A 3D Object Retrieval Method Using Segment Thickness Histograms and the Connection of Segments

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Abstract. We introduce a novel 3D object retrieval method that is based on not only the topological information but also the partial geometry feature of 3D object. Conventional approaches for 3D object similarity search depend only on global geometry features or topological features. We use the thickness distribution along the segment of curve-skeleton as the partial geometry feature of 3D object and define the connection of the segments of curve-skeleton as the topological feature of 3D object. In order to retrieve 3D objects, we match 3D objects by their thickness distributions along segment on the curve-skeletons. Furthermore, we use the connection information of segments to improve the accuracy of partial similarity retrieval. The experimental evaluation shows that our approach yields meaningful results in the articulated object database.

Keywords: 3D object retrieval, content-based similarity search 3D object partial matching.

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 objects, such as the Princeton Shape Benchmark Database [1], the 3D Cafe repository [2], and Aim@Shape network [3], 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 objects is an important area of research. Text descriptors associated with 3D shapes can be used to drive the search process [4], as is the case for 2D images [5]. However, text descriptions may not be available, and furthermore may not apply for part-matching or similarity-based matching. Several content-based 3D shape retrieval algorithms have been proposed [6] [7] [8].

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For the purpose of content-based 3D shape retrieval, various features of 3D shapes have been proposed [6] [7] [8] [9]. However, these features are global features. In addition, it is difficult to effectively implement these features on relational databases because they include topologic information. The shock graph comparison based retrieval method described in a previous paper [10] is based only on the topologic information of the shape. However, those methods are only based on the topological information of 3D shape. A geometrical, partial similarity based and efficient method is needed to retrieve 3D shapes from a 3D shape database.

In this paper, we propose a novel method to retrieve shapes based on their partial similarity. The proposed method is based on geometrical information and topological connection information of parts of 3D objects rather than on topological information alone. We compare the similarity of two shapes by the connection information and thickness information of their curve-skeleton segments.

In order to retrieve similar shapes, when a key shape was inputted, firstly, we thin it to a curve-skeleton and add the thickness of the partial shape on the correlative curve-skeleton voxel. Secondly, in our implement, we define a key segment that the volume size of the key segment is largest in the set of key object segments. We find and retrieve the most similar segments that belong to different objects by the Segment Thickness Histogram (STH) of the key segment. Thirdly, we find similar segments that connect to the retrieved segment and similar to the segments connecting the key segment. Fourthly, we continue do the third step until there are not any segments that are still not used as a retrieval key in the segment set of key object. If most of correspondence segments of two 3D objects are similar, we think that the two 3D objects are partial similarity. Finally, we retrieve the 3D objects that have most similarity segments.

Our proposed method has a few important properties. First, our method is invariant to changes in the orientation (translation, rotation and reflection) and scale of 3D objects. For instance, given a human object, we expect to retrieve other human objects, whether they bend, fold their legs, point forward or other poses, as illustrated in Table 6 and Table 7. Second, our 3D shape retrieval method is partial similarity retrieval. For instance, given a part of an animal object, we expect to retrieve the whole animal body. Third, an efficient index can be implemented in spatial database using the connection information of the segments of curve-skeleton.

The remainder of the paper is organized as follows. In section 2 we shortly review already existing 3D shape retrieval algorithm. Section 3 provides an overview of the Curve-Skeleton Thickness Histogram (CSTH). In Section 4, we describe the novel partial similarity retrieval method. A discussion of an empirical study and the results thereof are presented in Section 5. Finally, in Section 6, we conclude the paper and present ideas for future study.

2 Related Works

A number of different approaches have been proposed for the similarity searching problem. Using a simplified description of a 3D object, usually in lower dimensions (also known as a shape signature), reduces the 3D shape similarity searching problem to 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 objects. Osada et al. in [8] propose 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 at retrieving similar shapes. In [11], 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 descriptors that use the 3D properties of the object. In [12], Kazhdan et al. propose a shape description based on a spherical harmonic representation. Unfortunately, these previous methods cannot be implemented on partial matching, because the descriptions of these methods are global feature based. Another popular approach to shape analysis and matching is based on comparing graph representations of shape. Nicu et al [9] develop many-to-many matching algorithm to compute shape similarity on curve-skeleton's topologic information. Sundar et al [6] develop a shape retrieval system based on the shape's skeleton graph. These previous methods only focus on the shape's topologic information. Unfortunately, the most important information of shape that shape's geometric information is neglected. Moreover, it is highly cost that use graph to match shapes. We proposed a novel shape feature of a 3D object. That feature is named as CSTH (mentioned in section 1) [13]. It is based on shape's geometric information. In this paper we add a topological connection comparison process in our 3D shape retrieval process.

