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Using a Partial Geometric Feature for Similarity Search of 3D Objects

Yingliang Lu,† Kunihiko Kaneko† and Akifumi Makinouchi††

Searching in a spatial database for 3D objects that are similar to a given object is an important task that arises in a number of database applications, for example, in medicine and CAD fields. Most of the existing similarity searching methods are based on global features of 3D objects. Developing a feature set or a feature vector of 3D object using their partial features is a challenging. In this paper, we propose a novel segment weight vector for matching 3D objects rapidly. We also describe a partial and geometrical similarity based solution to the problem of searching for similar 3D objects. As the first step, we split each 3D object into parts according to its topology. Next, we introduce a new method to extract the thickness feature of each part of every 3D object to generate its feature vector and a novel searching algorithm using the new feature vector. Finally, we present a novel solution for improving the accuracy of the similarity queries. We also present a performance evaluation of our stratagem. The experiment result and discussion indicate that the proposed approach offers a significant performance improvement over the existing approach. Since the proposed method is based on partial features, it is particularly suited to searching objects having distinct part structures and is invariant to part architecture.

1. Introduction

Since 3D models are increasingly created and designed using computer graphics, computer vision, CAD medical imaging, and a variety of other applications, a large number of 3D models are being shared and offered on the Web. Large databases of 3D models, such as the Princeton Shape Benchmark Database [17], the 3D Cafe repository, are now publicly available. These datasets are made up of contributions from the CAD community, computer graphic artists, and the scientific visualization community. The problem of searching for a specific shape in a large database of 3D models is an important area of research. Text descriptors associated with 3D shapes can be used to drive the search process, as is the case for 2D images. However, text descriptions may not be available and may not apply for part-matching or similarity-based matching. In recent years, several content-based 3D shape retrieval algorithms have been proposed [6),8),10),15),19)].

For the purpose of content-based 3D object retrieval, various features of 3D object have been proposed [2),6),11),15),19)] . However, these features are global features. That is, they describe the geometry or topology information of a 3D object using one feature only. In addition, it is difficult to effectively implement these features on relational databases because they include topologic information. An efficient feature is proposed in Ref. 13) that can also be used in partial similarity matching of shapes. However, an efficient method by which to retrieve complex shapes by their partial similarity is not described in Ref. 13). A shock graph comparison based retrieval method is described in a previous paper [18)]. However, that retrieval method is based only on the topologic information of the shape. An approach based on a new geometric index structure is suggested in Ref. 8). The basic idea of this solution is to use the concept of hierarchical approximations of 3D objects to speed up the search process. However, it is still only based on global features. A method based on an efficient geometrical and partial similarity is needed to retrieve 3D objects. The objective of this paper is to propose such a method. by which 3D similarity objects can be effectively retrieved according to their partial thickness distribution and the ratio of the size of parts.

In this paper, we propose a novel feature vector of a 3D object, and we also proposed a novel method to search similar objects from a 3D object database using the proposed feature vector. In addition, our feature vector is based on geometrical information rather than

† Graduate School of Information Science and Electrical Engineering, Kyushu University
†† Department of Information and Network Engineering, Kurume Institute of Technology

☆ The real author is the Editorial Board of the Trans. IPSJ.

on topological information alone. The vector is herein referred to as the Segment Weight Vector (SWV). The SWV is more effective and flexible than the Curve-Skeleton Thickness Histogram ($CSTH$)[13] on partially based object matching. Furthermore, we refine the result with a filter using the Segment Thickness Histograms (STHs) of curve-skeleton. In our proposal, a number of similar 3D objects will be retrieved from a 3D model database if the volume feature of each part of the query object is similar to a part of the potential candidate 3D objects. The similar objects are inserted into the candidate pool. As an accuracy improvement step, the 3D objects will be removed from the candidate pool if the STH of the processing part of the query object is not similar to any STHs of the potential candidate object.

