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3D Shape Retrieval Using Point Spatial Distributions on the Surface

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ABSTRACT

Rapidly increasing 3D shape application has led to the development of content-based 3D shape retrieval research.

In this paper, we proposed a new retrieval method. The method is constructed on a spatial distribution computation of sampling points on the surface of 3D shape. The contribution is that we use an inner cylinder to contain the points distributed nearer on the largest principal axis, and its radius is the average distance of points to the largest principal axis. And then we compute the point spatial distribution by partitions of the minimum bounding box and the inner cylinder.

We have examined our method on a database of general objects and confirmed its efficiency. We also compared this method with other similar methods on the same shapes database, and it achieved better retrieving precision.

This method can be used to classify 3D shapes and retrieve similar shapes in shapes database.

1. Introduction

Over the past several years, steadfast efforts have been made to make machines or computers learn to understand, index, and retrieve texts and images representing a wide range of concepts. With the rapidly increasing of 3D data in many applications, such as computer games, computer aided design, VR environments, biology, e-business, etc., 3D shape data represents more complex human intelligence, and, description and retrieval of them also becomes more challenging.

Accordingly, there is an increasing need for computer algorithms to help people find their interesting 3D shape data and discover relationships between them. Recently, many efforts have concentrated on researching techniques for efficient content based retrieval of 3D objects [1].

The key of content-based 3D shape retrieval is to develop a description capturing and extracting the main feature of 3D objects, because 3D shapes can be discriminated by measuring and comparing their features. In fact, the process of feature extraction is a process of reducing dimension from high-dimensional 3D data to low-dimensional feature data. A feature descriptor is a d-dimensional vector of values, and as for all the 3D shapes, the dimension d is fixed. In the d-dimensional space, if two vectors are close, two shapes are considered to be similar.

In this paper we present a content-based 3D shape retrieval method relying on point spatial distributions on the surface. The shape feature is computed as the following:

1. Use of Principal Component Analysis. There are two motivations.

 1) Pose estimation: Translate the centroid of all the models into the origin of the coordinate system and use the Principal Component Analysis (PCA) method to get the rotation invariant dissimilarity measures.

 2) At the same time, we use the PCA method to let all the vertices distribute along the principal X-axis to compute an inner cylinder which axis is the principal X-axis.

2. Random point sampling: Unbiased random points can be generated according to the surface area of a triangle on the surface to ensure all the shapes have the same number of sampling points.

3. Computation of point spatial distributions. We compute the point spatial distributions based on subdivision (partitions) of the minimum bounding box and an inner cylinder. That is, where sampling points on the surface locate. By digitizing the spatial locations of

the points, the feature vector can be represented.

4. Feature matching. The produced feature vector can describe a 3D shape. It can be used to 3D shape matching.

We apply our method to a database of general objects collected from free Princeton Shape Benchmark Database [3]. This method is confirmed to be efficient.

The outline of the rest of the paper is as follows: in the next section we shortly review the previous work in 3D model retrieval and relevant methods. In section 3 we present our method of feature computation. We will put emphasis on the computation of point spatial distributions. Section 4 describes dissimilarity computation for feature matching. Section 5 shows experimental results and conclude in Section 6.

2. Previous Work

In this section, we will discuss the recent 3D retrieval methods and divide them into two main categories of shape matching, feature distribution and shape descriptors. Finally, we will introduce the other relevant developments.

2.1 Feature distribution

It is easy and fast to compare feature distributions of models, and it does not need any normalization of a 3D mesh-model.

Osada et al. [2] match 3D models with shape distributions. The key idea of this method is to present the signature of an object as a shape distribution sampled from a shape function measuring global geometric properties of an object. Another method presented in [5] extended the D2 shape function of shape distributions [2] by considering the inner product of the normals of sampled point pairs. Ankerst et al. [4] have used shape histograms decomposing shells around a model's centroid. X.Liu et al. [6] utilize the directional histogram model to characterize 3D shapes. The shape can be described by the thickness distribution in the directions per latitude and longitude. Ohbuchi et al. [7] construct the shape analysis using the moment of inertia about the principal axes of the model. Yi et al. [16] present a novel 3D shape descriptor "The Generalized Shape Distributions" for effective shape matching and analysis, by taking advantage of both local and global shape signatures, extended from shape distributions [2].

All the feature distribution methods have a common limitation that these methods can only catch the similar gross shape properties and be powerless to catch the detailed shape properties.

