Rotation-based Three Dimensional Shape Descriptor

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ABSTRACT: *Recent developments in techniques for modeling, digitizing and visualizing three dimensional shapes have led to an explosion in the number of available three dimensional models on the Internet and in many domain-specific databases. However, how to describe three dimensional shapes is a difficult problem. A new three dimensional shape description method based on rotation is proposed in this paper. The first step is to sample points on the surface and compute normal vectors. Secondly, we do Gauss mapping and rotate model, at the same time, rotate the Gauss sphere. The third step is to analysis normal distributions on the sphere surface. Then the Euclidean distance is computed, and finally a statistic histogram is constructed. Experimental results show the effectiveness of this method.*

Categories and Subject Descriptors
H.2.4 [Systems]; Multimedia databases **I.3 [Computer Graphics]:** Three Dimensional displays; **H.5.1 [Multimedia Information Systems]**

General Terms
Three dimensional models, Domain-specific databases

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1. Introduction

Three-dimensional (3D) content is literally invading the world of nowadays multimedia, within the framework of consumer and professional applications such as 3D games, virtual reality, computer assisted design, etc.

As one of the most important properties of 3D model, shape feature extraction is an essential task in 3D information processing. Therefore, 3D shape descriptors are widely used in some specific domains, such as 3D model retrieval, 3D object classification and recognition, etc. Nowadays, however, the performance of 3D shape descriptor is not very satisfactory.

Generally, the desirable properties of a 3D shape descriptor are as follows: invariance to transformation; robustness to noise; conciseness for storage; less computational complexity; shape discrimination, etc. In this paper, we present a novel 3D shape description method with above properties, besides these, it need no normalization. In particular, first we randomly sample points on the surface and compute their normal vectors. Secondly, Gauss mapping is performed and the model is rotated, actually rotating the Gauss sphere. The third step is to count normal distributions on the sphere surface. Next, the Euclidean distance is computed, and finally a statistic histogram is constructed.

The rest of this paper is organized as follows: Section 2 reviews available shape descriptors. In Section 3, we extensively describe the proposed shape descriptor. In Section 4, experimental results are presented and analyzed; Section 5 concludes the paper and opens perspectives of future work.

2. Related work

Most existing 3D shape description methods can be divided into four categories.

(1) Global feature based methods. These methods apply global properties, such as volume, surface area, curvature, moments, etc., to describe 3D shapes. Novotni et al. apply 3D Zernike moments to extract shape features. Kazhdan et al. [2] describe the shape based on spherical harmonics, and Vanic et al. [3] present a descriptor based on 3D Fourier Transform. These approaches are quick to compute, and can be applied to classify models. Since they fail to capture the details of a shape and they are also not very robust, they therefore fail to discriminate among locally dissimilar shapes.

(2) Statistic based methods. These approaches sample points on the surface of 3D models and extract characteristics from the sample points. These characteristics are organized in the form of histograms or distributions representing frequency of occurrence. Ankerst et al. [4] subdivide the space into spherical shells and sectors around the center of gravity of an object; the resulting partitions correspond to the bins of 3D shape histogram. Osada et al. [5] represent the shape signature as a probability distribution sampled from a shape function measuring the geometric properties of a 3D model. Ohbuchi et al. [6] improve Osada's method by constructing 2D histograms. Compared with other methods, statistic based methods are not only fast and easy to implement, but also have some desired properties, such as robustness and invariance. However, the discrimination ability of these methods is not good enough due to the fact that local shape features are not depicted explicitly.

(3) Topology based methods. Besides geometric and physical properties, topology structure is another important characteristic for 3D shapes. Hilaga et al. [7] propose a topology-based method, in which Multiresolutional Reeb Graph is constructed by using a continuous function such as the geodesic distance. Siddiqi et al. [8] present a shape description based on shock graphs. Sundar et al. [9] describe a method that encodes the geometric and topological information in the form of a skeletal graph. Topology-based methods have properties of intuition, invariance and generality. However, they require a consistent model of the object's boundary and interior, and a large amount of

computational resources are needed to compute the skeleton.