3 Curve-Skeleton Thickness Histogram

In this section, we briefly describe the methods used to build the thickness of a curve-skeleton from 3D polygonal models. We also introduce a novel method by which to break a curve-skeleton into independence parts called segments by its topology. In addition, we describe in detail the normalization that normalizes the thickness histogram of a single segment of curve-skeleton.

3.1 Skeleton Extraction

A number of methods of skeleton extraction have been reported [14] [15] [16] [17]. The electrostatic field function [14] can extract well-behaved curves on medial sheets. Their algorithm is based upon computing a repulsive force field over a 3D voxel object. They compute divergence of the vector-field at each voxel. Then, the topological characteristics of the resulting vector field, such as critical points are finded. Finally, they connect the critical points along with the direction of the vector of voxels. Even though the result is connected, extracted curves are divided into a number of segments based on electrostatic concentration. However, we need to split the skeleton into parts based on topology rather than on electrostatic concentration. In our implementation, the initial curve-skeleton based on the method described in a previous study [14] is first extracted. We introduced a similarity computation method of 3D shape models based on the curve-skeletons thickness distribution of the entire shape model when all of the curve-skeletons of the shape were connected and have no branches in Reference [13]. However, there must be several branches on the curve-skeleton of a complex shape (Figure 1). We must first merge all of the parts that are separated from the curve-skeleton by the electrostatic concentration into a connected curve. Then, we must break the connected curve into parts according to its topology (Figure 3). Of course, there are a few algorithms to dissever a shape into parts. Different to those algorithms, in this paper we break the curve-skeleton into segments on the connection points of its branches.

To compute the thickness of segments on a curve-skeleton, we use the algorithm proposed in [15]. Because the distance transform (DT) computation algorithm proposed in [15] has good performance on computing the proximate least Euclidean distance from a voxel to the boundary surface, we used this algorithm to compute the DT value of all voxels on the extracted curve-skeleton by step one (Figure 2). We define the DT value of a voxel of the extracted curve-skeleton as the thickness of curve-skeleton on this voxel in this paper. The Segment Thickness Histogram (STH) is compsed of the DT values of all voxels on a segment. The STH is proposed as a geometrical feature of a 3D shape on our 3D shape similarity retrieval system.

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

3.2 Normalize the Segment Thickness

In order to obtain a Segment Thickness Histogram (STH) representation that is invariant with the scale of a 3D object for similarity measuring, a normalization step is needed. 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 Segment Thickness Histogram (STH) of the shape as a feature of the shape. Furthermore, we treat the proportion of the length of a segment and the thickness distribution along with the segment as a component of the feature by this method.

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

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

4 Retrieval Algorithm

In this section, we describe our retrieval algorithm used to retrieve the partial similarity shapes by their STHs and their segment connections. Using this algorithm, we can retrieve shapes that are partial similarity, only using some parts but not all parts of the key shape.

4.1 The Similarity of Two Different Segments

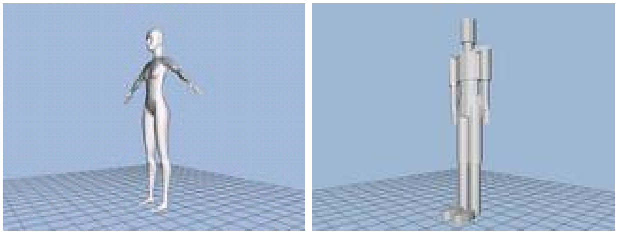
Having constructed the Segment Thickness Histograms (STH) of parts of two 3D objects, we are left with the task of comparing them in order to produce a dissimilarity measure. In our implementation, we have experimented with a simple dissimilarity measure based on the LN norms function with $n = 2$. We use the formula shown as Formula 1.

$$Dissimilarity = \sum_i (X_i - Y_i)^2 \tag{1}$$

where X and Y represent two STHs, X_i represent the thickness of the *i-th* voxel on the X STHs.

