A Novel Part-Salience-Based Approach to Fast Iterative 3D Mesh Segmentation

Hung-Kuang Chen
Dept. of Electronic Engineering,
National Chin-Yi University of Technology,
Taichung, Taiwan 40109
Email: hankchentw@gmail.com

Yu-Dai He
Dept. of Electronic Engineering,
National Chin-Yi University of Technology,
Taichung, Taiwan 40109
Email: ganton4649@gmail.com

***Abstract*—Mesh segmentation or shape decomposition is a crucial step in shape analysis, shape understanding, model retrieval, and shape composition, etc. To yield visually meaningful parts from an object, previous works suggest the concept of the minimal rule and the theory of part salience. However, they mostly rely on an integral of geodesic distance to approximate the part salience, which requires a high time-complexity approximation through a modified version of All-Pairs-Shortest Paths. To cope with such an issue, we propose a simple salience-based iterative segmentation technique featuring simpler protrusion approximation and low-time complexity method for the search of opposing features.**

Keywords: polygon mesh, segmentation, minima rule, salience.

I. Introduction

The prevalence of consumer-level 3D graphics hardware as well as the pursuit of immersion and realism have made modern computer graphics technologies and applications to sustain an explosive growth. Examples such as the computer games, 3D animation, virtual reality, scientific visualization and simulation etc., are rapidly popularized on various platforms.

The mesh segmentation as an essential techniques required by many geometric modelling and computer graphics tasks and applications have become increasingly important. Applications such as the shape matching, morphing, modelling, editing, compression, animation, and parametrization, etc., are benefited from mesh segmentation. Moreover, recent example such as modelling-by-example and model synthesis by interchangeable parts must rely on the extraction results from mesh segmentation.

To yield visually meaningful parts from an object, a number of previous works suggest the concept of the minimal rule and the theory of part salience [1]–[14]. However, they mostly rely on an integral of geodesic distance to approximate the part salience, which requires a high time-complexity approximation through a modified version of All-Pairs-Shortest Paths [3], [6], [8].

Addressed on this issue, we propose a simpler iterative segmentation scheme on the basis of the iterative framework of [3] with a faster salience feature estimation and an effective low time-complexity farthest-feature approximation, which is able to generate acceptable segmentation results at relatively lower computation cost.

II. Related Works

According to an earlier survey, well-known methods can be roughly categorized either by their segmented results or by the type of applied techniques. With respect to their outcomes, the segmentation algorithms can be classified into the part-type or patch-type algorithms [15].

The part-type segmentation methods are designed to segment the input object into meaningful parts for further processing such as shape understanding, shape composition, and 3D shape retrieval. On the other hand, the surface-type segmentation is to partition the surface mesh into patches for applications such as parametrisation, geometry image creation, etc. For further details, the readers may refer to the reviews by [15], [18]–[24]. In this paper, we only briefly review a limited number of related works as follows.

Wu and Levine [1] proposed an physically-based method that follows the minima rule. The algorithm applies the theory of the electrical charge distribution over the surface of conductors.

An iterative clustering approach proposed by Katz et al suggest a hierarchical decomposition of a 3D mesh [3]. This approach applies the concept of fuzzy clustering, which cuts the input mesh into two opposing parts and a fuzzy region in between. Then, applies the maximum-flow/minimum-cut algorithm to optimize the location of boundary with respect to a weighted combination of the geodesic and angular distances. However, to determine the initial opposing faces, a version of all-pair shortest paths algorithm is applied to find the distances between all pairs of faces by the shortest path between their dual vertices on the dual graph, which adversely increased the time complexity of the algorithm to $O(n^3)$.

Zhang et al. [9] proposed a part-type decomposition method for compound objects using Gaussian curvature analysis. Their method comprises three major steps: namely, the Gaussian curvature estimation, boundary detection, and region growing. Boundaries between two articulated parts with highly negative curvature are identified.

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Page et al. [2] introduced a new algorithm for mesh segmentation, called the Fast Marching Watersheds. Their new algorithm is based on a hill-climbing watershed algorithm that leverages a heap structure to control the flooding across the mesh and the minima rule to decomposed the mesh into visual meaningful parts.

Zhang et al. [5] proposed a region growing algorithm according to the minima rule, which proceeded by expanding the initial region from its seed vertices to those surrounded by the concave creases. The finale result of their algorithm is a set of volumetric parts whose boundaries lies on deep concavities.

Lin et al. proposed a quantitative approach [8], [25] to carrying out the theory of part salience from cognitive science [16]. To evaluate the protrusion of a given part, they have adopted the continuous function $\mu(v)$ defined by an integral of the geodesic distances proposed by Hilaga et al for Reeb Graph construction [17]. In a later work, Valette et al. [6] also applied the principle of the protrusion function to express the degree of closeness of a vertex to a protrusive part.