Since the proposed method is based on the curve-skeleton of shape, the object model of this paper is the 3D model that can be extracted a curve-skeleton using the skeletonization algorithm[3] without losing any necessary topological information. In this paper, we define this requirement as the skeleton requirement. In our experiments, almost all of the solid data models can meet the skeleton requirement. The polygon soup cannot be skeletonized to a curve-skeleton with existing skeletonization algorithm because that a polygon soup is just a list of triangles and it has no inherent structure. Consequently, the 3D models repressed by polygon soups are out of the range of the discussion in this paper. In addition, when a object is skeletonized to a curve-skeleton, if the curve-skeleton has lost the main topological information of the original object, the object is also out of the scope of the discussion in this paper. For example, the skeleton of a sphere object is only a point and the skeleton of a rectangular solid object is several segments. Therefore, our method can also be easily implemented on other multi-branch complex graph matching applications if there are different heavy values on segments.

The remainder of this paper is organized as follows. Section 2 provides an overview of research related to skeleton generation and content-based retrieval. In Section 3, we describe a feature vector (SWV) of a 3D object based on the topology of its curve-skeletons and partial geometries. In addition, we describe the Segment Thickness Histogram (STH) of a curve-skeleton. In Section 4, we describe the novel algorithm and a similar 3D object retrieval method based on the SWVs and STHs, of a 3D object. The performance test results of different strategies and a discussion thereof are presented in Section 5. Finally, in Section 6, we conclude the paper and present ideas for future study.

2. Related Work

Researches on skeleton detection and 3D object matching are related to this paper.

A number of different approaches have been proposed for the matching problem. Using a simplified description of a 3D model, usually in one or two dimensions (also known as a shape signature), the 3D matching can be implemented by comparing these different signatures. The dimensional reduction and the simple nature of these shape descriptors make them ideal for applications involving searching in large databases of 3D models. Osada, et al. in Ref. 15) proposed the use of a shape distribution, sampled from one of many shape functions, as the shape signature. Among the shape functions, the distance between two random points on the surface proved to be the most effective for retrieving similar shapes. In Ref. 1), a shape descriptor based on 2D views (images rendered from uniformly sampled positions on the viewing sphere), called the Light Field Descriptor, performed better than the descriptors using the 3D properties of the objects. In Ref. 7), Kazhdan, et al. propose a shape description based on a spherical harmonic representation. Kriegel, et al.[11] present an approach for describing voxelized objects. The cover sequence model approximates a voxelized 3D object using a sequence of grid primitives (called covers), which are basically large parallelepipeds. Lau, et al.[12] surveyed some representative research on 3D model retrieval, focusing their analysis on feature matching. The existing methods are divided into three groups: geometry-based, frequency-based, and topology-based. Unfortunately, these previous methods cannot deal with partial matching. Another popular approach to shape analysis and matching is based on comparing graph representations of shape. Nicu, et al.[2] developed a many-to-many matching algorithm to compute shape similarity on the topologic information of the curve-skeleton. Sundar, et al.[19] developed a shape retrieval system based on the skeleton graph of the shape. These previous methods focus only on the topologic information of the shape. Unfortunately, the most important shape information (i.e., geometric information) is neglected. Moreover, to match shapes using graph is more costly. Lu, et al.[13] proposed a novel shape feature of a 3D model, called the Curve-Skeleton Thickness Histogram (*CSTH*). The *CSTH* is based on the geometric information of the shape but only describes the matching algorithm of one segment on the curve-skeleton of a shape model. However, there was no discussion as to how to match two 3D models having multiple segments on their curve-skeletons.

