



An algorithm for 3D shape matching using spherical sectioning*

LEE Jaeho^{†1}, PARK Joonyoung¹, LEE Hyunchan²

¹Department of Industrial and System Engineering, Dongguk University, Seoul 100715, Korea)

²Department of Industrial Engineering, Hongik University, Seoul 121791, Korea)

[†]E-mail: rapidme@dgu.edu

Received May 20, 2006; revision accepted June 21, 2006

Abstract: 3D shape searching is a problem of current interest in several different fields. Most techniques are developed for a particular domain and used to reduce a shape into a simpler shape representation. The techniques developed for a particular domain will also find application in other domains. We propose a new shape matching method. The SSRD (spherical sectioning railroad diagram) algorithm has the general shape distribution's properties and overall features of the original model. The SSRD's useful properties are discussed. We show the experimental results for the validity of our method.

Key words: Shape search, Similarity metric, Shape histogram, Spherical sectioning railroad diagram (SSRD)

doi:10.1631/jzus.2006.A1508

Document code: A

CLC number: TP202

INTRODUCTION

There is a recent surge of interest in methods for retrieval of 3D models from large databases. Several 3D model search engines have become available within the last few years, and they cumulatively index tens of thousands of 3D polygonal surface models.

Conservative estimates suggest that more than 75% of design activities are composed of the case-based design. The reuse of previous design knowledge addresses a new design problem (Ullman, 1997). Design reuse spans across the entire product life-cycle. Design reuse includes the CAD design, the physical structures for manufacturing of the CAD design such as tooling, and other related knowledge for cost data with lead time information. For the reuse of design information, the deployment of a knowledge mining system would require a combination of

text and shape-based search (Blum, 1967).

There have been a few researches investigating which types of query and matching methods are the most effective for 3D data. Text based searching of 3D model is not robust primarily for the following reasons. First, all models will not have a well-defined attached context. Second, keywords such as project names or part names may be unknown to the user. Third, contexts may be too narrow or too broad to retrieve relevant models. Finally, contexts are changed as designers or naming conventions are changed.

Therefore, many searching methods for 3D models focus on the shape-based search (Min *et al.*, 2003). We discuss the shape-based search methods and propose a new shape-based algorithm.

The rest of this paper is organized as follows. In Section 2 we give a brief survey of related work. In Section 3 we propose SSRD model and give its implementation. Section 4 describes how the similarity between two SSRD models is calculated. We give the experimental results in Section 5. Conclusions are drawn at last.

* Project supported by the Basic Research Program of the Korea Science & Engineering Foundation (No. R01-2006-000-10327-0), and the Korea Research Foundation Grant funded by the Korean Government (MOEHRD) (No. KRF-2005-041-D00903)

RELATED WORK

Shape matching is one of the fundamental problems in computer vision, with a full treatment of the subject being beyond the scope of this paper. Retrieval of data based on shape has been studied in several fields, including computer vision, computational geometry, mechanical CAD, and molecular biology. For a survey of recent methods, refer to (Ankerst *et al.*, 1999). In this paper, we will only consider matching and retrieval of isolated 3D objects. For example, we do not consider recognition of objects in scenes, or partial matching. 3D shape retrieval methods can be roughly subdivided into three categories: (1) methods that first attempt to derive a high-level description like skeleton and then two 3D models are matched, (2) methods that compute a feature vector based on local or global statistics, and (3) miscellaneous methods (Blum, 1967).

Examples of the first type are skeletons created by voxel thinning, and Reeb graph as defined by Reeb. It is a skeleton structure which is determined by using a continuous scalar function on an object. Three types of scalar functions have been used, namely height function, curvature function, and geodesic distance (Min *et al.*, 2004). However, these methods typically require the input model to be 2-manifold, and usually are sensitive to noise and small features. Unfortunately, many 3D models are created for visualization purposes only, and often contain only unorganized sets of polygons, possibly with missing, wrongly-oriented, intersecting, disjoint, and/or overlapping polygons, which therefore make them unsuitable for most methods for deriving high-level descriptors (Min *et al.*, 2004).

The methods based on computing statistics of the 3D model are less sensitive to the integrity of the input model. Examples are shape histograms (Ankerst *et al.*, 1999), feature vector composed of global metric properties such as circularity or eccentricity and feature vector (or shape descriptors) created using frequency decompositions of spherical functions, the resulting histograms or feature vectors are then usually compared by computing their distance metric.