2.2 Shape descriptors

As a representative example, spherical harmonics is applied in a large field such as earth physics, image analysis, biology, and so on. It is firstly introduced in the 3D model retrieval by D. V. Vranic in [9]. Funkhouser et al. [10] profit from the invariance properties of spherical harmonics and present an affine invariant descriptor based on spherical harmonics. D. Saupe [11] constructs moment-based descriptor by representing a spherical function using spherical harmonics.

The feature extraction is performed using a rendered perspective projection of the object on an enclosing sphere in [12]. It is considered as a shading-based shape descriptor.

Novotni and Klein [13] present a so-called 3D Zernike descriptor by computing 3D Zernike descriptors from voxelized models as natural extensions of spherical harmonics based descriptors.

2.3 Other related developments

Joshua et al. [14] describe a planar reflective symmetry transform (PRST) that captures a continuous measure of the reflectional symmetry of a shape with respect to all possible planes. The symmetry transform is useful for shape matching.

Dmitriy et al. [15] present several distinctive benchmark datasets for evaluating techniques for automated classification and retrieval of CAD objects.

In our paper, we compared our method with two typical methods, shape distributions [2] and shape histograms [4]. For comparing fairly, we programmed and implemented the two methods and tested on the same database.

3. Feature computation

In this section, we present the basic ideas on how to compute the point spatial distributions. The following figure presents a preview of the computation process. A concrete process of generating the distributions for 3D shape will be discussed in details.

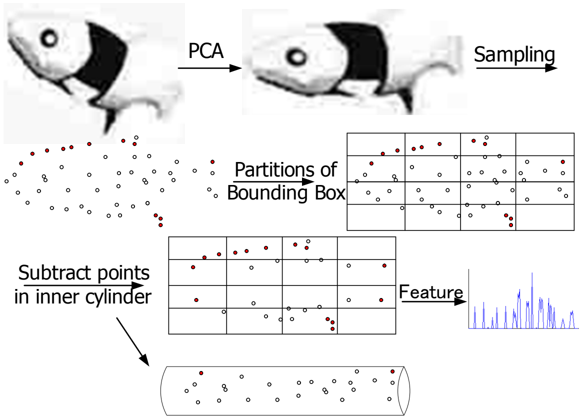

Figure 1 Preview of computation process

3.1 Principal Component Analysis

First, translate the centroid of all the models into the origin of the coordinate system. Secondly, use the PCA (Principal Component Analysis) method [8] to obtain a rotation invariant measure.

As we know, the eigenvectors of PCA are called principal axes and describe the three orthogonal axes where the scattering of the elements is greatest. The eigenvector corresponding to the largest eigenvalue coincides with the direction of largest variance of the 3D data set. The direction of the largest variance is usually regarded as the principal X-axis direction. A majority of vertices distribute along the direction.

Accordingly, we use the PCA method to let all the vertices distribute along the principal X-axis to compute the next inner cylinder which axis is the principal X-axis.

3.2 Random point sampling on the surface of a shape

Unbiased random points can be generated according to the surface area of a triangle on the surface. Here we use Monte-Carlo sampling approach.

Firstly, compute the area of each triangle and store the cumulative area of triangles visited in an array.

Secondly, generate a random number between 0 and the total cumulative area and perform a binary search on the array of cumulative area. The probability of finding a triangle is proportional to its area.

Lastly, in each selected triangle with vertices (A,B,C), sample a point P with respect to the following procedure:

Generate two random float numbers, r_1 and r_2 between 0 and 1. Compute the P according to the following equation:

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

$\sqrt{r_1}$ sets the percentage from vertex A to the opposite edge. r_2 sets the percentage along this edge. The consideration of taking the square root of r_1 is to get an unbiased random point with respect to surface area.

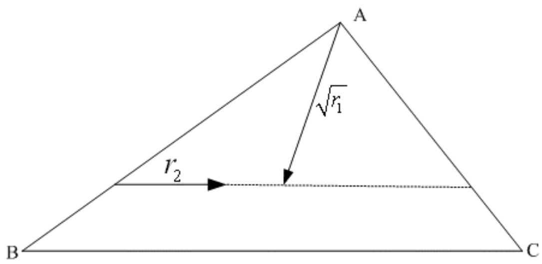

Figure 2 Sampling a point in a triangle

3.3 Computation of point spatial distributions

After pose normalization and random sampling, a shape can be represented as a set of points S. S includes T elements(points) in total. From these points, a bounding box and an inner cylinder can be calculated. This computation is based on partitioning of the bounding box and which ones of points are outside the inner cylinder.