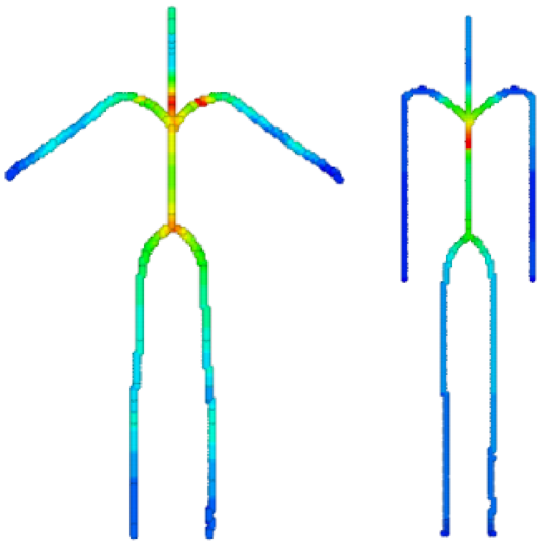
In addition, since there are two different align ways to compare two STHs, the different alignments will produce different dissimilarity results. For convenience, we use the minimum dissimilarity value in our experiments.

Table 1. Two 3D example objects to be matched



(a) (b)

Table 2. The curve-skeleton with thickness of the two 3D example objects shown in Table 1

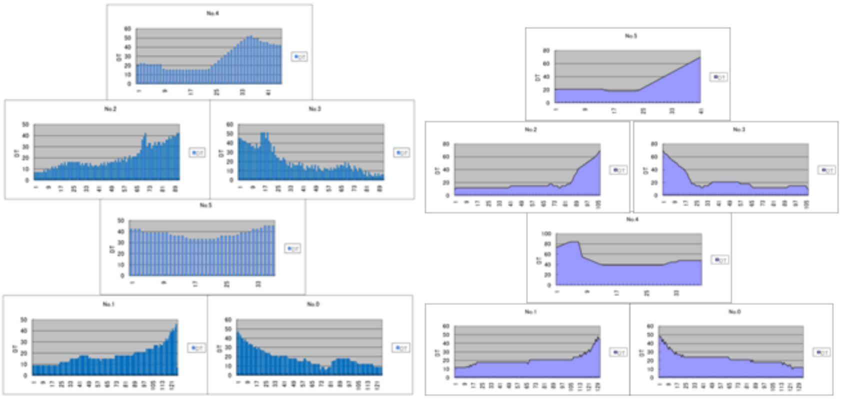


(a) (b)

4.2 Topological Connection Based Retrieval Algorithm

In general, similarity of objects can be evaluated only by the distances of STH. We can think that the key object is similar to the candidate object or similar to a part of the candidate object when each STH of a key object has a similar STH on the candidate object. Otherwise, if the each STH of a candidate has a similar STH on the key object, we can say that the candidate object is similar to a part of the key object. Obviously, this method is invariant to changes in the orientation (translation, rotation and reflection) and scale of 3D objects. However, the major drawback of this evaluation depended only on STH similarity is that the topological connection information of segments is neglected.

Table 3. The STHs of the two 3D example objects (cf. Table 1)



(a) (b)

To overcome the problem, we define two 3D objects are partially similar if a selected segments is similarity based on the distance of the STHs, furthermore, most of the segment connecting to the selected segment are similar to the segments connecting the segments that belong to another object.

In our implementation, when we will match the two 3D objects shown in Table 1, first, we generate *curve-skeleton with thickness* of each of them (Table 2). Second, we dissever the *curve-skeleton with thickness* into *segment with thickness* on the branch points of curve-skeleton. Third, we normalize the *segment with thickness* and generate the STHs of 3D shape like Table 3. The Table 3(a) is the set of STHs generated from the object A (Table 1(a)), and The Table 3(b) is the set of STHs generated from the object B (Table 1(b)).