(4) Image based methods. The human vision system has an uncanny ability to recognize objects from a single view. On the basis of this idea, Christopher et al. [10] adopt a concept named aspect graph to group all views and represent a 3D model with a set of 2D views. Thus, 3D problems can be transformed to 2D problems. Pu et al. [11] represent 3D shape accurately by three views. In these methods, several thumbnail images must be computed beforehand. Generally, these methods are robust but time-consuming.

3. Overview of the algorithm

In general, 3D content is represented by 3D mesh models, because of the simple and efficient visualization techniques supported, and performed in real time by most of the commercial graphic devices. Besides, other formats models can be easily converted into meshes using available 3D information processing software. Hence, this paper deals with the shape description of mesh models.

Our approach is to represent 3D shape as a one-dimensional histogram. The motivation originates from such a question: As a 3D model rotates in the spatial domain, why the human vision system, from the fixed viewing position, is sensitive to aware that the shape after rotation differs from the initial shape (see Figure 1)? If points are sampled uniformly on the model surface, we notice that the orientation of normal vector of points is changed after rotation. As shown in Figure 2, regardless of the position of the point p, we translate its normal vector $\vec{n}$ so that its origin coincides with the origin of the coordinate system, and the end of the unit normal lies on a unit sphere. This process is called Gaussian mapping, and the sphere is called the Gaussian sphere.

Let us assume that considerable points are sampled on the surface of a model. Repeating Gaussian mapping, we attain a sphere distributed normal vectors of these sample points. Thus shape feature extraction can be transformed into analyzing normal distributions on the sphere. Once randomly rotating a model K times, we attain K different shapes and corresponding spheres with different normal distributions. To describe the shape with a histogram, our approach statistically analyzes the normal distributions on K spheres.

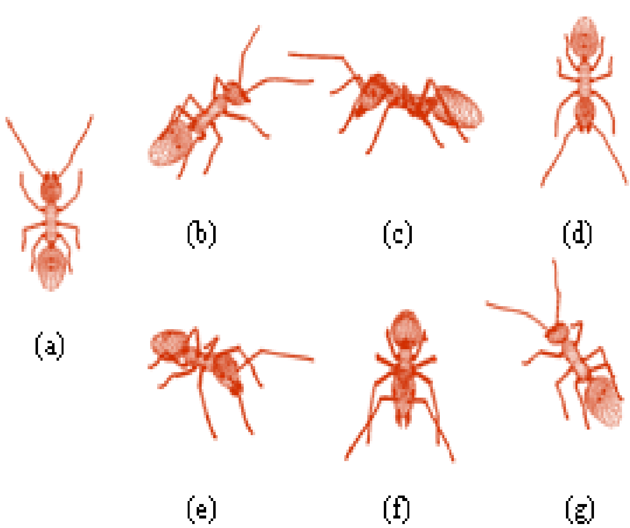

Figure 1. Shape of a 3D model viewing from the same angle after various rotations, (a) the shape of the original model, (b)-(g) shapes after various random rotations

The intrinsic properties of our proposed descriptor are as follows:

(1) Generality. The description scope of the method is for all classes of shapes. It can be applied to extract shape features of popular models, such as meshes, solid models and other geometric representations.

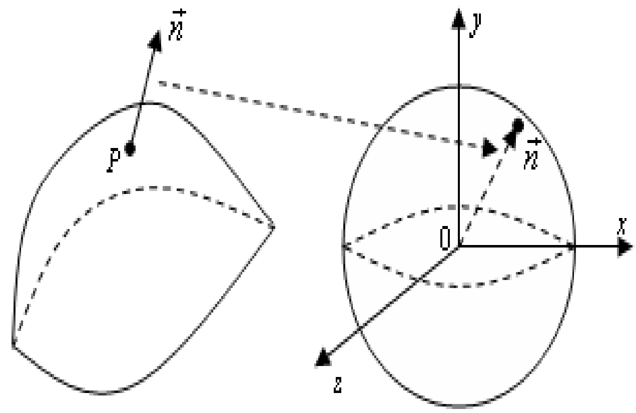

Figure 2. Gaussian mapping

(2) Invariance. The proposed descriptor is invariant to affine transform, including rotation, translation and scaling. The reason lies in that we only consider orientations of normal vectors, instead of positions of the sample points.