In Ref. 2), 19), curve-skeletons are a 1D subset of the medial surface of a 3D object and have recently been used in shape similarity matching. A number of algorithms and applications based on curve-skeletons have been developed in the last decade. Topological thinning methods[16] can directly produce a curve-skeleton that stores the topologic information of objects. Unfortunately, these algorithms are resolution-dependent and lose the geometric information of objects. Distance transform methods[4] use the distance field of volume data to extract the skeleton. Unfortunately, these methods do not produce a 1D representation directly. Using these methods requires some significant post-processing. However, some geometric information on the extracted voxel is maintained.

Various types of fields generated by functions are used to extract curve-skeletons. They can produce nice curves on medial sheets. A potential field function in which the potential at a point interior to the object is determined as a sum of potentials generated by point charges on the boundary of the object. Such functions include the electrostatic field function[5] and the visible repulsive force function[14]. The skeleton points are found by determining the "sinks" of the field and connecting them using a force following algorithm[3] or minimizing the energy of an active contour[20], which are used to generate an initial skeleton in this paper.

3. Feature Extraction

Extracting features to represent a part of a 3D model for similarity measurement is a significant challenge. In this section, we briefly describe the method that is used to build the thickness of a curve-skeleton from 3D polygonal models. Please refer to the reference Ref. 13) for details. We herein propose the *SWV* which is

Fig. 1 A 3D shape model used to extract the skeleton.

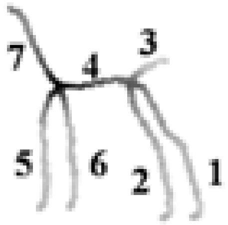


Fig. 2 The curve-skeleton with thickness of the 3D model in Fig. 1.

a novel feature of 3D object. We also introduce a novel method to break a curve-skeleton into independent parts, called segments, based on its topology. In addition, we describe in detail the normalization of the curve-skeleton thickness histogram of a single segment.

3.1 Skeleton Extraction

A number of methods of skeleton extraction have been reported[3),4)]. The electrostatic field function[3] can extract well-behaved curves on medial sheets. Even though the result is connected, the extracted curve-skeleton is divided into a number of segments based on electrostatic concentration. However, we need to split the curve-skeleton into parts according to its topology rather than according to its electrostatic concentration in this paper. In Ref. 13), the initial curve-skeleton based on the method in Ref. 3) is first extracted. The distance transform (DT) algorithm[4] was then used to compute the DT of all voxels on the extracted curve-skeleton (**Fig. 2**). In Ref. 13), all of the curve-skeletons of the objects were assumed to be connected and to have no branches. Finally, a similarity computation method of 3D objects based on the *CSTH* of the entire object model was introduced.

Generally, there are often several branches on the curve-skeleton of a complex object (**Fig. 1**). Firstly, we merge all of the parts separated from

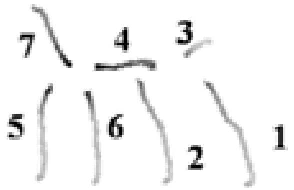


Fig. 3 The segments of curve-skeleton after splitting the curve-skeleton in Figure Fig. 2.

the curve-skeleton into a continuous curve. The continuous curve is then broken into parts according to its topology (**Fig. 3**). We use Micro AVS for generating the curve-skeleton figures in this paper.

3.2 Segment Thickness Histogram

We computed the distance transform (DT) of all voxels on the segments mentioned in Section 3.1. We generated the thickness distribution histogram (Fig. 6) from all of the segments of the curve-skeleton that were joined together based on the topological and curvature information. As a partial feature of 3D object, the thickness distribution histogram is used for partial similarity matching.

3.3 Segment Weight Vector

The SWV proposed in this paper is defined by the volume size of its segment thickness histogram. We compute the weight values of all of the parts, which correspond to the segments of the curve-skeleton of a 3D object. Furthermore, we use these weight values to assemble a vector, called the SWV (as mentioned in Section 1), to represent the global feature of the 3D model.