Some alternative approaches use 2D views (2D projections of a 3D model), justified by the heuristics that if two 3D shapes are similar, they should look similar from many different directions.

In general, there is no standard definition of a shape (Iyer *et al.*, 2005). Kendall defined the shape as, ‘All the geometric information that remains when location, scale and rotational effects (Euclidean transformations) are filtered out from an object’. For the purpose of this paper, we will use Kendall’s definition then. ‘3D shape searching’ refers to determining similarities among 3D shapes from a large database (Iyer *et al.*, 2005).

The data of shape is composed of various properties, for example, context knowledge, filename, project name, geometric information, and topological information (Min *et al.*, 2004). Fig.1 shows the various methods for the 3D model searching algorithms (Regli and Cicirello, 2000) and also shows the 3D shape model and related properties. Text filename and context knowledge depend on the specific system, but the geometric and topological information do not. The shape of an object can be defined by a combination of its geometry and topology. Thus, we focus on the shape matching which can acquire both geometric and topological feature information. Fig.2 shows two strategies for acquiring the shape feature. Capturing strategy from outside yields the picture representing the feature acquired in a specific viewpoint; however, capturing strategy from inside yields the picture representing the feature acquired in a center of the object. Our spherical sectioning is based on the capturing strategy from inside.

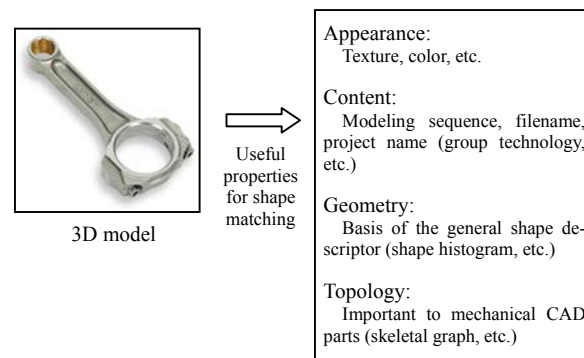


Fig.1 3D shape model and useful properties for the shape matching

OVERVIEW OF APPROACH

An overview of the proposed shape matching process is given in Fig.3. As shown in Fig.3, our shape

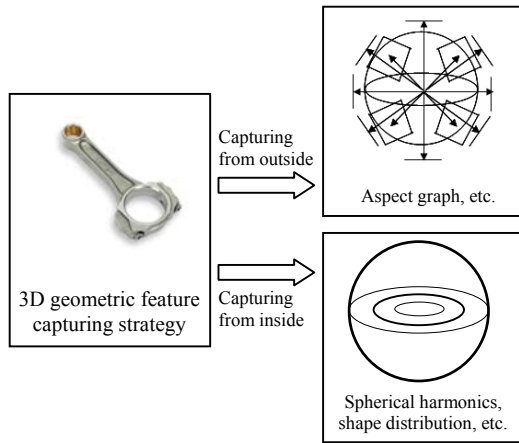


Fig.2 Two capturing strategies for object feature

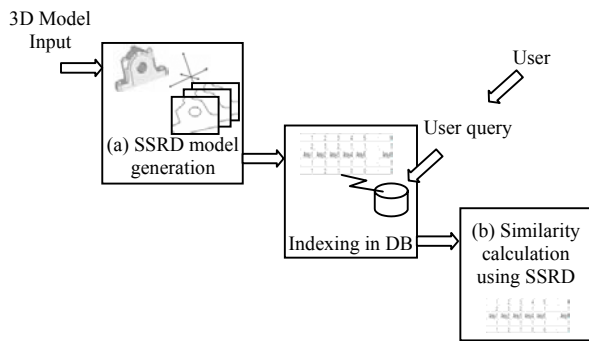


Fig.3 Our algorithm overview. (a) SSRD model generation; (b) Shape matching using two SSRD models

matching system has two major parts. One is the SSRD (spherical sectioning railroad diagram) generation and the other is the comparison of the two SSRDs which represent the original model respectively. The SSRD generation starts to input the 3D model from the DB. When the 3D model is inputted, each shape analysis module is working. First, the SSRD is generated. When the user begins to query in the online system, the SSRD comparison process will be started. The query model is interpreted by the two analysis models. The interpreted results are compared to each 3D model in the DB.

