ON 3D PARTIAL MATCHING OF MEANINGFUL PARTS

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ABSTRACT

In this paper a method suitable for partial matching between 3D objects is presented. The 3D objects are firstly segmented into meaningful parts extending a method which is based on the medial surface of the objects. Then, geometric features are extracted for each part based on the Spherical Trace Transform. The extracted features are combined and their covariance matrix is computed as a descriptor of each part. The contribution of the proposed approach is that a meaningful segmentation of 3D objects based on medial surface is achieved and that partial matching is performed on meaningful parts, in a rotation, translation and scaling invariant manner. The experimental results performed, proved that the proposed approach achieves accurate partial matching in terms of distinct meaningful parts as well as satisfactory overall accuracy.

Index Terms— 3-D processing, 3-D feature extraction, 3-D segmentation

1. INTRODUCTION

Three dimensional (3D) shape matching has evolved to a very promising research area during the last years and many approaches have been proposed aiming at the retrieval of geometrically similar objects. A new challenge in this research area is the partial matching, which is a very important prerequisite in search and retrieval of 3D objects which are contained in 3D scenes. In general, 3D objects found in 3D scenes do not contain full shape information. Many of them are partially occluded by other scene objects. In order to perform a 3D shape retrieval for these objects, partial matching methods are of particular interest.

Only recently, few researchers have investigated approaches for partial shape matching based on feature correspondences. The general idea behind the proposed methods is to compute local geometrical descriptors for every object. Then, a cost function is utilized to define the optimal matches, by minimizing the distances between corresponding local features. More specifically, in [1], for every object, a set of salient points is defined and local shape descriptors, centered on the salient points, are computed. Then, the non-rigid Thin-Plate-Spline (TPS) registration is used to identify the potentially homologous subparts as sets of matching salient point pairs. In [2], the proposed partial matching approach is based on salient geometric features. Every object is represented as a perfect triangular mesh and salient geometric features are extracted and stored using the geometric hashing approach. The number of the salient geometric features is kept small by applying an effective mesh simplification algorithm and by describing every saliency with the best approximated quadratic surface. In [3], partial matching is performed using a priority-driven search approach. Every object is described by a set of local 3D geometrical features. The method attempts to match any subset of the query's local features with any subset of any object in the database, using a priority queue, containing the potential sets of feature correspondences (partial matches) sorted by a cost function accounting both feature dissimilarity and geometric deformation.

All the aforementioned methods aim to find similarities between small parts extracted from the objects' surfaces which do not have any particular meaningful interpretation. In order to perform 3D object recognition contained in 3D scenes, where the goal is the identification of the scene objects, a partial matching method is required where "more" meaningful parts will be identified. Moreover, the approaches presented so far are not always efficient especially when the mesh resolution is low (i.e. when the 3D objects have small level-of-detail), or when noise is present.

In this paper, a novel partial matching method is presented, for matching large and meaningful parts of 3D objects. The proposed approach is as follows: Firstly, the object is segmented into meaningful parts and then, every part is described using a modification of Spherical Trace Transform (STT). The STT is computed many times for every part and the covariance matrix of the features constitutes the descriptor of the part. The parts are compared in pairs utilizing a suitable metric.

The rest of the paper is organized as follows: In Section 2

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the proposed approach is described. More specifically, the 3D segmentation approach is presented in subsection 2.1 and in subsection 2.2 the descriptor extraction method is analyzed, while the matching process is discussed in subsection 2.3. The experimental results are presented in Section 3 and the conclusions are drawn in Section 4.

