3D Model Retrieval Based on 3D Fractional Fourier Transform

Liu Yu-Jie[1], Bao Feng[1], Li Zong-Min[1], and Li Hua[2]
[1]School of Computer Science Communication Engineering, China University of Petroleum, China
[2]National Research Center for Intelligent Computing Systems, Chinese Academy of Sciences, China

Abstract: *In this paper, a new tool that is fractional Fourier Transform is introduced to 3D model retrieval. And we propose a 3D model descriptor based on 3D factional Fourier transform. Fractional Fourier transform is a general format of Fourier transform, and add a variables that is order. Our approach is based on volume. The first step of the approach is that voxelize these 3D models. A coarse voxelization is regarded as the input for the 3D Discrete Factional Fourier Transform (3DDFRFT). A set of (complex) coefficient is obtained by 3DDFRFT in each order. The absolute values of coefficients are considered as components of the feature vector in each order. We also can integrate these feature vectors into the mixed feature vector, which is named as Multi-Order fractional Fourier Feature Vector (MOFFFV). We finally present our results and compare our method to 3D descriptor based on 3D Fourier Transform on the Princeton Shape Benchmark database.*

Keywords: *3DDFRFT, 3D model, feature extraction, retrieval.*

Received September 23, 2010; accepted May 24, 2011; published online August 5, 2012

1. Introduction

With the development of the 3D data acquisition and graphics hardware technology, there are more and more 3D model reservoirs in virtual reality, 3D games and other fields. So, how to quickly find the model that we need becomes a hot topic. The 3D model retrieval research has been focused on primarily content-based retrieval technology. A challenging issue in content-based 3D model retrieval is the description of shapes with suitable numerical representations called shape descriptors. In general a shape descriptor should be discriminative, compact, easy to compute, and invariant under a group of transformations. In recent years, many authors propose their algorithms in order to describe 3D models. However, none of them can be fit for all situations.

In this paper, we propose a new approach to extract features of 3D objects. This approach is based on fractional Fourier transform. Before the extraction feature from 3D model, we firstly apply pose normalization in order to align the model into canonical position. Secondly, we will apply the algorithm of voxelization to voxelizing these objects. Thirdly, we apply the 3D Discrete Fractional Fourier Transform (3DDFRFT) is used to the volume model to representing the feature in the fractional domain. Finally, we extract the low-frequency fractional fourier coefficients in the fractional domain as the model feature vectors. In section 2, we describe related works. The Fractional Fourier Transform (FRFT) is introduced in section 3. In section 4, we give the algorithm to extract 3DDFRFT features of 3D models. In section 5, we display the experimental results. Finally, Conclusions and future works are addressed in section 6.

2. Related Work

The methods for feature extraction can be categorized into five major approaches including statistics-based approach, volume-based approach, extension-based approach, image-based approach and 3D closed curve-based approach. Statistical-based approaches reflect basic object properties like the number of vertices and polygons, the surface area, the volume, the bounding volume, and statistical moments. Paquet *et al.* [10], describe shape features using bounding volume, object orientation, and object volume density. Ohbuchi *et al.* [7], propose a statistical feature vector which is composed of three measures taken from the partitioning of a model into slices orthogonal to its three principal axes. A sampling window is moved along the principal axes, and its moment of inertia is calculated. Osada *et al.* [8], described the shape of a 3D object as a probability distribution sampled from a shape function, which reflects geometric properties of the object. Therefore, the method can avoid preprocessor of the model pose normalization. Paquet *et al.* [9], propose a descriptor that is cords-based. A cord is defined as a vector that points from the center of mass of a model to the center of mass of a triangle of a mesh. The feature vector is composed from three histograms: the distribution of the angles between the cords and the first principal axis, the distribution of the angles between the cords and the second principal axis, and the distribution of the cord lengths.