In order to generate the SWV, we first compute the volume size of each part of a 3D object in the database using the formula 1:

$$w_i = \int_x T_x \qquad (1)$$

where w_i is the weight of the i-th ($i \in [1, n-1]$) segment of the curve-skeleton, which represents a geometrical feature of the part of the corresponding 3D object to which the segment belongs, and T_x represents the thickness of the segment at the position x, which indicates the position of a voxel on the segment.

Second, in order to obtain a SWV representation that is invariant with the order of the 3D model parts for similarity matching, a sorting step is needed. We sort the weight values of all parts of a 3D object in decreasing order. The sorted values make up the SWV of the 3D object. $SWV = (w_0, w_1, \cdots, w_{n-1})$, where $w_0 \geq w_1 \geq \cdots \geq w_{n-1}$.

Therefore, in order to obtain an SWV that is invariant with the scale of a 3D model for similarity matching, a normalization step is needed. We normalize the vector by its maximum value, as the formula 2:

$$\overline{w_i} = w_i / w_0 \qquad (2)$$

where i represents the index of w_i in a SWV. The normalized SWV is denoted as $\overline{SWV}$ (formula 3).

$$\overline{SWV} = (1, \overline{w_1}, \overline{w_2}, \cdots, \overline{w}_{n-1}) \qquad (3)$$

3.4 Normalize the *STH*

In order to obtain the STH representations, a normalization step is necessary. The horizontal axis of the distribution should be normalized with a fixed value. Moreover, the vertical axis should be zoomed by a ratio that is equal to the zoom ratio of horizontal normalization. Using the normalization strategy, we use the variation of each STH of the object as a feature of the object. Furthermore, in this method, we treat the proportion of the length of a segment and the thickness distribution along with the segment as a component of the feature.

3.5 Invariance on Topology Changes and Scale

Obviously, since our features of 3D model are not including any topological information, the index is invariant to changes of the topology, including, translation, rotation and reflection. Since our features are not including any topological information of parts, our feature vector is also invariant to part architecture. Furthermore, since we normalized of features in the previous subsections (SWV in Section 3.3 and STH in Section 3.4), our features are invariant to the scale of 3D object. Therefore, our similarity retrieval method is invariant to changes in the orientation (translation, rotation and reflection) and scale of 3D objects.

4. Searching Algorithm

After the SWVs of the 3D models are constructed, we need a similarity measure in order to compare two 3D models. In this section, we describe how to compare two SWVs and how to retrieve 3D objects from a database by their partial geometrical features.

In order to make the bin-to-bin comparison flexible, the Warp Distance (WD)[9] is proposed for comparing time series, and the WD is then adapted to compare metric histograms. If two 3D objects are similar, each of their correspondent part must be similar. Therefore, the numbers of elements of their SWVs must be the same. However, the WD is obtained by a procedure in which each point from a sequence is compared not only with its correspondent. Therefore, in our solution, we cannot use the WD to compare different SWVs that belong to different 3D objects.

In our implementation, we have performed an experiment using a simple dissimilarity measure based on the L_N norms function with $n = 2$. The dissimilarity measure is shown as formula 4.

$$Dissimilarity = \sum_i (X_i - Y_i)^2. \qquad (4)$$

where X_i and Y_i represent the i-th elements in two different SWVs.

Our main idea is based on the fact that two objects are similar if all of their corresponding parts are geometrically similar. Thus, if the volumes and thicknesses of the histograms of two 3D objects are similar for each segment of their curve-skeletons, then the two 3D objects may be similar.

However, the similar STHs retrieval is a multidimensional database problem. We developed a new algorithm to improve the retrieval performance. First, we find 3D models from the database by matching the SWVs. Then, we need to use a similar object retrieval strategy that uses STHs to improve the retrieval accuracy.

In order to retrieve the most similar objects, we first sort the 3D objects by their SWV similarity. In our implementation, we retrieve only the 3D objects of which the total numbers of segments (number of elements in their SWVs) are the same. We then sort the retrieved result set based on the similarity of their SWVs and select only the top m objects for the next step.

