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

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Abstract

Searching a database of 3D objects for objects that are similar to a given 3D search 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 models are based on global features of 3D objects. Developing a feature set or a feature vector of 3D object using their partial features is challenging. In the present paper, we introduce a novel segment weight vector to 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 a 3D object into parts according to its topology. Next, we introduce a new method to extract the thickness feature of each part and generate the feature as a feature vector of the 3D object. We also propose a novel searching algorithm using the newly introduced feature vector. Furthermore, we present a new solution for improving the accuracy of the similarity queries. Finally, we present a performance evaluation of our stratagem. The result indicates 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 [10], the 3D Cafe repository [21], and Aim@Shape network [13], 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 [20], as is the case for 2D images [23]. However, text descriptions may not be available and may not apply for part-matching or similarity-based matching. Several content-based 3D shape retrieval algorithms have been proposed [3] [4] [5] [8] [19].

For the purpose of content-based 3D object retrieval, various features of 3D objects have been proposed [1] [5] [8] [19] [9]. However, these features are global features. That is, they describe the geometry or topology information of a 3D object using one feature. In addition, it is difficult to effectively implement these features on relational databases because they include topologic information. An efficient feature is proposed in [6] 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 [6] for a 3D shape database. In addition, the shock graph comparison based retrieval method described in a previous paper [7] is based only on the topologic information of the shape. An approach based on a new geometric index structure is suggested in [3]. The basic idea of this solution is to use the concept of hierarchical approximations of the 3D objects to speed up the search process. However, this is still based on global features. An efficient geometrical and partial similarity based method is needed to retrieve 3D objects.

In the present paper, we propose a novel feature vector of a 3D object. This feature vector is based on geometrical information rather than 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) [6] on partially based object matching. Furthermore, we propose a novel method to search similar objects from 3D object database using the feature. We refine the result with a filter using the Segment Thickness Histogram (STH) of the curve-skeleton. In our proposal, a number of similar 3D objects are retrieved from a 3D object model database if the volume features of the parts of the key object are similar to any 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 CSTH of the processing part of the key object is not similar to any CSTHs of the potential candidate object. Therefore, the proposed method can also be easily implemented on other multi-branch complex graph matching applications if there are different heavy values on the curves.

The remainder of the present 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 3D objects based on the topology of their curve-skeletons and partial geometries. In addition, we describe the Segment Thickness Histogram (STH) of the curve-skeleton. In Section 4, we describe the novel algorithm and a similar 3D object retrieval method based on the SWVs and STHs, as mentioned in Section 3, of the 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

Research on skeleton detection and 3D object matching are related to the present 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 [19] 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 [24], 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 [14], Kazhdan et al. propose a shape description based on a spherical harmonic representation. Kriegel et al. [1] 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. [2] surveyed some representative research on 3D model retrieval, focusing their analysis on feature matching. 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. [9] developed a many-to-many matching algorithm to compute shape similarity on the topologic information of the curve-skeleton. Sundar et al. [5] developed a shape retrieval system based on the skeleton graph oh 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, using a graph to match shapes is more costly. Lu et al. [6] 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 that have multiple segments on their curve-skeleton.

In [5] [9], 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 developed in the last decade. Topological thinning methods [15] 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 [12] 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 [16] and the visible repulsive force function [17]. The skeleton points are found by determining the "sinks" of the field and connecting them using a force following algorithm [11] or minimizing the energy of an active contour [18], which are used to generate an initial skeleton in the present paper.

3. Feature extraction

In this section, we briefly describe the method used to build the thickness of a curve-skeleton from 3D polygonal models. For details, please refer to Reference [6]. We also introduce a novel method by which to break a curve-skeleton into independent parts, called segments, based on by 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 [11] [12]. The electrostatic field function [11] can extract well-behaved curves on medial sheets. Even though the result is connected, the 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 Reference [6], the initial curve-skeleton based on the method in [11] is first extracted. The distance transform (DT) algorithm [12] was then used to compute the DT of all voxels on the extracted curve-skeleton (Fig. 2). Finally, in Reference [6], all of the curve-skeletons of the object were assumed to be connected and to have no branches. Then, a similarity computation method of 3D object models based on the curve-skeletons thickness distribution of the entire object model was introduced.

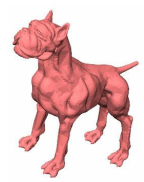

Fig. 1 Three-dimensional model used to extract the skeleton.

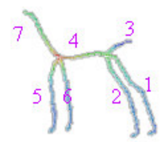

Fig. 2 Curve-skeleton with thickness of the 3D model in Fig. 1.

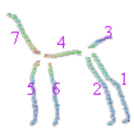

Fig. 3 Segments of the curve-skeleton after splitting the curve-skeleton in Fig. 2.

Generally, there must be several branches on the curve-skeleton of a complex object (Fig. 1). First, we merge all of the parts separated from the curve-skeleton into a continuous curve. The continuous curve is then broken into parts according to its topology (Fig. 3).

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. 7) from all of the segments of the curve-skeleton that were joined together based on topological and curvature information. As partial features of objects, the thickness distribution histogram is used for partial matching.