TWO STEP APPROACHES

The main idea of our approach is the Spherical Sectioning which is the slicing operation between the sphere and the rotational planes across the center of the sphere. Any geometric and topological feature can

be acquired by the spherical sectioning. In this work, the topological feature means the closed loop by intersection between the model and the rotational intersection planes.

These loops are originated from the cavity or holes of the model. Thus, using this information, we can make more intuitive similarity measure in the human visual system. Fig.4 shows the shape histogram by using the spherical sectioning and our model capturing concept by using the closed loops information and the intersection points. Although overall features cannot be captured, it gives us strong differentiating power between two models like human visual system. We describe more details about similarity measure in Section 4.4.

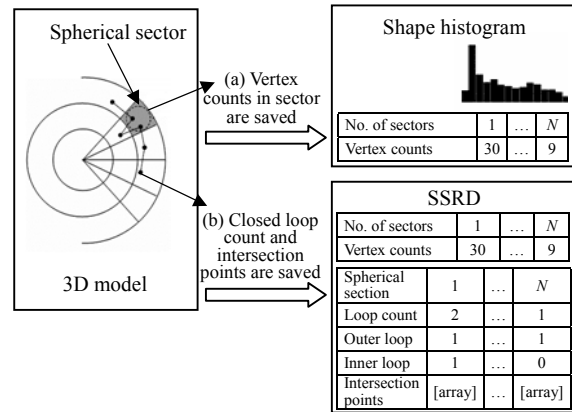


Fig.4 Spherical sectioning and model capturing concept. (a) Shape histogram using vertex counts in spherical sector; (b) Proposed SSRD model using closed loop count and intersection points in each sector as well as vertex counts in spherical sector

Concept and definition of SSRD

The shape histogram is known as a good shape descriptor in the geometric view (Ankerst et al., 1999). Shape histograms are based on a partitioning of space in which 3D models reside. The complete space is decomposed into disjoint cells, which correspond to the bins of the histograms. Three techniques are suggested for the space partitioning, a shell model, a sector model, and a spider Web model as a combination of the shell and sector model (Iyer et al., 2005). In a shell model, the space is decomposed into concentric shells around the center point. In a sector model, the space is decomposed into sectors that emerge from the center point of the model. In a spider

Web model, it represents more detailed information and has higher dimensionality than the above two models. For the ease of the implementation, our choice is the combined bins which are composed of the combination of the shell model and the sector model.

Although the shape histogram is robust and good descriptor for general geometry analysis, many defects exist (Sundar *et al.*, 2003). The shape histogram does not have any topological information and important feature of the shape. In Fig.5, the two objects are not similar in human visual system. However, they are similar by interpreting of the shape histogram. It is because the accuracy of the shape distribution depends on the number of the points in each sector (Rea *et al.*, 2004). As a result, we use the spherical sectioning railroad diagram for more accurate topological feature matching.

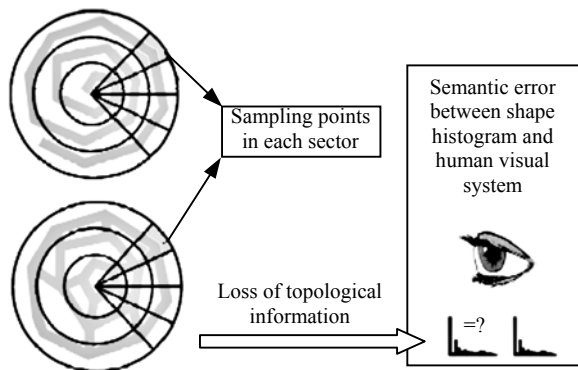


Fig.5 The absence of the topological information in shape histogram and the semantic gap in the human visual system

Our SSRD's concept is originated from the shape histogram concept, although it has some more advantages. Advantages of our SSRD are as follows: (1) reflection of the features (hole, cavity, etc.) in a model with the rotational intersection planes along the principal axis; (2) approximated volumetric errors calculated between two models; (3) robust and fast calculation based on the shape histogram method.