Volume-based approaches mainly rely on the models volumetric representation. The shape histogram is introduced by Ankerst *et al.* [1]. The enclosing object space is divided into a series of profiles and sectors for calculating the 3D shape histogram in 1999. Elmustapha [4] proposed a new method to describe 3D models based on 3D discrete cosine transform which is applied for the voxelized 3D model. Vrani´c and Saupe [18] present a shape descriptor based on the voxeled model. A coarse voxelization of a 3D model is used as the input for the 3D Discrete Fourier Transform (3DDFT), while the absolute values of obtained (complex) coefficients are considered as components of the feature vector. Then, magnitudes of certain *k* low-frequency coefficients are used for description. Funkhouser *et al.* [5], propose a descriptor based on the spherical harmonics representation of object samples. 3D space is divided into a series of concentric spheres with different radius. A frequency function that has rotation invariant is defined in the concentric sphere space. The functions constitute a 3D model of the feature vector.

Extension-based approaches build object descriptors from features sampled along certain spatial directions from an object's center. Vrani´c *et al.* [19], introduce a ray-based descriptor that describes a surface by associating to each ray from the origin the distance to the last point of intersection of the ray with the model.

Image-based approaches reflect the feature of spatial object in 2D image. Ohbuchi *et al.* [6], also proposed the depth buffer image method to extract model feature. 42 depth buffer images of the model are obtained by 42 viewpoints located on the model's bounding sphere. Then the generic Fourier descriptors are exacted from these depth buffer images. The similarity of models can be obtained by computing these generic Fourier descriptors. Chen-Tsung [2] proposes a 3D shape representation scheme based on a combination of principal plane analysis and dynamic programming in 2006. First, a 3D model is transformed into a 2D image by projecting the vertices of the model onto its principal plane. Second, the convex hall of the 2D shape of the model is further segmented into multiple disjoint triangles using dynamic programming. Finally, for each triangle, a projection score histogram and moments are extracted as the feature vectors for similarity searching.

3D closed curve-based approach is a way in recent years. Elmustapha *et al.* [3], propose a new method for describing 3D-shape.The main idea is to reconstruct a 3D closed curve that represents a 3D model given by a polygonal mesh, and to extract signatures from this 3D closed curve, such as the area descriptor, the dot product descriptor, the torsion descriptor and the radius descriptor. The FFT energy spectral feature vectors of their signatures are viewed as the feature vector of 3D model.

From the above, the Fourier transform is widely used in 3D model retrieval. The FRFT, as a generalization of the classical Fourier Transform (FT), is a unified time-frequency transform, and has many applications in the field of optics and signal processing. With the order from 0 increasing to 1, the FRFT can show the characteristics of the signal changing from the time domain to the frequency domain. The FRFT is more flexible than the FT for it has one more transform parameter than the latter. Through FRFT, we can obtain the information of a signal in the time-frequency domain. We shall describe in detail the FRFT in the next section.

3. Fractional Fourier Transform (FRFT)

FRFT is a generalization of the FT proposed some years ago. In addition, the FRFT is a special case of the more general linear canonical transform, and it provides a tool to compute the mixed time and frequency components of signals. The FRFT of a function $x(t)$ with a kernel $k_p(t,u)$ can be defined as:

$$X_p(u) = F_p[x](u) = \int_{-\infty}^{+\infty} x(t) k_p(t,u) dt \tag{1}$$

with the kernel:

$$k_p(t,u) = \begin{cases} \sqrt{(1-j\cot\alpha)} e^{j\pi(t^2\cot\alpha - 2ut\csc\alpha + u^2\cot\alpha)}, & \alpha \neq n\pi \\ \delta(t-u), \alpha = 2n\pi \\ \delta(t+u), \alpha = (2n\pm 1)\pi \end{cases} \tag{2}$$

where $\alpha = p\pi/2$, p is the order of FRFT. According to the definition, the FRFT with $\alpha = \pi/2 (p=1)$ corresponds to the classical FT, and one with $\alpha = 0 (p=0)$ corresponds to the identity operator. The FRFT has an important property that its operator is additive in order, that is:

$$F^{p_1}[F^{p_2}] = F^{p_2}[F^{p_1}] = F^{p_1+p_2} \tag{3}$$

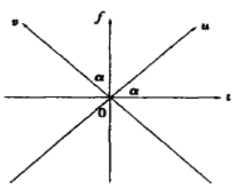


Figure 1. The rotation of time-frequency plane [14].