2. THE PROPOSED APPROACH

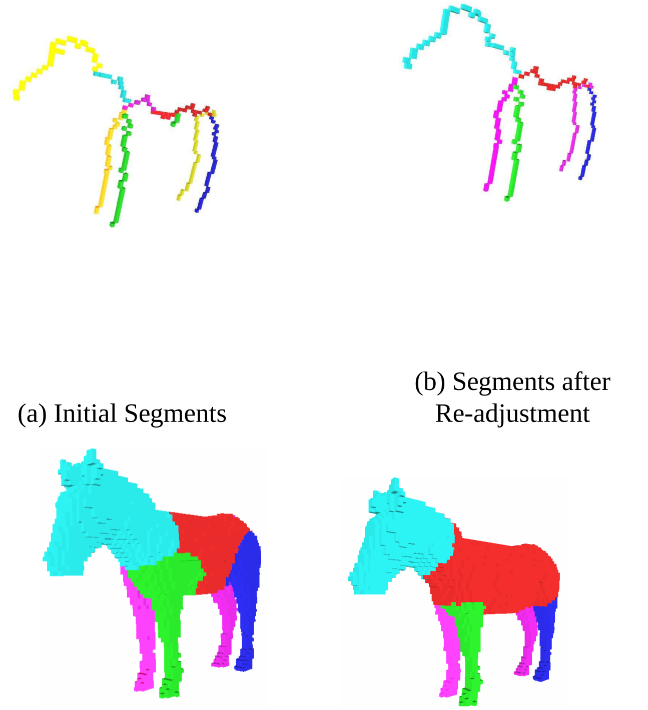
In this paper, the 3D object is segmented using a 3D segmentation method based on the medial surface in the sense of creating "meaningful" segments. In general, a meaningful segment represents a component that can be perceptually distinguished from the remaining object [4]. Then, every segment is described by a covariance matrix, computed on the Spherical Trace Transform's [5] feature vectors.

2.1. 3D Segmentation

In this section, a procedure for efficient extraction of *meaningful segments* from 3D objects is described. Firstly, the medial surface of the 3D object, which is represented as a binary volumetric function [5], is extracted based on the Hamilton-Jacobbi skeletonization algorithm presented in [6]. If the 3D object is represented as a polygon mesh, a voxelization process is prefaced [5]. Then, according to the notation used in [7], the medial surface is segmented. This results in an initial segmentation of the medial surface of the object (Figure 1a).

Secondly, a segment-readjustment technique is proposed in this paper, in order to remove noisy surface parts. More specifically, the segments whose size is considerably small, when compared to the overall medial surface size, are eliminated. Then, all the adjacent line segments that are connected with $degree-2$ nodes are merged into one segment. The degree of a node is the number of edges incident to that node. Finally, a segment which lies between two branch nodes and its size is considerably small, when compared to the overall size, is eliminated. This procedure leads to a more meaningful medial surface segmentation (Figure 1b).

Finally, a statistical-based approach is also proposed so as to segment the 3D object, by assigning every boundary voxel to a medial surface segment. The steps for achieving the latter are the following: Firstly, every surface voxel is assigned to the closest segment, in terms of Euclidean distance. This results in unacceptable segmentation in terms of meaningful parts (Figure 1c). Then, a correction step follows based on the assumption that the surface of a segment is uniformly distributed around the medial surface. By doing so, the Euclidean distance is appropriately weighted with a factor based on the standard deviation of the distances of the surface voxels from the medial surface; thus, the surface voxels are reassigned to the closest medial surface segments, based on the weighted Euclidean distance (Figure 1d).



(a) Initial Segments

(b) Segments after Re-adjustment

(c) Initial Segmented Object

(d) The Final Segmented Object

Fig. 1. 3D Segmentation of the object.

2.2. Descriptor Extraction of the Segmented Parts

Every part of the 3D object is described with a rotation, scaling and translation invariant descriptor, which is the covariance matrix of the Spherical Trace Transform (STT) [5], appropriately modified in order to be computed at every object's part.

More specifically, every part of the object is processed separately and independently from the other parts as follows:

- A sphere with radius r with center on every voxel's center is considered.
- The Spherical Trace Transform is computed for every sphere and a matrix $\mathbf{F} = [\mathbf{f}_1 \dots \mathbf{f}_N]$ is created, where $\mathbf{f}_i$ is the STT-based feature vector of the $i-th$ voxel and N is the number of the voxels of the considered part enhanced with the distance of the voxel from the mass center of the part. The process followed is analyzed in [5]. More specifically, for every sphere of the part:
    - R sample points of the sphere are considered, based

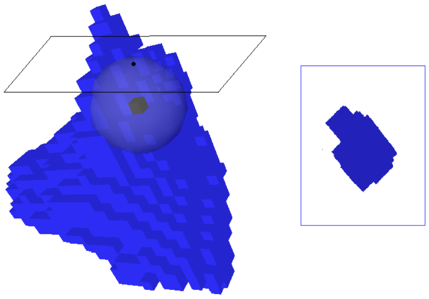


Fig. 2. Using Spherical Trace

on the icosahedral tessellation.