The definition of SSRD is as follows:

(1) SSRD is a collection composed of two parts. One is an array of vertex counts in spherical sections [1:N] in bounding sphere around the model and the other is a multi-dimensional array of spherical sections [1:M] which is composed of closed loop count

and the intersection points set in rotational intersection planes with 3D model.

(2) SSRD model consists of two part structure: shape histogram and railroad diagram (Fig.6).

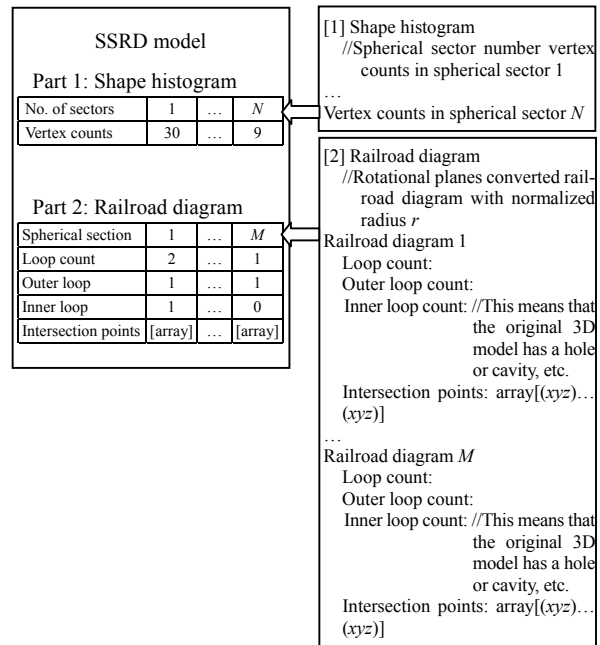


Fig.6 SSRD model structure composed of two parts

SSRD generation

For the generation of SSRD, the bounding sphere around the 3D shape model is generated. Exact bounding sphere generation is very difficult, so we use Ritter (1990)'s method. It is very fast. To compute the principal axis, we use the inertial principal axis proposed by Gottschalk (1999) using a statistical method. Pu *et al.*(2004) proposed the orientation fix method for the human visual system. By computing the eigenvectors of a 3x3 covariance matrix, the direction vectors for a good-fit box can be taken. Since the given principal axis of the model depends on the models' orientation, we take the normalization of the model pose. In this method, each component of the principal axis is allocated by each of the xyz axis. And, we can fix the model's orientation. Then, the spherical sectioning in the bounding sphere with the model is done. The procedure of the SSRD generation is as follows: (1) read the 3D model (input); (2) find the bounding sphere around the model; (3) find the principal axis of the object and fix the model's orientation using the pose normalization; (4) calculate the

spherical sectors and count the vertex in each sector; (5) generate the rotating planes with angle (α); (6) intersect the model and the rotating planes; (7) count the closed loops and save the intersection points in the railroad table; (8) make SSRD model composed of vertex count (Fig.7g) and railroad table (Fig.7h). This procedure is shown in Fig.7.

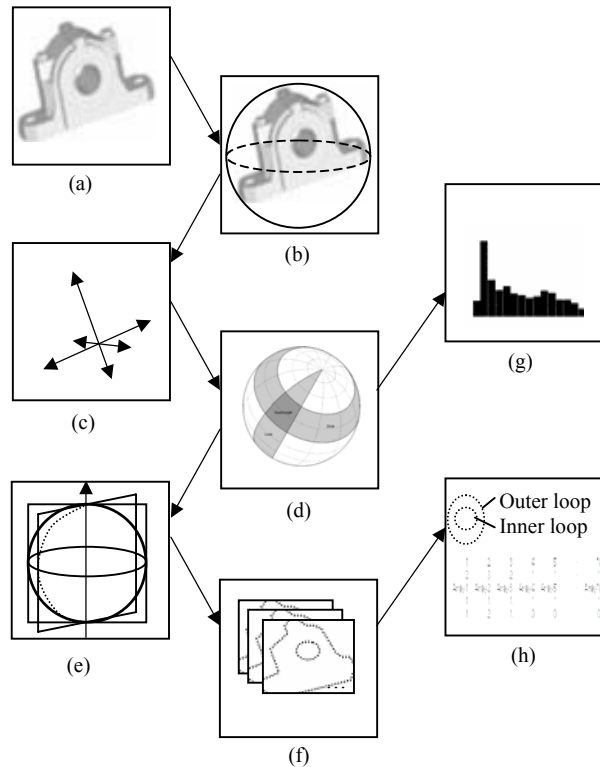


Fig.7 SSRD model generation process. (a) 3D Model; (b) Bounding sphere; (c) Principal axis; (d) Spherical sections; (e) Rotational intersection planes; (f) Intersection patterns; (g) Vertex count (shape histogram); (h) Railroad table (normalized railroad diagram)