Another important property will be introduced that the FRFT can be interpreted as a rotation in the time-frequency plane with angle α as shown in Figure 1. The property establishes the direct relationship between the FRFT and the time-frequency distribution, and founds the theory that the FRFT domain can be interpreted as a uniform time-frequency domain. With the order from 0 increasing to 1, the FRFT can show the characteristics of the signal gradually changing from the time domain to the frequency domain as shown in Figure 2. Thus it is concluded that the FRFT is a signal analysis tool between the time domain and the frequency domain.

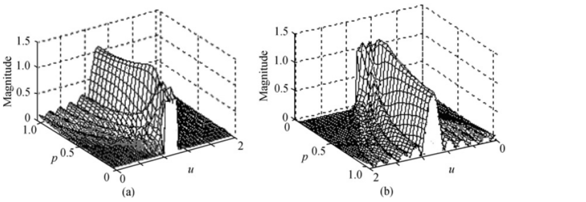


Figure 2. The FRFT of rectangle pulse [13].

The Discrete FRFT (DFRFT) is for the FRFT like what the DFT is for the FT. There is not a unique definition, but there is some general agreement on the definition given by Candan and co-workers. It is based on a fractional power of the DFT matrix. Due to the separability of kernel function, 3D DFRFT can be obtained by 1D DFRFT, The FRFT also has a number of important properties. Interested readers may refer to [11, 12, 14, 15, 16, 17].

4. Feature Vector Computation

4.1. Pose Normalization

Objects represented as polygonal meshes are given in arbitrary orientation, scale, and position in the 3D-space. Many authors have proposed many features, which possess the invariance with respect to translation, rotation, scaling, and reflection. However, the feature vectors proposed in this paper indeed depend upon sizes, locations, and orientations of given 3D shapes, pose normalization is necessary as a step preceding the feature extraction. Pose normalization is a process of adjusting the size, location, and orientation of a given object in a canonical space.

The normalization of translation, scaling, and reflection are easy solved. The center of gravity of models is moved to the origin of coordinate. This solves the issue of normalization of translation. We can resolve the issue of normalization of scaling via the maximum radius of model vertices. Nevertheless, the normalization of rotation is a difficult issue, and a crucial problem. The most prominent tool for solving the problem is the Principal Component Analysis (PCA), also known as the discrete Karhunen-Loeve transform. The PCA is based on the statistical representation of a random variable. This method is to replace the original data with less data. The less data can reflect more object information. In this paper, we solve the normalization of rotation by applying this method. The procedure of normalization can be obtained by applying following mapping τ finally. The mapping τ is defined by $\tau(p)=s^{-1}\cdot F\cdot R\cdot(p-c)\cdot p$. p is the set of vertices. c is the center of gravity of a model. s is the scaling factor of a model. F is a matrix on reflection. R is a rotation matrix.

4.2. Voxelization of Model

After the pose normalization of a model, the next step is voxelization. In this paper, the approach of feature extraction of model is based on volume. The volumetric representation plays an important role in computer graphics community. Voxelization transforms the continuous 3D-space, which contains models represented as polygonal meshes, into the discrete 3D voxel space. Its process mainly has three steps, which are discretization, sampling, and storing. The step of discretization yields the cellular subdivision of the continuous 3D-space into voxels (volume elements). Generally, a model is discretized into a $N*M*P$ grid of voxels. We discretize the models into $128*128*128$ and $64*64*64$ grid of voxels in this paper. After the sampling, the voxel is attributed a value $v_{ijk}\in\{0,1\}$ depending on positions of the polygons of a 3D-mesh model. Thus, if there is a point P laying inside, then we set $v_{ijk}=1$, otherwise $v_{ijk}=0$. Voxel values are stored in a 3D-array $[v_{ijk}]_{N*M*P}$.These models are converted into 3D-array $[v_{ijk}]_{N*M*P}$ by the above. In this paper, we apply the algorithm [20], of voxelization to voxelize these objects.