Second, we use STHs of the selected 3D objects to improve the accuracy of the retrievals. We retrieve the most similar n segments from the selected 3D object set. This 3D object set includes only the m objects output in the first step. In addition, each of the n retrieved segments belongs to different 3D objects. The retrieved result is shown in **Table 1**. In the table, KS indicates the query object with an m-segment curve-skeleton, and $KS.SG_1$ is the segment that has the largest STH volume. In addition, $CS_{21}.SG_x$ indicates that the segment SG_x is on the curve-skeleton of the CS_{21} object. Finally, the most similar 3D objects are found from Table 1 using SQL. The 3D objects having the largest number of similar segments are reported as the result of 3D object retrieval. In addition, the final step is to find the 3D objects having the most amounts in the candidate pool of Table 1.

Table 1 The candidate pool of a key shape.

Key	**Candidate pool**		
$KS.SG_1$	$CS_{11}.SG_x$	$\cdots$	$CS_{1n}.SG_x$
$KS.SG_2$	$CS_{21}.SG_x$	$\cdots$	$CS_{2n}.SG_x$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
$KS.SG_m$	$CS_{m1}.SG_x$	$\cdots$	$CS_{mn}.SG_x$

5. Experiment and Discussion

In order to test the feasibility of the proposed strategy of similar object retrieval, we implement the above mentioned algorithms on a Linux system by $C++$ and PostgreSQL. We set the resolution of the volume data as $200 \times 200 \times 200$ in the volume voxelization procedure. In our experiments, we defined the threshold of the STH similarity as 1000. If the Euclidean distance between the STHs of the query object and an object in database is less than 1000, then the object from database is selected as a candidate. Otherwise our program will filter out this STH in the similarity retrieval process. Of course, the users can adjust it by themselves to get the best results.

We used the Princeton shape database [17] as the test data in our study. Firstly, we transform the polygonal models in the database into a volumetric object with size $200 \times 200 \times 200$. The rough data is normalized inhere. Secondly, we extract the curve-skeleton from the volumetric object and compute the thickness of the curve-skeleton graph. Finally, we use our filtering algorithm to retrieve similar 3D object from database. We found that the proposed method works well for similar object retrieval based on the geometrical feature of partial bodies. Although there are 1,814 3D models that are collected from the web in the Princeton shape database, we can only generate the curve-skeletons for 1,453 3D models because the skeletonizing algorithm cannot generate a curve-skeleton from some 3D models and some 3D models cannot be expressed with curve-skeleton. For example, since the model illustrated in **Fig. 4** is a surface, we cannot use any curve-skeleton to represent it exactly. In addition, the generated 1,453 curve-skeletons include 51,952 segments in our test database.

The query object (**Fig. 5** (a)) of the test has

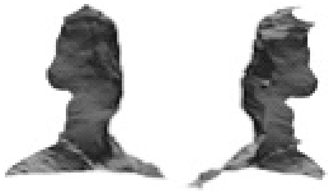
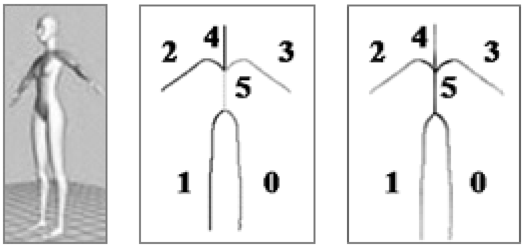


Fig. 4 Two views from different directions of a model no curve-skeleton.



(a) Model (b) Segments (c) Thickness

Fig. 5 Query object used to search the 3D model database.