Generation of basic element of SSRD and the normalization

After the spherical sections are generated by using spherical sectioning in Section 4.2, then the basic element of SSRD is generated. The basic element of SSRD means the sector line between the origin and sphere outer surface. It is used for our similarity calculation in Section 4.4. This length of the line is the radius of the bounding sphere. Fig.8 shows the basic element of SSRD and the intersection process. Each basic element of SSRD intersects with the object model. Their intersection points tell us the feature of the model and the simple shape distribution

information.

Thus we intersect each sector line and the model. The result of the above process is shown like the railroad. So we call it the SSRD (spherical sectioning railroad diagram) described in Section 4.1. Fig.8c shows the basic element generation of the SSRD. All intersection points lay on the bar with the radius r . We call this bar as the basic element of the SSRD. This bar is normalized by using the transformation from the distance range $[0\sim r]$ to the distance range $[0\sim 1]$.

Fig.8d shows the normalization process. The normalized bars represent the original features of the shape. Although the area of the SSRD is not equal to that of the original shape, all features are captured by clouds of the intersection points as a sliced part of the original feature like cavity, hole, etc. For more exact shape matching between two models, we generate the closed loops of the intersection points on the SSRD as shown in Fig.8c.

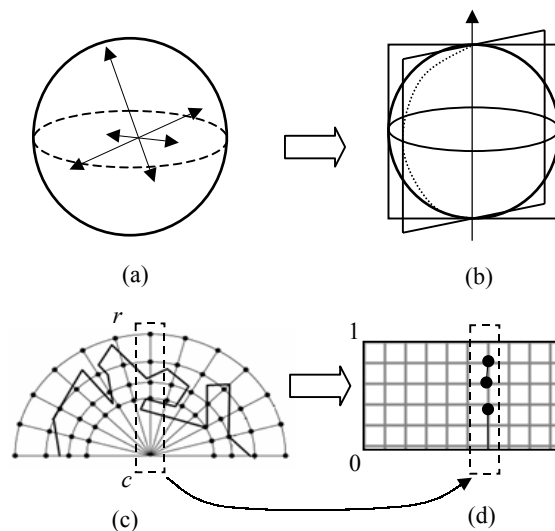


Fig.8 Intersection point calculation and normalization into the SSRD. (a) Generate the rotational intersection plane by using the spherical section and the principal axis; (b) Intersection between rotational intersection plane and 3D model; (c) Find the loop count from Intersection Points; (d) Generate basic SSRD element

Then we can obtain the number of the closed loops. This information can be used for our similarity measure calculation in Section 4.4.

Similarity measure of the SSRD and the shape matching

Our SSRD based shape matching algorithm uses

the transformed polygons of the original shape as described in Section 4.2. We compare the geometric and topological aspects of the shape. Fig.9 shows the SSRD-based shape matching structure.

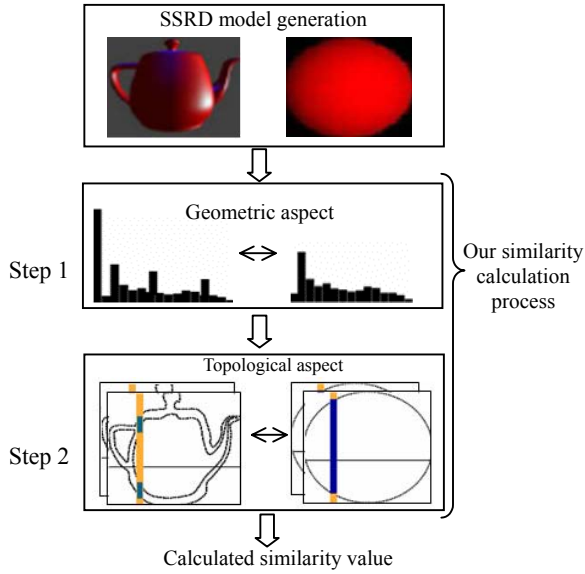


Fig.9 Our shape matching structure in a hybrid approach using two steps

Our shape matching metric is the distance based metric. Most 3D shape representation schemes convert a shape into a feature vector or a relational data structure (e.g. graphs or trees). Feature vectors are represented as points in the feature space in a database. The similarity between two feature vectors reflects the distance between corresponding points in the feature space. For the purpose of the similarity measure calculation between two feature vectors, the Minkowski distance metric is generally used. The Minkowski distance metric between two points is defined as