4.3. Feature Vector Based on 3DDFRFT

The last step accomplishes the conversion from continuous 3D-space to voxels. And then the goal is the feature extraction based on 3DDFRFT. FRFT have been described in detail in section 3.

FRFT is a generalization of the classical FT, and can be interpreted as a rotation in the time-frequency plane. With the order from 0 increasing to 1, the FRFT can show the characteristics of the signal changing from the time domain to the frequency domain. For 3DDFRFT, it has three orders in three directions respectively. Thus we can extract feature with different order. Let $V=\{v_{ijk} \mid v_{ijk}\in\{0,1\}, -\frac{N}{2}\le i,j,k\le\frac{N}{2}\}$ be the set of all voxels, $G=\{g_{i,j,k}^{p_0p_1p_2} \mid g_{i,j,k}^{p_0p_1p_2}\in C, -\frac{N}{2}\le i,j,k\le\frac{N}{2}, 0\le p_0,p_1,p_2\le 1\}$ be the set of coefficients, which is transformed from V by 3DDFRFT, and p_0, p_1, p_2 be the order of 3DDFRFT in three directions, such as x-axis, y-axis and z-axis. Let:

$$F^{p_0,p_1,p_2}[x](u,v,w)=\iiint x(s,t,q)k_{p_0,p_1,p_2}(s,t,q,u,v,w)dsdtdq \quad (4)$$

be 3DFRFT. Due to the variety of the digital computation of FRFT, 3DDFRFT has not uniform formula like 3DFFT. Thus, the equation of model voxels spectrum in the fractional domain is given as follows: $G=F^{p_0,\ p_1,\ p_2}[V]$. Owing to increasing three variables (order), 3DDFRFT become more flexible. With these orders from 0 increasing to 1, we can process different transform from the time domain to the frequency domain. Thus, in different order, we can obtain different the feature of models. When the orders are p_0, p_1, p_2, G is obtained finally. We take a part of low-frequency coefficients as components of the feature vector in the fractional domain. Feature vector of model in orders that are p_0, p_1, p_2 is denoted by

$F_V^{p_0p_1p_2}$ as shown below:

$$F_V^{p_0p_1p_2} = \{f_{0,0,0}^{p_0p_1p_2}, f_{0,0,1}^{p_0p_1p_2}, ..., f_{0,0,D-1}^{p_0p_1p_2}, ..., f_{0,D-1,0}^{p_0p_1p_2}, ..., f_{D-1,0,0}^{p_0p_1p_2}, ..., f_{D-1,D-1,D-1}^{p_0p_1p_2}\} \quad (5)$$

where $f_{i,j,k}^{p_0p_1p_2} = \frac{g_{i,j,k}^{p_0p_1p_2}}{|g_{0,0,0}^{p_0p_1p_2}|} (-D/2 \le i,j,k \le D/2)$,and D is dimension of the voxel feature vector in a direction. Thus, its total amount dimensions is $D*D*D$.

