Content-Based 3D Model Retrieval for Digital Museum

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Abstract. In this paper, we propose a new shape feature for shape-similarity search of 3D polygonal-mesh models in digital museum. The shape feature is an extension of the D2 shape functions proposed by Osada. Our proposed shape feature is a combination of geometry and texture which is also invariant to similarity transformation. Experiments showed that, our method achieved better performance improvement especially for appearance retrieval of 3d model.

1 Introduction

3D models now play an more and more important part in many applications, such as computer game, computer aided design, cultural relic preservation, computer aided education etc. These applications lead to the number of models dramatically increasing in the past decade. With the recent increase in the number and complexity of 3D geometric models, development of the technology for effective content-based search and retrieval of 3D models has become an important issue.

A 3D model could be searched by textual annotation by using a conventional text-based search engine. However, this approach wouldn't work in many scenarios. The annotations added by human beings depend greatly on culture, language, age, etc.. It is thus necessary to have a content-based search and retrieval systems for 3D models that are based on the features intrinsic to the 3D models.

Till now, the most important feature used by almost all 3d model search engine is shape similarity[1-7]. However, in digital museum, a lot of digital collections are sharing the similar geometry but different appearance. Therefore, geometry, as well as texture has to be considered when designing such a 3d retrieval engine for digital museum.

In this paper, we propose a new shape feature for shape-similarity search of 3D polygonal-mesh models in digital museum. The shape feature is an extension of the D2 shape functions proposed by Osada[2][4]. Our proposed shape feature considered both geometry and texture, which is also invariant to similarity transformation. Ex-periments showed that, our method achieved better performance improvement especially for appearance retrieval of 3d model.

The rest of the paper is organized as follows. We review the previous work on 3D shape similarity search in the next section. Osada's shape-matching algorithms is described in Section 3, Our enhanced feature descriptor is explain

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detailedly in section 4, and experimental evaluation results of our algorithm are presented in Section 5. Finally, we conclude and discuss future work in Section 6.

2 Previous Work

Generally, 3d shape matching methods could be categorised into three classes: (1) feature based methods[2][8-15], (2) graph based methods [6][16-17]and (3) view based methods[18-20]. For 3D shape matching, features denote geometric and topological properties of 3D shapes. Therefore 3D shapes can be discriminated by measuring and comparing their features. Feature based methods represent a shape using a single descriptor consisting of a d-dimensional vector of values. Thus the descriptor of a shape could be viewed as a point in a high dimensional space, and two shapes are considered to be similar if they are close in this space. Retrieving the k best matches for a 3Dquery model is equivalent to finding the k nearest neighbours. The feature based methods consider only the pure geometry similarity. However, in many cases, we need topology similarity instead. Therefore graph based methods appeard, which try to extract a geometric meaning from a 3D shape. Unfortunately, it is not easy to realize efficient computation of existing graph metrics for general graphs: computing the edit distance is NP-hard and computing the maximal common subgraph is even NP-complete. The main idea of view based similarity methods is that two 3D models are similar, if they look similar from all viewing angles.

3 Shape Features

There are four major steps in shape-based retrieval of 3D models from a 3D model database: First, as an offline step, geometric features for each model in a database are extracted and stored as an indexed table. Second, for one query, the input model is parsed for feature extraction. Third, the feature of the input model is compared with the features in the indexed table for similarity measuring. Fourth, the return of the query can be the k-nearest models or models within a tolerance of the feature measuring errors with the input model.

Osada[4] proposes a shape based 3d model descriptor which is named as D2. The most favorable qualities of the D2 is its topological and geometrical robustness, and the lack of need for pose normalization. To compute the D2 shape function for a 3D model, points are generated at random location on every surface of the model. Then, distance is computed for every possible pair, i.e., N(N-1)/2 pairs for N points generated (Fig. 1). The 1D feature vector of D2 shape function is a histogram generated by counting the population of pairs that falls within a certain distance interval. It is robust against variation in tessellation, not sensitive to connectivity of surfaces nor surface orientation. The following formula is adopted to generate a point **P** at a random location on a triangle:

$$P = (1 - \sqrt{r_1})\,A - \sqrt{r_1}\,(1 - \sqrt{r_2})\,B + \sqrt{r_1}r_2C \tag{1}$$

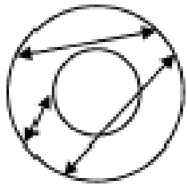

Fig. 1. D2 shape descriptor

In the formula, A, B, and C are vertices of the triangle, and r1 and r2 are two random numbers between 0 and 1. Intuitively, $\sqrt{r_1}$sets the percentage from vertex A to the opposing edge, while r2 represents the percentage along that edge. Taking the square-root of r1 gives a uniform random point with respect to surface area.