$$L_p(x, y) = \left[\sum_{i=0}^N |x_i - y_i|^p \right]^{1/p} \quad (1)$$

The L_2 distance metric is defined as

$$L_2(x, y) = \left[\sum_{i=0}^N |x_i - y_i|^2 \right]^{1/2} \quad (2)$$

We use the L_2 distance which is the Minkowski distance with $p=2$. Simply, it is called the Euclidean

distance between two points. Our algorithm uses a similarity measure, which is defined as the double occupation length in each bar on SSRD and the number of feature entities that match between two SSRD. Since we can obtain the closed loops from the model's rotational intersection planes, we can take the number of closed loop and common occupation area between each closed loops of two models. However, for more simple computation, we cannot use the polygonized area of the closed loops. We use each double occupation length which is defined as the length of the double occupation between line segments in a bar of normalized railroad diagram in our SSRD.

Fig.10 shows the double occupation length and counting process of the number of the feature in SSRD.

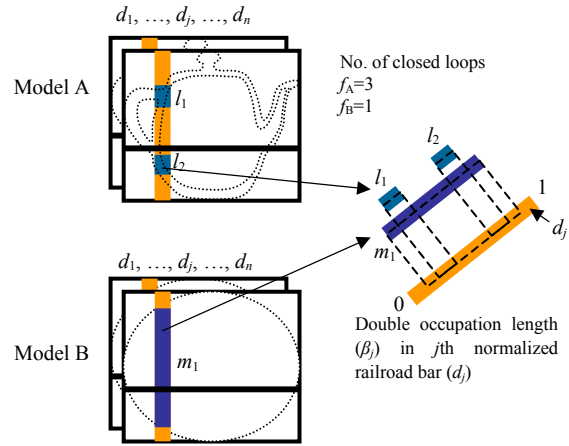


Fig.10 Our shape matching process using the number of closed loops and the double occupation length of SSRD

The number of closed loops reflects the aspect of the topological structures of the model. Double occupation length is calculated as the length of the double occupied range in both bars on each SSRD. This value can be easily calculated because of the line segment property on a bar.

Our similarity metric is composed of two parts. One is the similarity measure part using the shape histogram proposed by Ankerst *et al.*(1999). The other is the SSRD part. Our similarity measure is as follows:

$$Sp = \frac{\left(\sum_{i=1}^p \alpha_i \right) / p + \left(\sum_{j=1}^q \beta_j \right) / q + \gamma}{3} \quad (0 \leq Sp \leq 1), \quad (3)$$







$$\alpha_i = 1 - \frac{f_A}{f_A + f_B} \quad (0 \leq \alpha_i, \beta_j, \gamma \leq 1).$$

In Eq.(3), S_p is our similarity measure. α_i is the ratio of the closed loops between two SSRD's and β_j is the double occupation length between line segments of two models. γ is the similarity measure value of the shape histogram by using Ankerst's method. p is the number of the rotational intersection planes, q is the number of the bar on the SSRD. f_A and f_B are the numbers of closed loops in the models A and B. d is the bar on a SSRD. l is the intersection line on a bar of SSRD in the model A. m is the intersection line on a bar of SSRD in the model B. For simple computation, we set $p=9$ and $q=8$. To compare between two SSRD, our similarity measure procedure presented is as follows: (1) calculate the similarity by using Eq.(3) and the Ankerst method; (2) write the result in the text code.

EXPERIMENTAL RESULTS

Table 1 shows some experimental results. In Table 1, the query model is the teapot, then our shape matching algorithm finds the most similar shape in the database by using the SSRD of each model. The result of the given query is the second model in our Table 1.