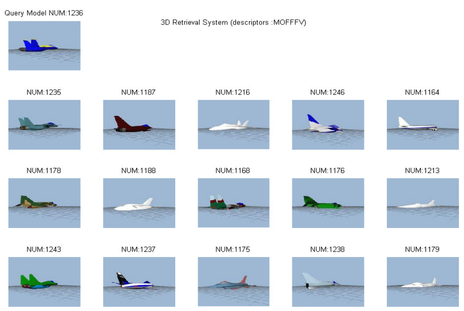
With the change of order, we can extract different feature in different order. Thus, we can integrate the different features in different orders. Multi-Order Fractional Fourier Feature Vector (MOFFFV) is combined with the features in different orders, and given by the formula.

$$MOFFFV = w_0 F_{v_0}^{p_{0,0}p_{1,0}p_{2,0}} + ... + w_i F_{v_i}^{p_{0,i}p_{1,i}p_{2,i}} ... + w_{n-1} F_{v_{n-1}}^{p_{0,n-1}p_{1,n-1}p_{2,n-1}} \quad (6)$$

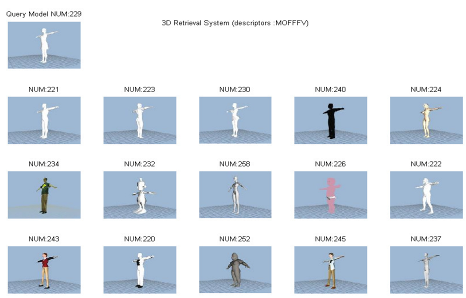
where n is the count of feature vector in different order, w_i is the weight of each feature vector.

5. Experiments

In this section, we present results of experiments with feature vector based on 3DDFRFT. We investigate the performance of feature vector in arbitrary order and Multi-Order fractional Fourier Feature Vector. And we also compare the performance of feature vector based on 3DDFRFT and the traditional 3D Fourier Transform (3DFT). All experiments were based on the 3D data provided in the Princeton Shape Benchmark (PSB) [13]. The database consists of 1814 manually categorized 3D models collected from the Web. The database is segregated into a training set consisting of 907 models and spanning 90 model classes, and a test set consisting of the remaining 907 models and spanning 92 model classes.



a) Query for an airplane using PSB database.



b) Query for an person using PSB database.

Figure 3. The retrieval results.

In our experiment, we will evaluate all algorithms through the training set and the test set of PSB. We use the average Precision versus Recall (PR) plots to evaluate our method. PR plot describe the relationship between precision and recall in a ranked list of matches. The horizontal axis represent the recall while the vertical axis representing the precision. The recall and precision are computed by formula.

$$Precision = \frac{N}{K}, \ Recall = \frac{N}{T} \quad (7)$$

where N is the number of relevant models retrieved, K is the total number of retrieved models, and T is the total number of relevant models in the database.

We apply our 3D retrieval system with all models of PSB as the model library. Figure 3 shows the retrieval results. The results illustrate that our retrieval system has brilliant performance.

5.1. Feature Vector in Arbitrary Order

In our experiment, three orders (p_0, p_1, p_2) of 3DDFRFT are same in three directions for symmetry. We take the orders (p), which are 1, 0.98, 0.95, 0.9, 0.8 and 0.7. When the order is 1, 3DDFRFT become the traditional 3DFT, feature vector only contain the information of frequency domain. The 3DFT-based approache is proposed by Vrani´c [6]. When the orders are others, feature vector contain the information of time and frequency domain. The experiments results in different orders are shown in following figure.

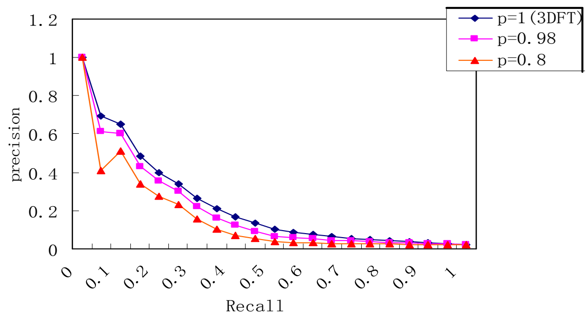


Figure 4. The precision-recall plot comparing p=1(3DFT), p=0.98 and p=0.8 in D=8 using the test set of PSB database.

