by step (1) in 2.1.

(2) Show the voxel grid of 3D model into front elevation, plan, left side elevation, right side elevation, rear elevation and bottom elevation as Fig. 3. The graphs are gray level images. The gray level value is higher when the pixel is more close to viewer. On the other hand, the gray level value is lower when the pixel is far away from viewer.

(3) Decompose the elevation into a collection of functions defined on concentric circles. We compute sum of gray level between radius r-1 and r of the elevation, as $g_{k,r}$, r=1, 2, …, 32, and k=1, 2, …, 6. Note that, k is the index of elevation. And the gray level sum for each elevation is defined as $G_k = \sum_{r=1}^{32} g_{k,r}$, k=1, 2, …, 6. Then, $g_{k,r}$ is normalized by G_k:

$$ED_{k,r} = \frac{g_{k,r}}{\sum_{k=1}^{6} G_k}$$

ED is used as our feature vector for 3D model retrieval.

3. 3D MODEL RETRIEVAL

Many kinds of features have been commonly used for searching a similar 3D object. However, most of the current 3D model retrieval systems only use one feature to search the similar object. In fact, no single feature can appropriate for all kinds of 3D models. To treat this problem, a composite feature set that is robust for object deformation and don't request to align the objects by the unstable PCA will be proposed in this section.

In general, our proposed elevation descriptor for most 3D models will have the best retrieval result. Only for few special types of rotational 3D models, other methods may have better results. . Two kinds of 3D features, including the spherical harmonics [25] and 3D shape spectrum descriptor of MPEG-7 [24], will be also composed to construct our feature set. These features are selected because they are invariant to object rotation, translation, and scaling. Moreover, they don't request to register an object in a Cartesian system first.

In this section, a similarity measure between two objects is provided first. Then, since each kind of feature is especially appropriate for some types of objects, to get an optimal retrieval result, a relevance feedback algorithm [5] is proposed to automatically determine the most appropriate feature among our feature set according to the user's response.

3.1 Similarity Measure

Based on the four kinds of feature vectors introduced, the similar 3D model retrieval will be conducted. To do retrieval, a similarity measure is first proposed to evaluate the similarity between two objects.

Then, in the elevation descriptor, we sort G_k, k=1, 2, …, 6, in a decreasing order as $G_{k'}$, k=1, 2, …, 6, where G_6> G_5> …> G_1. For a query object q and any matching object s, define the differences of elevation descriptor (ED) as:

$$Dis\_ED_{q,s} = \sum_{k'=1}^{6}\sum_{r=1}^{32}\left|ED^{q}_{k',r} - ED^{s}_{k',r}\right|$$

And define the differences of adaptive D2 (AD2), spherical harmonics (SH) and shape spectrum descriptor (SSD) as:

$$Dis\_AD2_{q,s} = \sum_{i=1}^{256}\left|AD2^{q}_{i} - AD2^{s}_{i}\right|$$

$$Dis\_SH_{q,s} = \sum_{r=0}^{31}\sum_{m=0}^{15}\left|SH^{q}_{r,m} - SH^{s}_{r,m}\right|$$

$$Dis\_SSD_{q,s} = \sum_{i=1}^{N}\left|SSD^{q}_{i} - SSD^{s}_{i}\right|$$

where $SH_{r,m}$ is defined as m-th spherical harmonics frequency of r-th radius on concentric sphere, and SSD_i is defined as i-th feature vector of SSD.

Then, the similarity measures between q and s are defined as

$$Sim\_ED_{q,s} = \frac{1}{Dis\_ED_{q,s}},$$

$$Sim\_AD2_{q,s} = \frac{1}{Dis\_AD2_{q,s}},$$

$$Sim\_SH_{q,s} = \frac{1}{Dis\_SH_{q,s}},$$

$$Sim\_SSD_{q,s} = \frac{1}{Dis\_SSD_{q,s}}.$$

Note that the larger $Sim\_ED_{q,s}$ a matching object has, the more similar it is to the query one. Based on $Sim\_ED_{q,s}$, we can find objects similar to the query one by taking those with high values. Using the same concept, some similar objects also can be retrieved based on $Sim\_AD2_{q,s}$, $Sim\_SSD_{q,s}$ or $Sim\_SH_{q,s}$. Since the scales of the four kinds of feature vectors are different, the traditional similarity measure that uses the summation of all the differences of the feature vectors between query and matching objects is unsuitable in this paper. Thus, based on the two features, a grade evaluation method will be provided to measure the similarity between a query object and each matching object.