(3) Robustness. Randomly sampling ensures the descriptor is insensitive to noise. In other words, as a statistic method, the descriptor lays emphasis on the global shape feature.

(4) Without normalization. In order to capture features, a model is usually placed into a canonical coordinate frame. This is called pose estimation or normalization. Nowadays normalization is an important task to preprocess a 3D model. However, it is still a difficult operation. The proposed descriptor does not need to normalize 3D model so that shape feature extraction is speeded up.

4. Proposed algorithm

The proposed method consists of four steps as follows:

Step 1. Sample points and compute normal vectors. For a triangulated mesh model, N random points are sampled uniformly on its surface. Let us assume s_i and k denote area of the triangle i and number of triangles, respectively. Then we can compute n_i, namely the number of sample points on the triangle i with the Formula (1).

$$n_i = \frac{Ns_i}{\sum_{i=1}^{k} s_i} \qquad (1)$$

The normal vector of the point p is estimated by the normal of triangle ΔABC where p lies on, as shown in Formula (2).

$$\vec{n}_p = \vec{n}_{\Delta ABC} \qquad (2)$$

Hereto a mesh model is translated into a point set with orientations. Notice that the proposed method does not need to accurately determine position of random points, only needs to attain the normal orientations. Unlike this, positions of sample points must be obtained in Osada's D2 [5] and Ohbuchi's improvement [6]. Consequently computational complexity of our descriptor is smaller than [5] and [6].

Step 2. Rotate Models. In this step, the model is randomly

$$R=\begin{bmatrix} \cos\beta\cos\gamma & -\cos\beta\sin\gamma & \sin\beta \\ \sin\alpha\sin\beta\cos\gamma+\cos\alpha\sin\gamma & -\sin\alpha\sin\beta\sin\gamma+\cos\alpha\cos\gamma & -\sin\alpha\cos\beta \\ -\cos\alpha\sin\beta\cos\gamma+\sin\alpha\sin\gamma & \cos\alpha\sin\beta\sin\gamma+\sin\alpha\cos\gamma & \cos\alpha\cos\beta \end{bmatrix}$$

rotated, controlled by α, β, γ, *i.e*. rotation angles relative to *x*, *y*, *z*-axes respectively. (3)

As shown in Formula (3), *R* is the general 3D rotation matrix. When a 3D point p is rotated by *R* p is transformed to p' as shown in Formula (4).

$$p' = Rp \qquad (4)$$

Actually, we rotate a model in order to find the shape difference after rotation. This can be reduced to analyzing normal distributions on the unit sphere. Let us assume we rotate a model *T* times with *T* group of rotation angles; α, β, γ are randomly selected in the range of [0, 2 π]. When rotating a model, the normal distribution of points is changed accordingly.

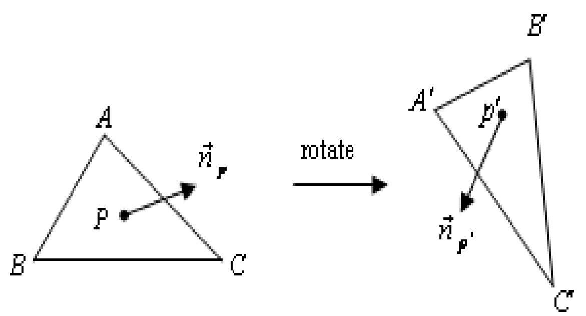

Figure 3. Rotate a triangle on the surface

As shown in Figure 3, the triangle $\triangle A'B'C'$ and point p are rotated to $\triangle A'B'C'$ and p' respectively. Then $\vec{n}_p$ and $\vec{n}_p$ have the relationship as shown in Formula (5).