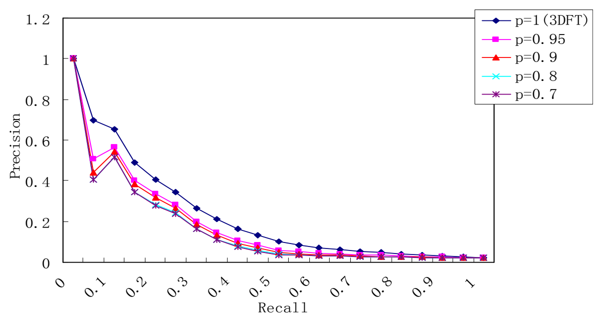


Figure 5. The precision-recall plot comparing p=1(3DFT), p=0.95, p=0.9, p=0.8 and p=0.7 in D=16 using the test set of PSB database.

From the Figures 4, 5 and 6, we can see that the performance of retrieval decrease with the decline of orders. The performance in p=1(3DFT) is best. The performances in other orders are worse than in p=1(3DFT).

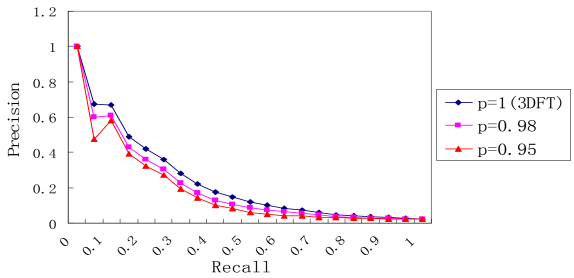


Figure 6. The precision-recall plot comparing p=1(3DFT), p=0.98 and p=0.95 in D=16 using the training set of PSB database.

5.2. Multi-Order Fractional Fourier Feature Vector

Although the performances in other orders are worse than in p=1(3DFT), the feature vector of each order should contain much the information of model. Thus, we can integrate the different features in different orders into a feature. In our experiment, we combine the feature vectors in different orders. These orders include 1, 0.98, and 0.95. The mixed feature vector is Multi-Order Fractional Fourier Feature Vector (MOFFFV). The following figure shows the experiments results of MOFFFV.

According to the precision-recall plot shown in Figure 7 and Figure 8, MOFFFV performs better than the feature vector based on the traditional 3D Fourier transform. That is because MOFFFV contain more the information of model.

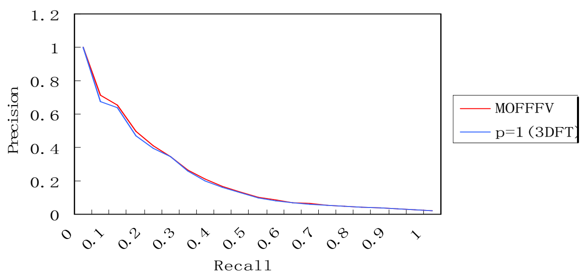


Figure 7. The precision-recall plot comparing the MOFFFV of p=1, p=0.98 and p=0.95 (w0=0.61, w1=0.23, w2=0.15) and the feature vector of p=1 (3DFT) using the test set of PSB database.

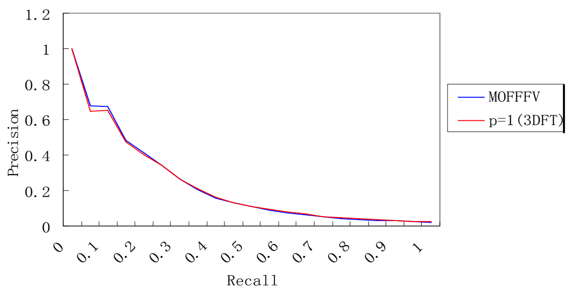


Figure 8. The precision-recall plot comparing the MOFFFV of p=1, p=0.98 and p=0.95 (w_0=0.61, w_1=0.23, w_2=0.15) and the feature vector of p=1 (3DFT) using the training set of PSB database.