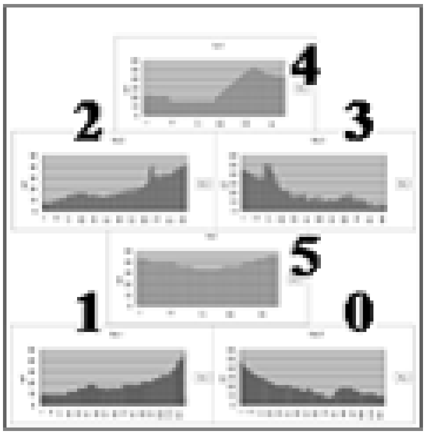


Fig. 6 Thickness distribution graph on the segments of the curve-skeleton of the query object.

six segments on its curve-skeleton (Fig. 5 (b)). These segments include a head (number of segments: 4), a trunk of a body (number of segments: 5), and four limbs (numbers of segments: 0, 1, 2, and 3). Since each segment has its own thickness histogram, the query object has six independent thickness histograms (**Fig. 6**). The segment numbers of thickness histograms in Fig. 6 have the same order with the segment numbers in Fig. 5 (b).

In order to test the feasibility of the proposed retrieval strategy, we implement the proposed algorithms in two ways. Each query object of experiments is illustrated in the top-left of the result **Fig. 7**, **Fig. 8**, **Fig. 9**. The other objects illustrated in the result Figs is the retrieval result of the corresponding query object.

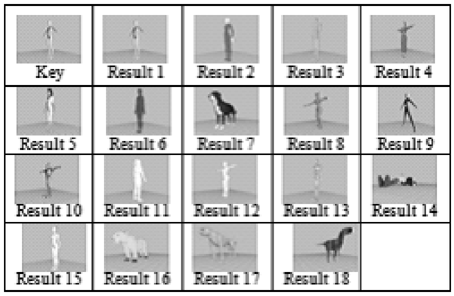


Fig. 7 Results of retrieval by the dissimilarity of Segment Weight Vector initially.

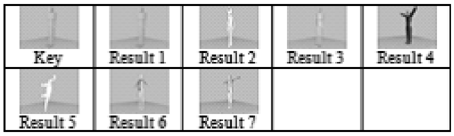


Fig. 8 Results of retrieval by the dissimilarity of Segment Weight Vector initially.

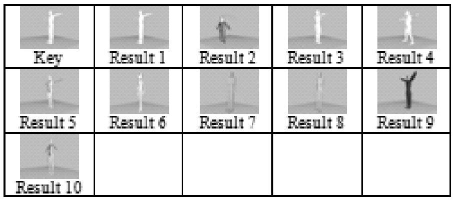


Fig. 9 Results of retrieval by the dissimilarity of Segment Weight Vector initially.

First, we test the retrieval strategy using *STH*s only. The results are shown in Fig. 7. In addition, in order to find no more than 30 objects using a segment of a query object (Fig. 5 (a), also be illustrated in the top-left of Fig. 7), we set the parameter n (the number of maximum retrieval results) as 30 for the experiments. Our filtering program retrieves 30 objects by each *STH* of the query object and then inserts these objects into the temporary table. In order to find the objects of which the *STH*s match the query object for the head, the trunk of the body, and the four limbs, we need to find the best objects from each result set of the six parts. We obtain eighteen objects in which each of the six key parts has a matching part. The retrieved result objects shown in Fig. 7 indicates that the proposed method can find similar objects and retrieve the models having parts that are similar to the query object (e.g., result 7 in Fig. 7). The tail in the result 7 does not have a corresponding part in the query object, and

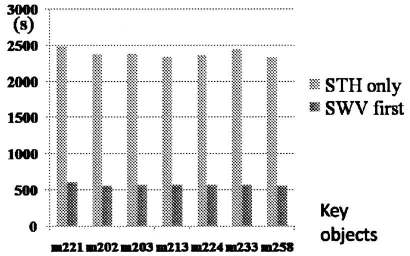


Fig. 10 Retrieval performance comparison of the two methods mentioned above.

therefore it cannot be reported based on global features.