3.2 Relevance Feedback Algorithm

The grade evaluation method is first proposed to measure the similarity of objects based on the composite feature set. Then a relevance feedback algorithm is used to select the best features among the feature set.

First, sort $Dis\_ED_{q,s}$, s =1, 2, …, n (n is the total number of matching objects) in an increasing order. For the top g objects, we define their grades, $G\_ED_{q,s}$, as g, g-1, g-2, …, and 1, respectively. In addition, $G\_ED_{q,s}$ of all other objects are defined as zero. That is, the objects with highest similarity measure will have the highest grade. We also apply the spherical harmonics and the shape spectrum descriptor to evaluate the corresponding grades denoted as $G\_AD2_{q,s}$, $G\_SH_{q,s}$ and $G\_SSD_{q,s}$. For each matching object *s*, the summation of grades is defined as

$$Grade_{q,s} = w_1 G\_ED_{q,s} + w_2 AD2_{q,s} + w_3 G\_SH_{q,s} + w_4 G\_SSD_{q,s}$$

where $w_1, ..., w_4$ are the weights. Initial $w_1, ..., w_4$ are set to 1. Based on the $Grade_{q,s}$, a group of objects similar to the query one can be retrieved. Note that the four weights, $w_1, ..., w_4$, will affect the retrieval results, and it is impossible to determine a set of fixed weights that is appropriate for any kind of objects. For example, for those 3D objects that are constructed by several components, the weight for $G\_AD2_{q,s}$, $G\_SH_{q,s}$ or $G\_SSD_{q,s}$ should be increased. To treat this situation, a relevance feedback algorithm is provided to determine the best method according to the user's response. A user can choose *p* similar objects, $l_1, l_2, ..., l_p$, from the query results. Based on the grades of these objects, the new $w_1, ..., w_4$ are calculated by

$$w_1 = \sum_{j=1}^{p} G\_ED_{q,l_j},$$

$$w_2 = \sum_{j=1}^{p} G\_AD2_{q,l_j},$$

$$w_3 = \sum_{j=1}^{p} G\_SH_{q,l_j},$$

$$w_4 = \sum_{j=1}^{p} G\_SSD_{q,l_j}.$$

Since only using the most appropriate feature vector usually gets better retrieval result than using combined features, the best feature will be selected instead of using combined features. This can be done by modifying $w_i's$ as

$$w_i = \begin{cases} 1 & \text{if } w_i = \{w_1, w_2, w_3, w_4\}; \\ 0 & \text{otherwise.} \end{cases}$$

Using these new weights, a user can get a better retrieval result.

4. EXPERIMENTAL RESULTS

To demonstrate the effectiveness of the proposed methods on different kinds of objects, experiments have been conducted based on our test database that is constructed to

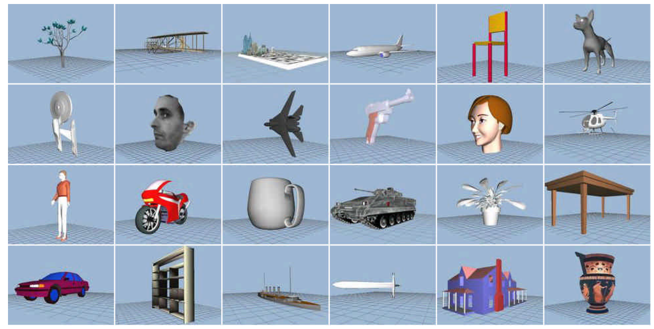

Fig. 5. Some classes in our test database.