The D2 computed and used only the distance among a pair of points. Ohbuchi proposes two enhanced shape descriptor, i.e. Angle and Distance (AD) shape feature and Absolute Angle and Distance (AAD) shape feature. For AD, they measure both distance between a pair of points and the inner product of the surface normal vectors of the triangles on which the pair of points are located. Then, the AD is a 2D histogram using the inner product and the distance as the two independent variables. The AD shape feature described is sensitive to the orientation of the surface. If models have properly oriented surfaces, the AD shape feature performs quite well. If, however, models have surfaces that are inconsistently oriented, the performance of the AD shape feature suffers. Therefore, Ohbuchi[13] put forward the Absolute Angle and Distance (AAD) shape feature, which takes absolute value of the inner product instead.

4 Improved D2 Algorithm

4.1 Enhanced Feature Descriptor

D2, AD and AAD are fast and effective shape descriptors for geometry, which are also easy to implement. However, during our constructing of 3d model retrieval engine for digital museum, we found that lots of collections sharing similar geometric characteristic, but different appearance. For example, some mineral specimens have almost the same shape, but they have different textures, which lead to different appearances and separate them from each other.

Considering that, we propose a new 3d feature descriptor which combines both geometry and texture of a 3d model. Like AD and AAD, our feature descriptor is also a 2d descriptor. One variable is the distance between a pair of random points, the other is the grey level difference between these two points. Since most textures are colourful pictures, we first convert the colourful picture into grey level picture using:

$$Gray = 0.3R + 0.59G + 0.11B \tag{2}$$

In which, R, G, B are red, green and blue components respectively.

4.2 Dissimilarity Computation

The descriptor we get in the above section is a 2D histogram. One variable is the distance between a pair of random points, the other is the grey level difference be-tween these two points. How to design the interval along these two axes could affect the dissimilarity computation results. If we consider more about the geometry, the number of intervals along the distance should be increate. In contrast, if we consider more about on the appearance, the number of intervals along the texture difference should be increate. More interval number means more computation time. Therefore, we have trade between speed and precision. Usually, we set the interval number of distance as 64, and the interval number of texture as 16.

We test our 3D model feature descriptor with two dissimilarity computation methods, i.e. L_1 norm (Manhattan distance) and L_2 norm (Euclidian distance), which are both very easy to implement. Let $X=(\mathrm{x}_{i,j})$, and $Y=(\mathrm{y}_{i,j})$ be the feature vectors for the model A and B, respectively. Assuming the number of intervals for the distance be Id and the texture difference be It, the L_1 norm $D_{L1}(X, Y)$and the L_2 norm $D_{L2}(X, Y)$ are defined as follows:

$$D_{L1}(X, Y) = \sum_{i=1}^{I_d} \sum_{j=1}^{I_t} |x_{i,j} - y_{i,j}| \tag{3}$$

$$D_{L2}(X, Y) = \sum_{i=1}^{I_d} \sqrt{\sum_{j=1}^{I_t} (x_{i,j} - y_{i,j})^2} \tag{4}$$

5 Experiments and Results

We implement a prototype 3d search engine using our enhanced feature descriptor. The query formation is simplest query-by-example. As the preprocess, we normalize the model size to the outer bounding sphere with the radius be 1. We sample 2000 random points on each model, and compute the 2D feature descriptor. Since this is just a test system, we did not adopt any indexing policy. The target models are re-trieved through similarity computing using L_1 norm and the L_2 norm.

The testing database consists of about 400 3D models which come from both the Princeton University and our digital collections. They are categorized manually into 40 categories.

We compared the performance of our proposed descriptor with D2 and AD. Fig 2 shows the recall-precision curves of those three methods.

From the precision-recall curves, we could see that our method performs better than D2 and a little worse than AD. This is because that the testing models we used mainly have only geometry information. Therefore, the texture information is the same, which we set it as 0. And then our method is the same as D2, while AD con-tents more geometry information, it is not strange that it

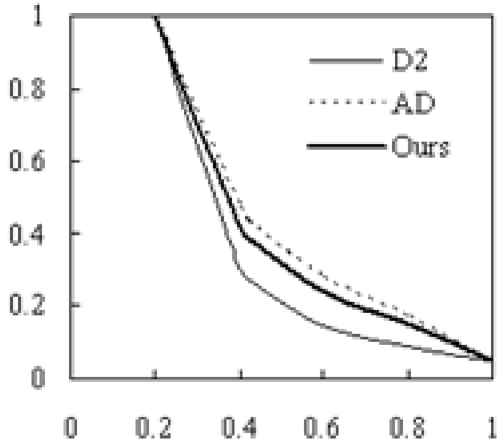

Fig. 2. Comparison of Precision-Recall curves for 3 descriptors

performs better than ours method. However, when we test those method on the models with textures, our method performs much better than the other two do.

As for the time consuming, since both AD and our method need to calculate a 2D histogram, these two methods run slower than D2 does.

6 Conclusion and Future Work

In this paper, we propose a new method to retrieve 3D models based on the combina-tion of their geometry and texture, which is useful in digital museum project. The method characterizes a model using the distance between a pair of random points as well as the grey level difference between these two points. Thus, both geometry and texture information are included in the descriptor.

Future work includes the effective and efficient dissimilarity computing metric as well as some other algorithms to do the categorization such as SOM.

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