3.3.1 Subdivision (Partition) of the bounding box

Subdivide the bounding box to $N \times N \times N$ bins (partitions).

With respect to this subdivision, accordingly, the set of points S is divided into $N \times N \times N$ subsets of points, $S_1, S_2, \ldots S_{N^3}$. The subset S_i includes all the points reside in the i -th bin.

3.3.2 Inner cylinder computing

After the computation of PCA, all the points distribute along the principal X -axis. And next, compute the distance of every point to the X -axis.

As for an arbitrary point $P_j\ (x_j, y_j, z_j)$, the distance d_j is as follows:

$$d_j = \sqrt{{y_j}^2 + {z_j}^2}$$

The average distance $\overline{d}$ of all the distances d_j ($j = 1,...,T$) is:

$$\overline{d} = \frac{1}{T}\sum_{j=1}^{T} d_j$$

Produce a closed cylinder, with which the central axis is X -axis, and the radius is $r = \overline{d}$. And it has infinite height. Among the set of points S, a subset of points C resides inside the cylinder. That is, As for an arbitrary point in S, if it is inside the cylinder, it belongs to the subset C.

$$C = \left\{ P_j \middle| d_j < r, P_j \in S \right\}$$

The complement of the subset C:

$$\overline{C} = \left\{ P_j \middle| P_j \in S, P_j \notin C \right\}$$

Obviously, the subset $\overline{C}$ belongs to the set S. That is, $\overline{C} \subset S$.

The motivation of the inner cylinder computing is to eliminate those nearer points distributed round X -axis.

3.3.3 Revision of the subsets in the bounding box

As for $N \times N \times N$ subsets of points, $S_1, S_2, ...S_{N^3}$, the following gives the revision.

As for an arbitrary subset S_i, P_{ij} is one arbitrary point of the subset. The revision S_i' of S_i can be computed according to the following formula.

$$S_i' = S_i \cap \overline{C}$$

$$= \left\{ P_{ij} \middle| P_{ij} \in S_i, P_{ij} \in \overline{C} \right\}, \quad i = 1,2,....N^3$$

3.3.4 Computing the number of elements in every subset S_i'

v_i is marked as the number of elements in the subset S_i'. It is a positive integer or zero. v_i composes an array V:

$$V = [v_1, v_2, ...v_i, ...v_{N^3}]$$

3.4 Feature vector

The array V can be used as the feature vector of one shape after the following computation.

$$V = \frac{1}{T}[v_1, v_2, ...v_i, ...v_{N^3}]$$

4. Dissimilarity computation

Having computed the point spatial distributions for one shape, the left task is how to produce a dissimilarity measure. There are several standard ways of comparing two vectors. We tested two general ways including L_1 and L_2 norm, and found L_1 norm performed better than L_2 norm.

Accordingly, as for two shapes a and b, the dissimilarity can be defined as the following.

$$D_S = \|V_a - V_b\| = \sum_{i=1}^{N^3} \left| v_{a,i} - v_{b,i} \right|$$

5. Experiment results

We implemented this method using C# on the environment of Visual Studio 2005 of Windows operating system. In the experiment, we adopted 22 classes, in total 110 models collected from Princeton Shape Benchmark in the internet.

We tested the parameters including sampling points T and the subdivision number N, and compared the computation time and retrieval performance. The table 1 shows the test results. The retrieval performance is evaluated by the Precision/Recall plot. If the plot of one test is located upon the plot of another test, we think it performs better. So we use the words “Best, Better, Bad” to express the retrieval performance.

Table 1. Testing parameters and the results

T (Sampling Points)	N (Subdivision Number)	Comput -ation Time (s)	Retrieval Perform -ance
9000	5	0.2	Best
9000	3	0.18	Bad
9000	7	1.1	Bad
1000	5	0.05	Better
1000	3	0.03	Bad
1000	7	0.1	Bad
18000	5	1.5	Best
18000	3	1.4	Bad
18000	7	2	Bad

After tested, we found, in the same Subdivision Number $N = 5$, the more points we sampled, better the results become. Finally, we chose $T = 9000$ and $N = 5$ based on the balance of computation time and retrieval performance. Accordingly, after pose normalization, we generated 9000 random points for every model. According to our point spatial distribution computation with $N = 5$, we calculated the feature vector for every model and compared the dissimilarity between two arbitrary models.