$$\vec{n}_{p'} = R\vec{n}_p \qquad (5)$$

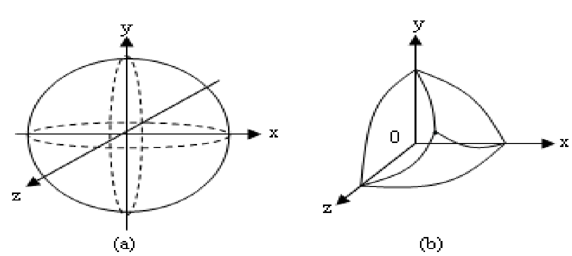

Figure 4. Segmentation of Gaussian sphere, (a) 8 sections (b) 24 sections

Step 3. Count Normal Distributions. As a model is rotated *T* times, we obtain *T* Gaussian spheres; each being distributed by *N* normal vectors. To analyze the distributions, we segment the surface of a Gaussian sphere into *L* sections. As an example, the spherical surface is segmented into 8 sections by *x-y*, *y-z*, and *x-z* planes, as shown in Figure 4 (a). We count the normal on each section in turn. To determine which section a normal belongs to, we only need to capture signs of each component of a normal, as shown in Figure 5 (a). Thus we obtain *T* groups 8 dimensional vectors, as shown in Formula (6) and (7). The element v_i is the number of normal distributed in the *i*-th section.

$$V=(v_1, v_2, v_3, v_4, v_5, v_6, v_7, v_8) \qquad (6)$$

$$N = \sum_{i=1}^{8} v_i \qquad (7)$$

Base on these 8 sections, the spherical surface also can be further segmented into 24 sections. As shown in Figure 4(b), one eighth of surface is divided into three Subsections. In this case, a sample point can be localized by finding the maximum absolute value of three components of normal.

x	y	z	Section
-	-	-	1
-	-	+	2
-	+	-	3
-	+	+	4
+	-	-	5
+	-	+	6
+	+	-	7
+	+	+	8

(a)

-0.2673	-0.5345	-0.8018
-0.1231	-0.4924	0.8616
0.2338	0.9584	0.1636
...		
...		
...		

(b)

Figure 5. Count normal distributions, (a) signs and corresponding section (b) example of normal

Step 4. Construct Histograms. To construct a one-dimensional histogram, we compute the Euclidean distance L_2 between two vectors *Vx* and *Vy*, as shown in Formula (8). Thus, we obtain $\frac{T(T-1)}{2}$ distances for *T* groups vectors, and a histogram is then constructed.

$$L_2(V_x, V_y) = \left(\sum_{i=0}^{k} \left|V_x(i) - V_y(i)\right|^2\right)^{\frac{1}{2}} \qquad (8)$$

5. Experimental Results

In the experiment, we test the descriptor with a set of parameters as *N*={32768, 65536, 131072}, *T*={1000, 2000, 3000}, *L*={8, 24}. In order to achieve a preferable tradeoff between better performance and lower computational complexity, we find that *N*=65536, *T*=2000, and *L*=24 yields a histogram with good discrimination ability. Experimental models are randomly selected from the database of Princeton Shape Benchmark (PSB), a publicly available 3D model database with 1814 mesh models. We classify the experimental models into 10 classes; each class contains

2-9 models. All histograms are normalized under the same mode with 256 bins. From Figure 6 we can find that: models in the same class have similar histograms, while models in the different classes have dissimilar histograms. Experimental results show effectiveness of the proposed descriptor.

6. Conclusions

This paper proposes a novel method based on rotation to characterize 3D shapes. Experimental results show its effective to discriminate different models. In order to improve the performance of our descriptor, a 2D histogram is constructed as shape features in the future work instead of 1D histogram, for in the 1D histogram, the positions information of sample points is not taken into account. In addition, the descriptor will be utilized in some specific applications such as 3D model retrieval, 3D object classification, 3D object recognition, etc.

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