- For every sample point of the sphere, the tangent plane is computed and the intersection of the plane with the part is extracted (Figure 2).
- Every intersection can be treated as an image and appropriate features can be computed. For the needs of this paper, 4 Krawtchouk and 4 Zernike moments have been computed [5].
- The Spherical Fourier Transform is applied separately on each feature of all tangent planes of the same sphere so as to form the feature vector $\mathbf{f}_i$ [5]

- The covariance matrix of the features vectors $\mathbf{f}_i$ is computed as follows:

$$\mathbf{C} = \bar{\mathbf{F}}^T \times \bar{\mathbf{F}} \quad (1)$$

where $\bar{\mathbf{F}} = (\mathbf{F} - \bar{\mathbf{f}} \times [1 \ldots 1])$ and $\bar{\mathbf{f}}$ is the mean of $\mathbf{f}_i$

The covariance matrix $\mathbf{C}$ fully describes the object in a translation, rotation and scale invariant manner. The rotation invariance is achieved by utilizing the STT, which is a native rotation invariant method. Scale invariance is accomplished by computing the covariance matrix of the STT-based extracted features. Translation invariance is achieved by using relative coordinates, centered at the mass center of the part. It has to be mentioned that the covariance matrix is a square and symmetrical matrix $M \times M$ where M =size($\mathbf{f}_i$), which is constant and invariant to the number of the part's voxels.

The advantage of using covariance matrices as a descriptor for every 3D part are:

- The computed descriptors are compact. The required number of descriptors is $\frac{M(M+1)}{2}$, where M depends on the selected number of STT's features.
- With the selection of the appropriate metric, fully rotation, translation and scaling invariance can be achieved.

2.3. Matching Method

The matching is performed by comparing the parts in pairs and then sorting the results. The computed distance is based on the generalized eigenvalues of the covariance matrices of the two parts.

Let us assume that $\mathbf{C}_i$ and $\mathbf{C}_j$ are two covariance matrices describing two parts P_i and P_j, respectively, not necessarily of the same object. The distance between these parts is computed as follows [8]:

$$d(P_i, P_j) = \sum_{k=1}^{M} \ln^2(\lambda_k) \quad (2)$$

where λ_k is the $k-th$ generalized eigenvalue of r
and $\mathbf{C}_j$. The generalized eigenvalues are the solu
equation:

$$\mathbf{C}_i\mathbf{x} = \lambda \mathbf{C}_j\mathbf{x}$$

3. EXPERIMENTAL RESULTS

The proposed approach was tested using using a su
ITI Database [5] consisted of 90 objects.