On assumption of an object comprising a core body and a set of protrusive parts, Agathos et al [10] proposed a segmentation algorithm similar to Lin's approach [8], [25]. On the basis of prominent feature extraction and core approximation, their method is able to decompose the input object into perceptually meaningful parts. Likewise, a minimum cut algorithm is also applied to trace the partitioning boundaries.

To locate concave creases and seams, Au et al. [12] presents an automatic mesh segmentation algorithm exploiting shape concavities using a set of concavity-sensitive scalar fields computed by a Laplacian system solver with concavity-sensitive weights. The computed scalar fields are then used to evaluate the candidate cuts by employing a score-based greedy algorithm.

Kaick et al. [14] present a shape segmentation method for complete and incomplete shapes by directly optimizing the decomposition according to the geometric characterization of the parts on the basis of an intermediate-level analysis. Instead of processing polygon meshes, it focused on the treatment of incomplete shapes in point clouds acquired by a range scanner.

III. Our Approach

To yield a hierarchy of parts, we have adopted the iterative framework proposed by Katz and Tal [3]. An outline of our algorithm is summarized as follows:

1) Protrusion degree estimation.
2) Fast Opposite feature selection.
3) Region growing controlled by Guass Mapping.
4) Boundary determination.
5) Repeat Steps 1 to 4 until the part size is less than the threshold.

We will discuss the details of each step with the following subsections.

A. The protrusion degree estimation

According to [16], the protrusion of a part is defined relative to the part's base; for a viewer-independent representation, an invariant base of the part is assumed to be the minimal surface delimited by its boundary curve. The invariant protrusion of a part M_i is then given by the ratio of its outlier surface area $S(M_i)$ and its base area $B(M_i)$.

Previous works toward the quantisation of the part's protrusion involves an integration of geodesic distances over the entire surface [17], which introduces a complicated computation process [6], [8], [25]. To cope with such an issue, we proposed quantising the degree of protrusion as follows.

We may define the protrusion degree of a vertex v with respect to its k-ring neighbourhood, $R_k(v)$ as follows. Let

$$c_0(v) = v, c_i(v) = \frac{1}{\|\partial R_i(v)\|} \sum_{\forall v_j \in \partial R_i(v)} v_j, i = 1, 2, \cdots k. \tag{1}$$

We may define the protrusion degree of v, denoted as $P(v)$, by

$$P(v) = \frac{\sum_{i=0}^{k} c_i c_{i+1}}{\mathbf{max}\{\|\overline{v_i v_j}\| | v_i \ \texttt{and} \ v_j \in \partial R_k(v)\}}. \tag{2}$$

B. Fast Opposite Features Selection

To bipartite the input mesh, Katz et al. [3] used a modified version of All-Pairs-Shortest-Paths(APSP) to evaluation the weighted distances between each pair of features. Then, the pair with longest weighted distance are selected as the initial features. However, such approach takes $O(C_2^m n^2 \log n)$ for an input of size n with m initial features, a rather high time complexity. To deal with this problem, we proposed a quick and effective approach, called *fast opposite face selection*, which is stated as follows.

The idea is rather simple. We take each pair of feature points, say, v_a and v_b, as well as the center of the input mesh, C, as a triangle $T(v_a, v_b, C)$. We may approximate the distance $D(v_a, v_b)$ between any pair of features, v_a and v_b, by the perimeter of the triangle $T(v_a, v_b, C)$ as follows.

$$D(v_a, v_b) = \|\overline{v_a v_b}\| + \|\overline{v_b C}\| + \|\overline{C v_a}\| \tag{3}$$

Consequently, the farthest features can be found by the ones with largest D value.

C. Region Growing Controlled by Gauss Mapping

Inspired by the work of Yamauchi et al. [26], we distinguish the high curvature parts from the low curvature ones by accumulating a combination of gauss area and common surface area rather than merely the surface area during the region growing process. To distinguish from the notation of common surface area, $A(T)$, we denote the gauss area of a triangle $T(v_a, v_b, v_c)$ as $A_G(T)$.

According to the Gauss-Bonnet theorem, given a traingle $T(v_a, v_b, v_c)$ of an orientable surface mesh M, we may find its gauss area $A_G(T)$ by mapping the normal vectors of the three vertices N_a, N_b, N_c to the vector space of unit sphere. The spherical triangle spanned by these three normal vectors N_a, N_b, N_c are called the *Euler triangle*, and its area can be given by

$$A_G(T) = \alpha + \beta + \gamma - \pi \tag{4}$$

where α, β, and γ are the interior angles at the vertices of T.