Second, we test the similar object retrieval by partial geometry. In addition, we retrieve 3D objects from the database using their SWV similarities. Furthermore, we use the STH similarity to improve the retrieval accuracy. The results retrieved by different keys are shown in Fig. 8 and Fig. 9. The query objects is illustrated respectively in the top-left of Fig. 8 and Fig. 9.

Finally, we also compare the performance of the two methods mentioned above. The second method performs better. See the result illustrated in **Fig. 10**. In this experiment, we test the retrieval performance by the different query objects (m221, m202, m213, m224, m233, m258 in the Princeton shape database). Fig. 10 shows the average response time of different query objects. The horizontal axis represents the query objects, and, the vertical axis is the average response time. In addition, the average response time of second method include the preprocessing of the 3D models. The result shown in Fig. 10 indicates that the second method can obtain the result more quickly. In addition, the second method has better accuracy.

6. Conclusions and Future Studies

The 3D object retrieval method proposed in this paper is based on partial geometry similarity between 3D objects. Firstly, the proposed method extracts a curve-skeleton with thickness. Secondly, the dissimilarity of the SWV (mentioned in Section 1) was computed and proposed a novel 3D object retrieval strategy using the computed dissimilarity. Thirdly, the dissimilarity of the Segment Thickness Histograms (STHs) of each part was computed with respect to the objects. Finally, we use the dissimilarity of STHs to improve the accuracy of the retrieval. The discussion and experiments show that it is possible to effectively retrieve 3D models by partial similarity.

Since these SWVs and STHs are extracted from 3D objects using the geometrical information of a 3D object, the 3D objects can be compared based on geometrical information rather than on topologic information only. Since the STH and each of the elements of the SWV are a partial feature of a 3D object, both the SWV and the STH can be used to compare two 3D objects based on their partial features, rather than on their global features only. Better efficiency and better matching were obtained in our experiments using the proposed method.

In the future, we intend to add the thickness ratio on the connected parts as a feature of objects to filter out models, as shown by results 7, 16, 17, and 18 in Fig. 7 and result 5 in Fig. 8. In addition, we intend to develop an algorithm that efficiently searches 3D models from 2D drawings.

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References

1) Chen, D.Y., Tian, X.P., Shen, Y.T. and Ouhyoung, M.: On Visual Similarity Based 3D Model Retrieval, *Computer Graphics Forum*, Vol.22, No.3, pp.223–232 (2003).

2) Cornea, N.D., Demirci, M.F., Silver, D., Shokoufandeh, A., Dickinson, S.J. and Kantor, P.B.: 3D Object Retrieval using Many-to-many Matching of Curve Skeletons, *Shape Modeling and Applications* (2005).

3) Cornea, N.D., Silver, D., Yuan, X. and Balasubramanian, R.: Computing hierarchical curve-skeletons of 3D objects, *The Visual Computer*, Vol.21, No.11, pp.945–955 (2005).

4) Gagvani, N. and Silver, D.: Parameter-controlled volume thinning, *Graphical Models and Image Processing*, Vol.61, No.3, pp.149–164 (1999).

5) Grigorishin, T., Abdel-Hamid, G. and Yang, Y.H.: Skeletonisation: An electrostatic field-based approach, *Pattern Analysis and Applications*, Vol.1, No.3, pp.163–177 (1998).

6) Hilaga, M., Shinagawa, Y., Kohmura, T. and Kunii, T.L.: Topology matching for fully auto-