Finally, we select a STH that has largest original volume size and use it as the key STH to retrieval similar STHs from spatial database. In this example, we select the STH of the trunk of the Object A as a key STH of the object A. In our experiment, we find that the STH of the trunk of the Object B is the most similarity STH in the six STHs of the object B. Then, we select the STHs that connect to the key STH as new key STHs to retrieval similar STHs that are connect to the retrieved STHs on topology other than the retrieved STHs. For instance, the STHs of head and the four limbs the object A are defined as new key STHs to retrieve similar STHs from spatial database. As illustrated in Table 4, the STH of the head of object A is similar the STH of the head of object B, furthermore, the head of object A is connect to the trunk of object A and the head of object B is connect to the trunk of object B. the four limbs of each objects are similar in Table 2. Then, we think that the 2 3D objects are similar.

5 Experiment and Discussion

In order to test the proposed feasibility of the similar object retrieval strategy, we implement the present algorithms on a Linux system by C++ and PostgreSQL.

Table 4. The most similar objects to the key chess retrieved by ascending order of the similarity

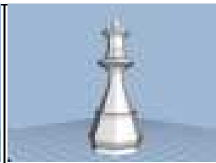
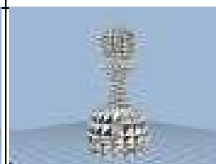
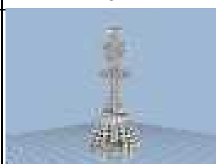
 Key	 1	 2	 3
 4	 5	 6	 7
 8	 9		

Table 5. The most similar objects to the key chess retrieved by ascending order of the similarity

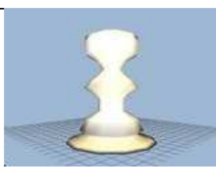
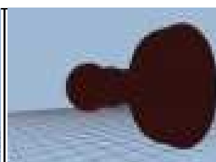
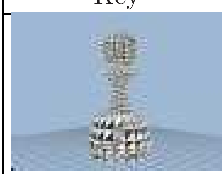
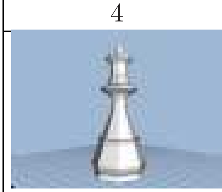
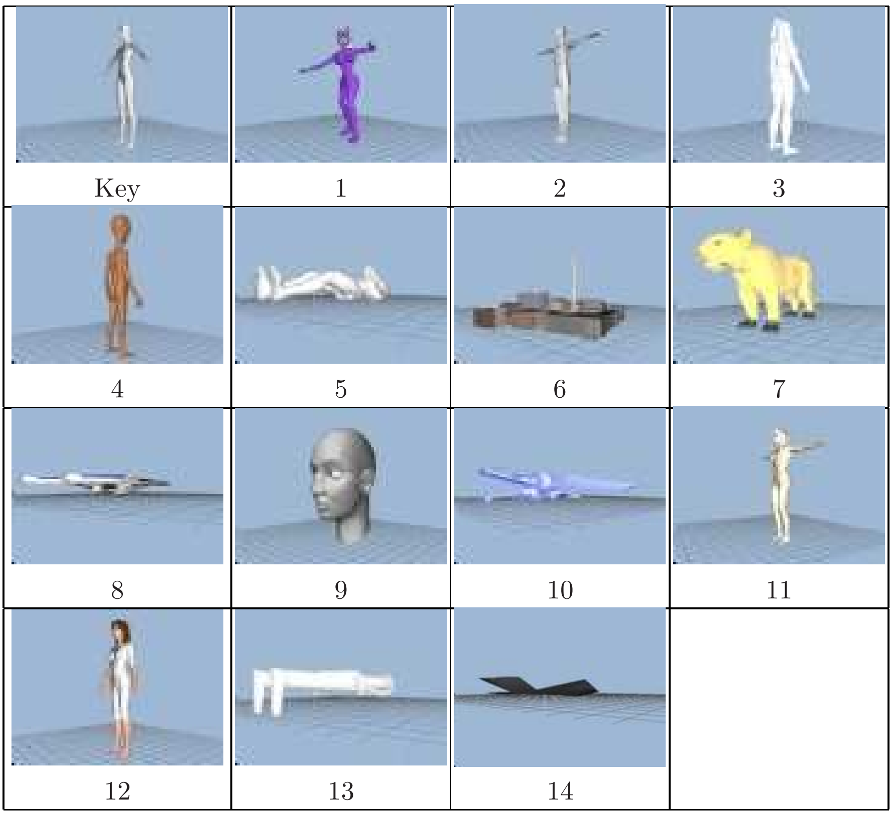
 Key	 1	 2	 3
 4	 5	 6	 7
 8	 9		