Fig. 6. All 3D models in the military tank class in our test database.

contain several kinds of 3D models. We use the Princeton Shape Benchmark [34, 35] to be our test database. The Princeton Shape Benchmark provides a database of 3D models for evaluating shape-based retrieval and analysis algorithms. And then, combining all the database of the Princeton Shape Benchmark, our test database has 1814 3D models clustering 161 classes. For example, Fig. 6 shows all 3D models in the military tank class which includes 16 models.

The performance is measured by the recall [27]. Note that the *recall* is defined as:

$$\mathbf{recall} = \frac{N}{T} \;,$$

where *N* is the number of relevant objects retrieved and *T* is the total number of relevant objects. In order to compare the performances of the proposed method and others using D2 of the shape distribution, spherical harmonics, and SSD as features, we also implement those methods and show the experimental results.

Table 1. The *recall* for the test database.

D2 of the shape distribution (D2)	0.174529
MPEG-7's SSD (SSD)	0.201029
Spherical Harmonics (SH)	0.245121
Adaptive D2 (AD2)	0.257626
Elevation descriptor (ED)	0.315523
Using Relevance Feedback (RF)	0.337415

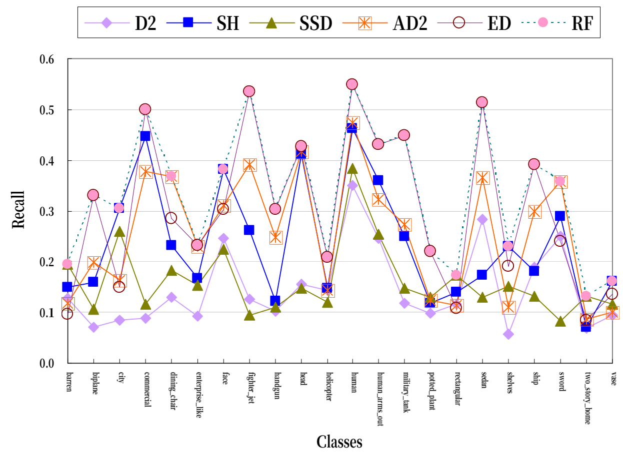

Fig. 7. The recall comparison for some class of the test database among the proposed method and other methods.

As shown in Table 1, the proposed methods, AD2 and ED, are better than other methods. The detail comparison of recall for some classes is shown in Fig. 7. As shown in Table 1, the elevation descriptor have good performance for most of classes except the barren, city, face, rectangular, shelves, sword, two_story_home and vase models that are constructed by several components. And, the adaptive D2, spherical harmonics and 3D SSD just have better performance for these classes. That can explain why the spherical harmonics and 3D shape spectrum descriptor are also composed as our feature set. However, as Fig. 7 shown, if $w_1, \ldots, w_4$ are set to 1, the best retrieval results can not be obtained for each class. Moreover, since it is impossible to find a 3D feature that is suitable for any kind of images, a relevance feedback algorithm is provided to determine the most appropriate feature among our feature set according to the user's response. In our experiments, we choose several relevant objects from the top 100 retrieved objects and query again. As shown in Table 1 and Fig. 7, after using the relevance feedback algorithm, the best performance can be obtained.

5. CONCLUSIONS

In this paper, an efficient and effective 3D model retrieval system is proposed. We investigate a new method for automatic shape-based retrieval of 3D models. The main research contribution is a new shape descriptor that is both discriminating and robust. In the beginning, four features are presented. The elevation descriptor is used to treat general 3D models. The adaptive D2, spherical harmonics and 3D shape spectrum descriptor are more robust to those models that are constructed by several components.

Then, in the retrieval process, a grade evaluation method is provided to measure the similarity between a query object and each matching object. Since each kind of feature is proper for some special kinds of models and it is impossible to automatically find the best feature for each model. Hence, in this system, to meet to the preferences of users, a relevance feedback algorithm is proposed to automatically determine the most appropriate feature according to the user's response. The proposed system can be used in the application of digital library for the content-based 3D model retrieval.

6. ACKNOWLEDGMENT

This research was supported in part by the National Science Council, R. O. C. under Contract NSC 92-2213-E-216-023.

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