3.3 Segment Weight Vector

Extracting features to represent a part of a 3D model for similarity measurement has been a significant challenge. We herein propose a new partial feature based 3D object feature. The partial feature of each 3D object is defined by the volume size of its segment thickness histogram. We compute the weight value 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 each 3D object using the following formula:

$$w_i = \int_x T_x$$

where w_i is the weight of a segment on 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 a segment at 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 of parts of a 3D object by descent. The sorted values make up the SWV of a 3D object.

$$\mathrm{SWV} = (w_0, w_1, \cdots, w_{n-1})$$

where w_i represents the weight of the i-th segment, and $w_0 \geq w_1 \geq \cdots \geq w_{n-1}$.

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 follows:

$$\overline{w_i} = w_i / w_0 ,$$

where i represents the index of w_i in a sorted SWV, and $w_0 \geq w_1 \geq \cdots \geq w_{n-1}$, $i \in [1, n-1]$. The normalized and sorted SWV is denoted as $\overline{SWV}$,

$$\overline{SWV} = (1, \overline{w}_1, \overline{w}_2, \cdots, \overline{w}_{n-1}) .$$

3.4 Normalization of the segment thickness

In order to obtain the Segment Thickness Histogram (STH) representation that is invariant with the scale of a 3D model for similarity measurement, 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 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.

4. Searching algorithm

After the SWVs of the 3D models are constructed, we need a dissimilarity 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) [25] is proposed in order to compare time series, and the WD is then adapted in order to compare metric histograms. If two 3D objects are similar, all of their correspondent parts 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. We used the following formula:

$$Dissimilarity = \sum_i (X_i - Y_i)^2 \quad , \qquad (1)$$

where X_i and Y_i represent the i-th elements in two 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 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 segment thickness histograms 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. Therefore, 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 key 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 that they have the most amounts in the candidate pool of Table 1.

Table 1 Candidate pool of the key object.

Key	Candidate pool		
$KS.SG_1$	$CS_{11}.SG_x$	···	$CS_{1n}.SG_x$
$KS.SG_2$	$CS_{21}.SG_x$	···	$CS_{2n}.SG_x$
⋮	⋮	⋮	⋮
$KS.SG_m$	$CS_{m1}.SG_x$	···	$CS_{mn}.SG_x$

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. We set the resolution of the volume data as $200 \times 200 \times 200$ in the volume voxelization procedure. We used the Princeton shape database [10] as the test data in the present study. 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 objects in the Princeton shape database, we only generated 1,453 curve-skeletons of 1,453 3D models from the database because the skeleton-making algorithm cannot generate a curve-skeleton from some 3D models. In addition, the generated 1,453 curve-skeletons include 51,952 segments in our test database.

The key object (Fig. 4) of test has six segments on its curve-skeleton (Fig. 5). 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 (Fig. 7).

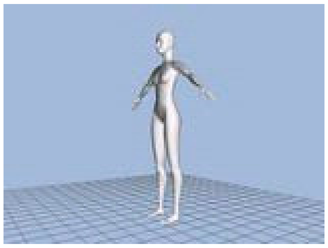

Fig. 4 Key model used to search the 3D model database.

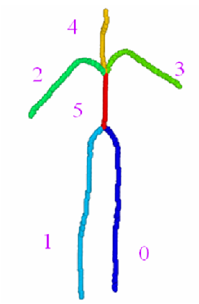

Fig. 5 Segment number of the curve-skeleton of the key model in Fig. 4.

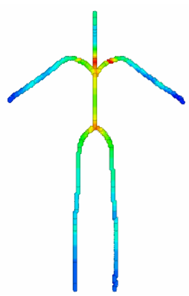

Fig. 6 Curve-skeleton with thickness of the key model in Fig. 4.

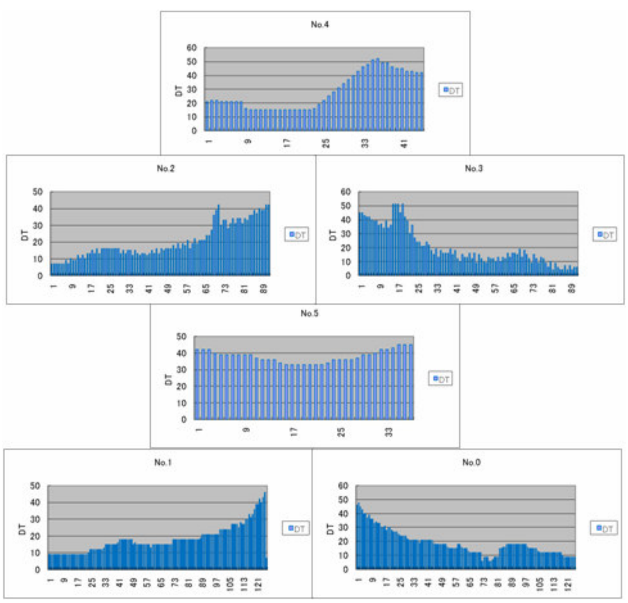

Fig. 7 Thickness distribution graph on the segments of the curve-skeleton of the key model in Fig. 4.