Table 6. The mostly partially similar objects (the number of similarity STHs = the number of STHs of the query object)

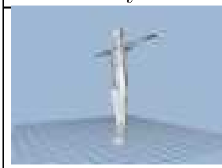
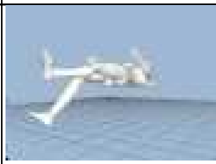
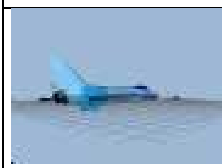
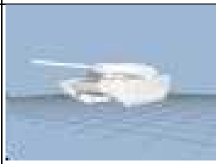
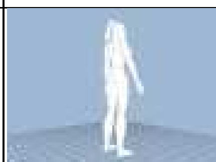
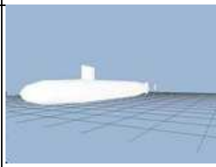
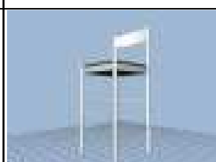
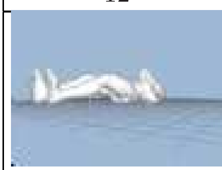
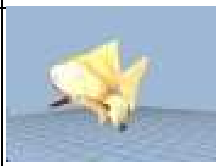
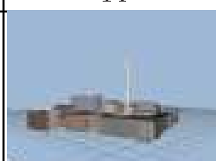


We set the resolution of the volume data as in the volume voxelization procedure. We used the Princeton shape database [1] as the test data in the present study. We found that the proposed method works well for similar object retrieval.

In order to test the feasibility of the similar object retrieval strategy proposed herein, we implement the proposed algorithms in two ways.

First, we test the similar object retrieval strategy only by STHs but not using the segment connection information. There is only a STH on the curve-skeleton of key object in Table 4 and Table 5. The STH of each result object shown in Table 4 match the STH of key object. In addition, in order to improve accuracy, we only retrieve the objects that the count of their STHs is same as the key object. Another test result by search from one STH is shown in Table 5. Therefore, we retrieve 3D objects that each of them has only one segment on their curve-skeleton and their STHs are similar to the STH of the key object. It turned out that the STH similarity algorithm yields meaning results when the key object has only one segment on its curve-skeleton.

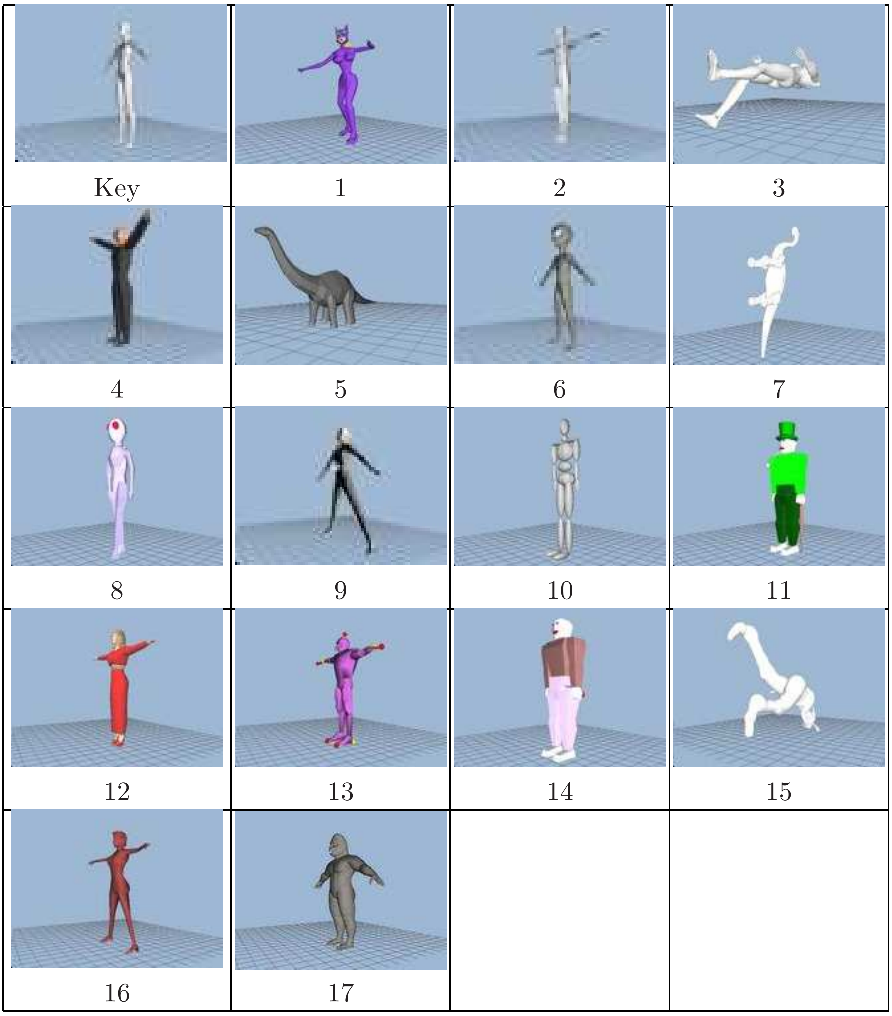
Table 7. The mostly partially similar objects (the number of similarity STHs < the number of STHs of the query object)