6. Conclusions and Future Work

In this paper, we introduce a new tool to 3D model retrieval and propose a 3D model descriptor based on the FRFT. The performances of extracting feature vector in arbitrary order are worse than the feature vector based on the traditional 3DFT. For the energy distribution of the FRFT, aggregation level of energy increase with the increasing order. When the order is smaller than 1, the energy of low-frequency coefficients in the fractional domain is less than in frequency domain. Thus the information of feature vector in arbitrary order is less than the feature vector based on the traditional FT. However, we can obtain the different feature in different order. So, we can integrate the information. MOFFFV is the mixed feature vector. The information of MOFFFV is more than the feature vector based on the traditional Fourier transform. Therefore, MOFFFV performs much better than the feature vector based on the traditional 3DFT.

A drawback of the presented descriptor is the increase of MOFFFV dimensions. The feature vector in arbitrary order has much redundancy. It bring about that the performance of MOFFFV is difficult to be raised.

In the future, we would like to introduce the FRFT to image-based approach. In addition, we introduce other methods to lessen the redundancy.

Acknowledgement

This work is partly supported by National Natural Science Foundation of China (Grant No.60873164), National High-Tech R&D Plan (Grant No. 2009AA062802), the Shandong Provincial Natural Science Foundation (Grant No.ZR2009GL014),the Scientific Research Foundation for the Excellent Middle-Aged and Youth Scientists of Shandong Province of China (Grant No.BS2010DX037), Ministry of Culture Science and Technology Innovation Project (Grant No. 46-2010) ,the Fundamental Research Funds for the Central Universities (Grant No. 09CX04044A, 10CX04043A, 10CX04014B, 11CX04053A, 11CX06086A, 12CX06083A, 12CX06086A).

References

[1] Ankerst M., Kastenmuller G., Kriegel H., and Seidl T., "3D Shape Histograms for Similarity Search and Classification in Spatial Databases," *in Proceedings of the 6th International Symposium on Advances in Spatial Databases*, London, pp. 207-226, 2004.

[2] Chen T. and Shyi C., "3D Model Retrieval using Principal Plane Analysis and Dynamic Programming," *Pattern Recognition*, vol. 40, pp. 742-755, 2007.

[3] Elmustapha L., Ahmed O., Driss A., Mohamed D., and Mohammed K., "A 3-D Search Engine Based on Fourier Series," *Computer Vision and Image Understanding*, vol. 114, no. 1, pp. 1-17, 2010.

[4] Elmustapha L., Ahmed O., Mohammed K., Abdellah O., and Mohammed S., "3D Model Retrieval Based on 3D Discrete Cosine Transform," *The International Arab Journal of Information Technology*, vol. 7, no. 3, pp. 264-270, 2010.

[5] Funkhouser T., Min P., Kazhdan M., Chen J., Halderman A., Dobkin D., and Jacobs D., "A Search Engine for 3D Models," *ACM Transactions on Graphics*, vol. 22, no. 1, pp. 83-105, 2003.

[6] Ohbuchi R., Masatoshi N., and Tsuyoshi T., "Retrieving 3D Shapes Based on their Appearance," *in Proceedings of the 5th ACM SIGMM International Workshop on Multimedia Information Retrieval*, USA, pp. 39-45, 2003.

[7] Ohbuchi R., Otagiri T., Ibato M., and Takei T., "Shape-Similarity Search of Three Dimensional Models using Parameterized Statistics," *in Proceedings of the 10th Pacific Conference on Computer Graphics and Applications*, USA, pp. 265-274, 2002.

[8] Osada R., Funkhouser T., Chazelle B., and Dobkin D., "Shape Distributions," *ACM Transactions on Graphics*, vol. 21, no. 4, pp. 807-832, 2002.

[9] Paquet E. and Rioux M., "Nefertiti: A Tool for 3D Shape Databases Management," *Image Vision Computing*, vol. 108, no. 1, pp. 387-393, 2000.