Table 1 Comparison between the models using the proposed algorithm

Query model	3D model	Similarity result
		0.42
		0.87
		0.56
		0.14
		0.71

CONCLUSION

In this paper, we propose the SSRD generation algorithm based on the spherical sectioning and the feature extraction techniques. The initial results suggest that the proposed algorithm has some useful

properties.

SSRD includes the advantages of the shape histogram as general shape descriptor which is very simple and robust. The SSRD generates the feature map which is composed of the pattern with useful properties of the object. Our SSRD is based on the principal axis. Due to the rotation variant property of the principal axis generated from a given model orientation, we fix the orientations of the SSRD of the models in order by size of the direction vector of three component of the principal axis, thus it is somewhat a limitation in a special case in which three axes are the same size in each direction. Then our ordering system is repeated in each direction. Then the number of SSRD is three times larger. Our approach is essentially neutral for their input data type, thus various graphics format can be handled by our approach. Our method can be easily extended to various model types like B-rep solid, polyhedral surface net, parametric surface, implicit surface and volumetric data. However our rotational intersection step is time-consuming for a parametric surface model case.

As part of our future work, we are willing to handle both problems effectively. We expect that the use of SSRD will enrich the more effective shape matching and retrieving for reducing the semantic gap.

References

- Ankerst, M., Kastenmuller, G., Kriegel, H.P., Seidl, T., 1999. Nearest Neighbor Classification in 3D Protein Databases. Proc. 7th Int. Conf. on Intelligent Systems for Molecular Biology (ISMB 1999), Heidelberg, Germany, p.34-43.
- Blum, H., 1967. A Transformation for Extracting New Descriptors of Shape. In: Whalen-Dunn, W. (Ed.), Proc. Symp. Models for Perception of Speech and Visual Form. MIT Press, Cambridge, MA, p.362-380.
- Gottschalk, S., 1999. Collision Queries Using Oriented Bounding Boxes. Ph.D Thesis, Department of North Carolina at Chapel Hill.
- Iyer, N., Jayanti, S., Lou, K., Kalyanaraman, Y., Ramani, K., 2005. Three-dimensional shape searching: state-of-the-art review and future trends. *Computer-Aided Design*, **37**(5):509-530. [doi:10.1016/j.cad.2004.07.002]
- Kazhdan, M., Chazelle, B., Dobkin, D., Finkelstein, A., Funkhouser, T., 2002. A Reflective Symmetry Descriptor. Proceeding of European Conference on Computer Vision, p.642-656.
- Min, P., Halderman, J., Kazhdan, M., Funkhouser, T., 2003. Early Experience with a 3D Model Search Engine. Proceeding of Web 3D Symposium, p.7-18.

- Min, P., Kazhdan, M., Funkhouser, T., 2004. A Comparison of Text and Shape Matching for Retrieval of Online 3D Models. Proceeding of European Conference on Digital Libraries, p.209-220.
- Pu, J.T., Liu, Y., Xin, G.Y., Zha, H.B., Liu, W.B., Yusuke, U., 2004. 3D Model Retrieval Based on 2D Slice Similarity Measurements. Proceeding of the 2nd International Symposium on 3D Data Processing, Visualization, and Transmission, 2004 (3DPVT 2004), Thessaloniki, Greece, p.95-101.
- Rea, H., Corney, J., Clark, D., Taylor, N., 2004. A Surface Partitioning Spectrum (SPS) for Retrieval and Indexing of 3D CAD Models. Proceedings of the 2nd International Symposium on 3D Data Processing, Visualization and Transmission, 2004 (3DPVT 2004), Thessaloniki, Greece, p.167-174.
- Regli, W.C., Cicirello, V.A., 2000. Managing digital libraries for computer-aided design. *Computer-Aided Design*, **32**(2):119-132. [doi:10.1016/S0010-4485(99)00095-0]
- Ritter, J., 1990. An Efficient Bounding Sphere. Graphics Gems, Academic Press Professional, Sandiego, CA, p.301-303.
- Sundar, H., Silver, D., Gagvani, N., Dickson, S., 2003. Skeleton Based Shape Matching and Retrieval. Proceeding of Solid Modeling International, p.130-139.
- Ullman, D., 1997. The Mechanical Design Process (2nd Ed.). McGraw-Hill, New York.