The following figures give two groups of retrieval examples.

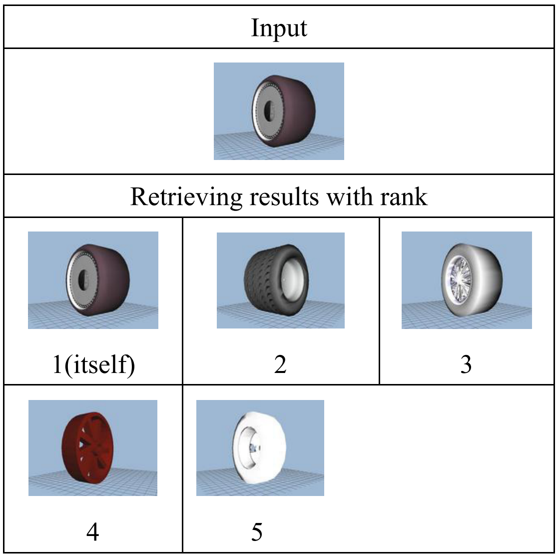

Figure 3. Retrieving examples 1

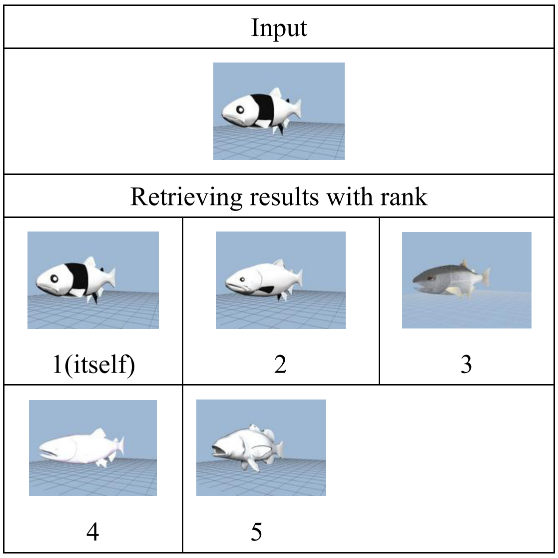

Figure 4. Retrieving examples 2

We also compared our method with the two other methods, Shape Distributions and Shape Histograms. In programming and implementing the two methods, we adopted the recommended parameters in their papers. For example, according to [2], we used D2 shape function and produced 1024*1024 distances. And according to [4] we produced 120 shells. Lastly, we also tested our method and the two other methods in the same database. The following figure shows the precision/recall plots of our method and the other two methods.

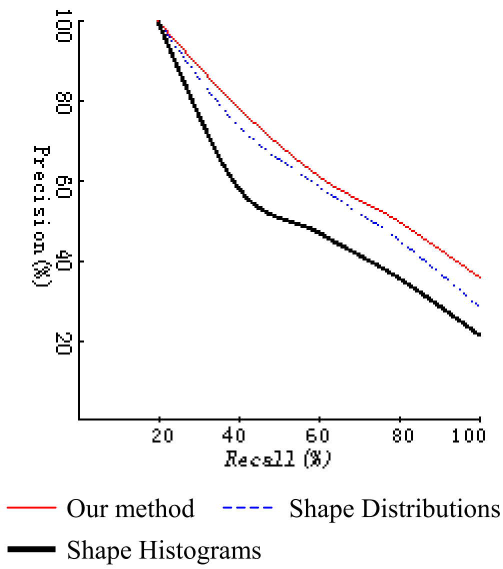

Figure 5. Precision/Recall plots

Now we complement the definition of Precision/Recall plot used in the above plots. (Please note retrieved results of one shape include itself) Precision is the percentage of qualifying (similar) shapes retrieved with respect to the total number of retrieved shapes. And Recall is the percentage of qualifying shapes retrieved with respect to the total number of similar shapes in the database.

6. Conclusion and Future Work

In this paper, we proposed a 3D shape retrieval method based on our point spatial distributions. The method is confirmed to be efficient according to our experiments, and can be applied to classify 3D shapes and construct a 3D retrieval system.

In future, we will consider replace the Monte-Carlo sampling approach by an interest point detector [17], to alleviate the computational burden of generating a large random number of shape signatures. About aligning objects in a canonical coordinate system, we will use the symmetry transform to define two new geometric properties, center of symmetry and principal symmetry axes, and they are more useful for aligning objects than PCA. Moreover, we will improve our method and use it to extract local features of a shape.

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