 Key	 1	 2	 3
 4	 5	 6	 7
 8	 9	 10	 11
 12	 13	 14	 15
 16	 17	 18	 19

The query object of experiments (Table 6 - 8) has six segments of its curve-skeleton (shown in the Table 2(a)). These segments belong to 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 key object has six independent thickness histograms (Table 3).

In order to find the objects of which the STHs match the key 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 retrieve 3D objects that each of them has

Table 8. The mostly partially similar objects (the connection information between segments is used)



same number of segments as the number of segments of key object and each of their STHs is similar to the correspondence STHs of the key object in Table 6.

To analyze the performance of the partial similarity retrieval, we retrieved the similarity of 3D objects that each of STH of key object has a similar STH on their curve-skeleton. Therefore, the number of segments on the key object is equal with or less than the number of segments on each of the retrieved objects. For instance, in Table 7, the result objects such as 12, 15, 19, are animal objects with seven segments. Obviously, the segment of tail on the curve-skeleton of them is not existed on the curve-skeleton of key object.

Second, we test the partial similarity retrieval using the similarity of two correspondence STHs and the connection of segments. The results shown in Table 8, show that our new approach yields more meaningful results with topological connection of parts. In addition, the partial similarity retrieval is shown to be efficient in our method, for instance, the result 5, 7 are partial similarity with the key object in Table 8. It also turned out that our method is invariant to changes in the orientation, translation, rotation, pose and scale of 3D articulated objects.

6 Conclusions and Future Studies

The 3D object retrieval method proposed in this paper is based on partial geometry similarity between 3D objects. First, the proposed method extracts a curve-skeleton with thickness. Second, we compute the dissimilarity of the STH (mentioned in Section 1) of each part with respect to the objects. Third, we propose a novel 3D object partial similarity retrieval strategy using the computed dissimilarity and the topological connection information of parts of 3D object. Finally, implement our method on 3D shape database. It is possible to effectively retrieve 3D objects by partial similarity in the present experiments.

Since the STH is extracted from 3D objects using the geometrical information of a part of 3D object, the 3D objects can be compared based on geometrical information rather than on topologic information alone. Since each of the STH is a partial feature of a 3D object, the STH can compare two 3D objects based on their partial features, rather than on their global features alone. Furthermore, since the topological connection information of STHs is a topological and simple feature of a 3D object, an efficient index can be implemented in spatial database using the connection. The index can improve the efficient of partial similarity retrieval on the STH feature. Good efficiency and good results were obtained in the present experiments using the proposed method.

In the future, we intend to develop an algorithm that can generate a *curve-skeleton with thickness* from a 2D shape of sketch, and then develop an efficient algorithm that can search 3D objects from 2D sketch.

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