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. The results are shown in Fig. 8. In addition, in order to find no more than 30 objects using a segment of a key object (Fig. 4), we set the parameter n (number of maximum retrieval results) as 30 for the experiments. Our filtering program retrieves 30 objects by each STH of the key object and then inserts these objects into the temporary table. 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 obtain eighteen objects in which each of the six key parts has a matching part. Figure 8 shows a number of result objects of the object retrieval test and reveals that the proposed method can find similar objects and retrieve the models that have parts that are similar to the key object (e.g., result 7 in Fig. 8). The part of the tail of result 7 does not have a part that is similar to the key object, and therefore cannot be reported based on global features.

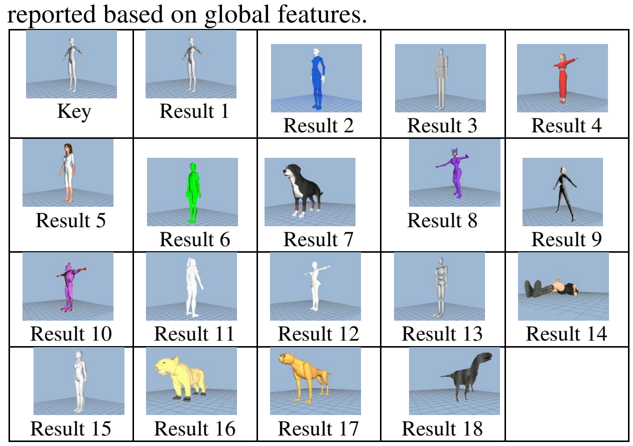

Fig. 8 Results of retrieval by the dissimilarity of the Segment Thickness Histograms only.

We test the similar object retrieval by partial geometry. In addition, we retrieve 3D objects from a database using their SWV similarity. Furthermore, we use the STH similarity to improve the retrieval accuracy. The results retrieved by different keys are shown in Figs. 9 and 10.

Finally, we also compare the retrieval performance of the two methods mentioned above. We test the retrieval performance by the different key objects (m221, m202, m213, m224, m233, m258 in the Princeton shape database). The result, shown in Fig. 11, indicates that the second method can be used to more quickly obtain the result set. In addition, the second method can retrieve a more accurate result set from the test database.

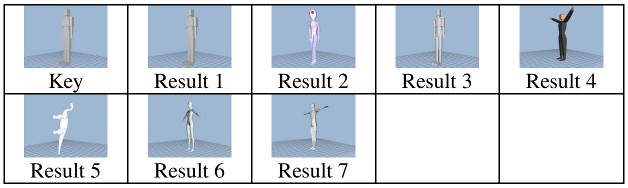

Fig. 9 Results of retrieval by the dissimilarity of Segment Weight Vector initially.

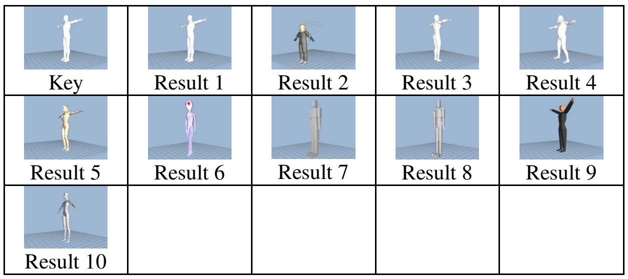

Fig. 10 Results of retrieval by the dissimilarity of Segment Weight Vector initially.

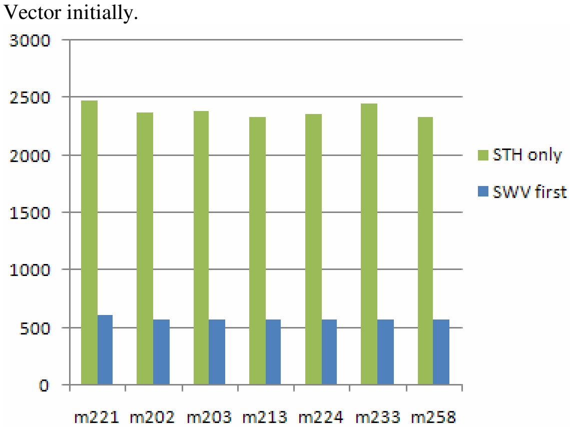

Fig. 11 Retrieval performance comparison of the two methods mentioned above.

6. Conclusions and future studies

The 3D object retrieval method proposed in the present 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 SWV (mentioned in Section 1) and propose a novel 3D object retrieval strategy using the computed dissimilarity. Third, we compute the dissimilarity of the Segment Thickness Histograms (STHs) of each part with respect to the objects. Finally, we use the dissimilarity of STHs to improve the accuracy of the retrieval. It is possible to effectively retrieve 3D models by partial similarity in the present experiments.

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 alone. Since each of the elements of the SWV and the STH are a partial feature of a 3D object, both the SWV and the STH can compare two 3D objects based on their partial features, rather than on their global features alone. Good efficiency and good results were obtained in the present 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. 8 and result 5 in Fig. 9. In addition, we intend to develop an algorithm that efficiently searches 3D models from 2D drawings.

7. References

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