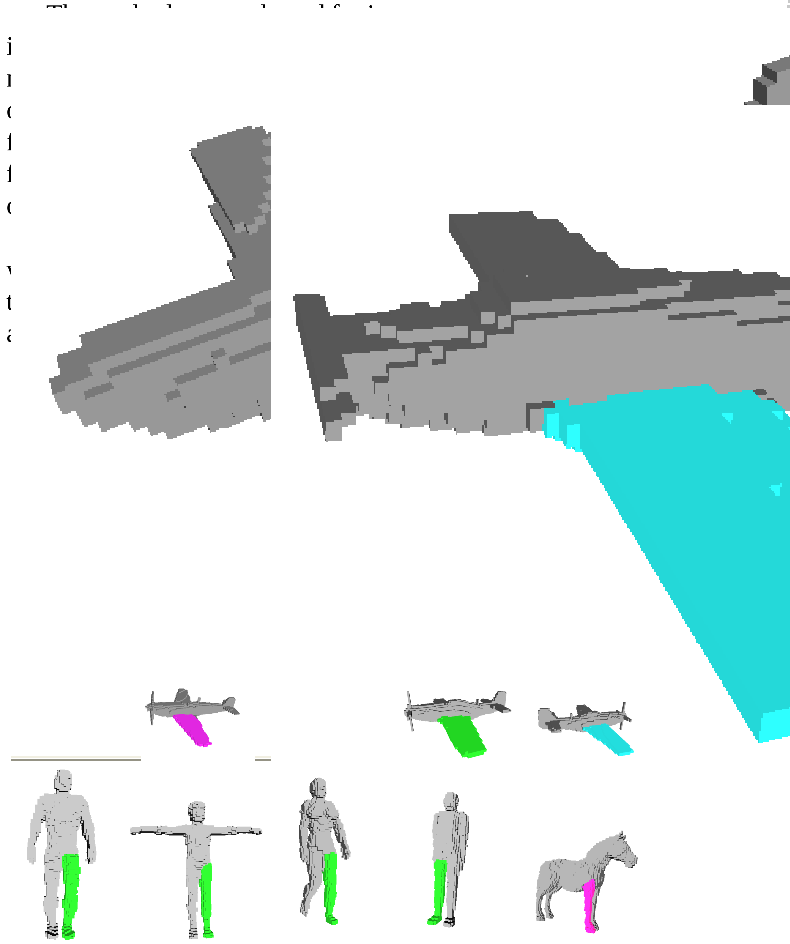


Fig. 3. Retrieved Results.

Moreover, the method has been examined for global 3D search and retrieval application as follows: The query 3D object is segmented and then all meaningful parts querying the database. Then, the global similarity metric is computed based on the similarities of every pair. More specifically, suppose that O_1 and O_2 are two 3D objects segmented into N and M parts respectfully ($P_i^1, i = [1 \dots N]$, $P_i^2, i = [1 \dots M]$). Without loss of generality, it is assumed that $M < N$. Then the distances $d(P_i^1, P_j^2)$ for all (i, j) are calculated. According to the computed part distances, every part of the object O_1 is associated to a part of O_2 and form M pairs $d(P_i^1, P_j^2)$. The global similarity metric is then computed as:

$$D(O_1, O_2) = \frac{1 + 0.1(N - M)}{M} \sum_{i=1}^{M} d(pair_i) \tag{4}$$

The results are depicted in Figure 4 in terms of Precision-Recall diagrams [5] and are compared with the Spherical Harmonics Descriptor (SHD) presented in [9].

Precision-Recall Diagrams are commonly used to evaluate the performance of search and retrieval tools. Precision is the ratio of the number of the correct retrieved results with the number of the total retrieved results, while recall is the ratio of the number of correct retrieved results with the number of the total correct objects stored in the database [5]. The proposed method slightly outperforms the Spherical Harmonics Descriptor, however the main goal of the proposed approach is to achieve partial matching.

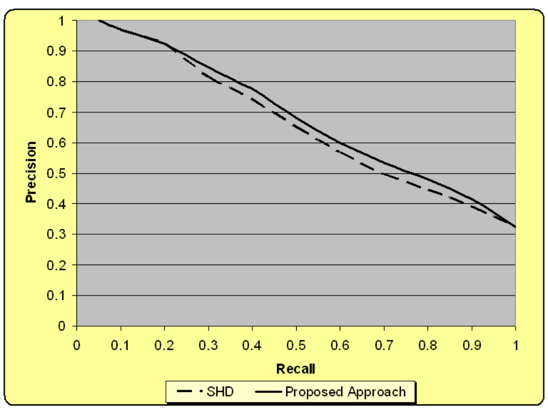


Fig. 4. Precision vs Recall

4. CONCLUSIONS

In this paper a novel approach for 3D object partial matching applications, was proposed. In this approach, the aim was the matching of rather meaningful parts instead of small surface parts, which is more important for practical applications. The medial surface of the 3D object was extracted and segmented. Based on the medial surface segments, the object was segmented into meaningful parts. Every part was described by the covariance matrix of Spherical Trace Transform descriptors computed on every part's voxel. The matching is performed in pairs utilizing a dissimilarity metric based on the generalized eigenvalues of the covariance matrices. The experimental results proved that the proposed algorithm can accurately retrieve similar parts. The main benefits of the presented approach are: Firstly, it performs native scale and rotation translation invariant 3D part comparison, which are essential for part matching in 3D scenes. Secondly, the aim of the presented approach is on retrieving similar *meaningful* parts rather than small surface patches. Finally, the proposed approach can also used effectively for global 3D object retrieval.

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