matic similarity estimation of 3D shapes, *Proc. 28th annual conference on Computer graphics and interactive techniques*, pp.203–212 (2001).
7) Kazhdan, M., Funkhouser, T. and Rusinkiewicz, S.: Rotation invariant spherical harmonic representation of 3D shape descriptors, *Proc. Eurographics/ACM SIGGRAPH symposium on Geometry processing*, pp.156–164 (2003).
8) Keim, D.A.: Efficient geometry-based similarity search of 3D spatial databases, *ACM SIGMOD Record*, Vol.28, No.2, pp.419–430 (1999).
9) Keogh, E. and Ratanamahatana, C.A.: Exact indexing of dynamic time warping, *Knowledge and Information Systems*, Vol.7, No.3, pp.358–386 (2005).
10) Korn, F., et al.: Fast Nearest Neighbor Search in Medical Image Databases, *Proc. 22th International Conference on Very Large Data Bases*, pp.215–226 (1996).
11) Kriegel, H.P., Brecheisen, S., Kröger, P., Pfeifle, M. and Schubert, M.: Using sets of feature vectors for similarity search on voxelized CAD objects, *Proc. 2003 ACM SIGMOD international conference on Management of data*, pp.587–598 (2003).
12) Lau, R.W.H. and Wong, B.: Web-Based 3D Geometry Model Retrieval, *World Wide Web*, Vol.5, No.3, pp.193–206 (2002).
13) Lu, Y., Kaneko, K. and Makinouchi, A.: 3D Shape Matching Using Curve-Skeletons with Thickness, *1st Int. Workshop on Shapes and Semantics* (June 2006).
14) Ma, W.C., Wu, F.C. and Ouhyoung, M.: Skeleton extraction of 3D objects with radial basis functions, *Shape Modeling International, 2003*, pp.207–215 (2003).
15) Osada, R., Funkhouser, T., Chazelle, B. and Dobkin, D.: Shape distributions, *ACM Trans. Graphics (TOG)*, Vol.21, No.4, pp.807–832 (2002).
16) Saito, T., Banjo, S. and Toriwaki, J.: An improvement of three dimensional thinning method using a skeleton based on the Euclidean distance transformation — A method to control spurious branches, *IEICE Trans. Inf. Syst., Japan, J*, Vol.84, pp.1628–1635 (2001).
17) Shilane, P., Min, P., Kazhdan, M. and Funkhouser, T.: The Princeton Shape Benchmark, *Shape Modeling Applications, 2004, Proceedings*, pp.167–178 (2004).
18) Siddiqi, K., Shokoufandeh, A., Dickinson, S.J. and Zucker, S.W.: Shock Graphs and Shape Matching, *International Journal of Computer Vision*, Vol.35, No.1, pp.13–32 (1999).
19) Sundar, H., Silver, D., Gagvani, N. and Dickinson, S.: Skeleton based shape matching and retrieval, *Shape Modeling International, 2003*, pp.130–139 (2003).
20) Wu, F.C., Ma, W.C., Liou, P.C., Liang, R.H. and Ouhyoung, M.: Skeleton Extraction of 3D Objects with Visible Repulsive Force, *Computer Graphics Workshop* (2003).

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Yingliang Lu is a Ph.D. student in information science at Kyushu University. He received a B.S. degree in School of Science from Beijing Institute of Technology, and M.S. degree in information science from Kyushu University. His research interests include spatial database systems, spatial data compression algorithms and similarity searching technologies.

Kunihiko Kaneko received his Ph.D. degree form Kyushu University. Since 1996, he has been with Graduate School of Information Science and Electrical Engineering, Kyushu University, Japan, where he is an associate professor. His research interests include spatial databases, and biomedical databases. He is a member of IPSJ, IEICE, ACM, and IEEE.

Akifumi Makinouchi received his B.E. degree from Kyoto University, Japan, in 1967, Docteur-Ingénieur degree from Univercité de Grenoble, France, in 1970, and D.E. degree from Kyoto University, Japan, in 1985, respectively. In 1970, he joined Fujitsu Ltd. as a research engineer. From 1989 to 2006, he was a professor in Graduate School of Information Science and Electrical Engineering, Kyushu University, Japan. He is currently a Professor at Kurume Institute of Technology. His research interests include spatial databases, multi-dimensional index, database systems for medical applications, and medical data science. He is a member of IPSJ, IEICE, ACM, and IEEE.