[10] Paquet E., Rioux M., Murching M., Naveen T., and Tabatabai A., "Description of Shape Information for 2D and 3D Objects," *Signal Processing Image Communication*, vol. 16, no. 1, pp. 103-122, 2000.

[11] Pei C. and Yeh H., "Two Dimensional Discrete Fractional Fourier Transform," *IEEE Signal Processing*, vol. 67, no. 1, pp. 99-108, 1998.

[12] Pei C., Yeh H., and Tseng C., "Discrete Fractional Fourier Transform Based on Orthogonal Projections," *IEEE Transaction Signal Processing*, vol. 47, no. 5, pp. 1335-1348, 1999.

[13] Shilane P., Min P., Kazhdan M., and Funkhouser T., "The Princeton Shape Benchmark," *in Proceedings of Shape Modeling International*, Italy, pp. 167-178, 2004.

[14] Tao R. and Wang Y., "Fractional Fourier Transform and its Applications to SAR Imaging of Moving Targets," *in Proceedings of the 2nd Asian-Pacific Conference on Synthetic Aperture Radar*, Shanxi, pp. 709-712, 2009.

[15] Tao R., Deng B., and Wang Y., "Research Progress of the Fractional Fourier Transform in Signal Processing," *Science in China Series F: Information Science*, vol. 49, no. 1, pp. 1-25, 2006.

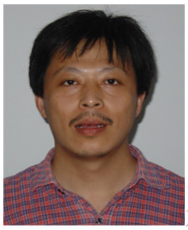
[16] Tao R., Qi L., and Wang Y., *Theory and Applications of the Fractional Fourier Transform (in Chinese)*, Tsinghua University Press, Beijing 2004.

[17] Tao R., Zhang F., and Wang Y., "Research Progress of the Fractional Fourier Transform Discretization," *Science in China Series E：Information Science*, vol. 38, no. 4, pp. 481-503, 2008.

[18] Vranic D. and Saupe D., "3D Shape Descriptor Based on 3D Fourier Transform," *in Proceedings of the EURASIP Conference on Digital Signal Processing for Multimedia Communications and Services*, Hungary, pp. 271-274, 2001.

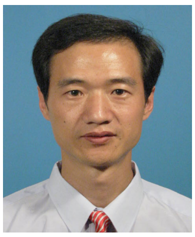
[19] Vranic D. and Saupe D., "3D Model Retrieval with Spherical Harmonics and Moments," *in Proceedings of the 23rd DAGM-Symposium on Pattern Recognition*, London, pp. 392-397, 2001.

[20] Zhao D., Chen W., Bao H., Zhang H., and Peng Q., "Real-Time Voxelization for Complex Polygonal Models," *in Proceedings of the 12th Pacific Conference on Computer Graphics and Applications*, Korea, pp. 43-50, 2004.



Liu Yu-Jie received his PhD degree from Institute of Computing Technology, Chinese Academy of Sciences in 2006. Currently, he is an assistant professor at China University of Petroleum (East of China). His main research activities are focused on computer graphics and 3d shape analysis.

Bao Feng received his MS degree from College of Computer & Communication Engineering, China University of Petroleum (East of China) in 2011. His main research activities are focused on 3d digital watermark and 3d shape analysis.



Li Zong-Min received his PhD degree from Institute of Computing Technology, Chinese Academy of Sciences in 2005. Currently, he is a professor at China University of Petroleum (East of China). His main research activities are focused on computer graphics, pattern recognition and 3d shape analysis.

Li Hua received his PhD degree from Institute of Computing Technology, Chinese Academy of Sciences in 1989. Currently, he is a professor at Institute of Computing Technology, Chinese Academy of Sciences. His main research activities are focused on computer graphics and visualization. He is a Member of IEEE, a member of executive committee of IEEE Beijing Section, a secretary-in-chief of IET Beijing network; a senior member of China Computer Federation, vice director of TCCADCG; a member of Standing Committee of Directors, China Engineering Graphics Society and a member of Standing Committee of Directors, China Image and Graphics Society.