To provide proper control, the accumulated area are approximated by incrementing with a combination of surface area and gauss area as follows.

Suppose at the i-th iteration, a triangle T_i is attached to a part, then the increment is given by

$$\Delta A(T_i) = \delta \times A(T_i) + (1-\delta)A_G(T_i) \tag{5}$$

Hence, in each step, two triangles, say T_a and T_b are selected from the fuzzy or unclassified region along the boundary of parts A and B extended from initial features v_a and v_b, respectively. But only the part with smaller accumulated area are allowed to grow. After which, the selected triangle is attached to the part and the increment is added to the accumulated area. Following this manner, the accumulated area of the two parts are kept growing in balance until a prescribe constraint is met.

D. Boundary Determination

In order to leave some space for the location of the finale cut, roughly 10% of surface area are left unclassified after region growing. To match with the concept of part salience, we borrow the idea of boundary strength in locating the part boundary by optimizing the sum of edge weights of the part boundary.

Considering an edge an edge $e_{i,j}$, the weight $w_{i,j}$ of $e_{i,j}$ is given by

$$w_{i,j} = w(e_{i,j}) = \frac{1}{1 + \frac{D_{angle}(\alpha_{i,j})}{D_{angle,average}}}, \tag{6}$$

where $\alpha_{i,j}$ is the dihedral angle and the angle distance of $\alpha_{i,j}$, denoted as $D_{angle}(\alpha_{i,j})$, is given by

$$D_{angle}(\alpha_{i,j}) = \phi \times (\frac{1-\cos\alpha_{i,j}}{2}) = \phi \times (\frac{1 - N_i \cdot N_j}{2}), \tag{7}$$

where $\phi = 1$, if $\alpha_{i,j} = [0, \pi]$; $\phi = -1$, if $\alpha_{i,j} = [-\pi, 0)$;

IV. Experimetal Results

To test our method, we have conducted a series of experiments using a number of commonly used models from public domain. All the experiments were performed on a PC running Microsoft Windows 8.1 equipped with Intel(R) Core(TM) i5-3570 processor, 4GB RAM, and an ATI Radeon HD 4550 powered display card.

The Running Times for Selecting Initial Features

The statistics of each test mesh along with their processing time are listed in Table I shown as follows.

According to Table 1, our method(FOFS) excels the ones that adopted All-Pairs-Shortest-Paths(APSP) algorithm significantly in terms of the running time.

TABLE I

The test meshes used in our experiments and their processing times for initial feature selection using All-Pair-Shortest-Paths(APSP) and our Fast Opposite Feature Selection(FOFS) method.

Model	$\|V\|$	F	Processing Time(Sec.) APSP	FOFS
Cactus	620	1236	0.02	0.01
Triceratops	2832	5660	18.13	0.13
Dinopet	4500	8996	27.58	1.413

The Segmented Outputs

The results of the Dinopet mesh with colored segments corresponding to [3], [8], [27] and our method are shown in Figure 1(a) to 1(d), respectively.

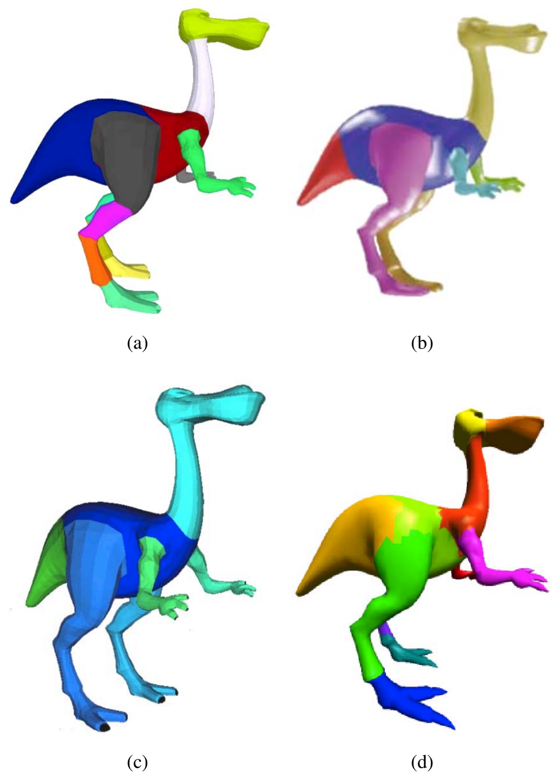

Fig. 1. The segmented Dinopet:(a)fuzzy clustering [3]; (b)core extraction [27]; (c)Lin's salience-based method [8];(d)our method.

As can be seen from the figure, our method is the only approach that can successfully segmenting the beak of the Dinopet from the head. For the rest parts, our result very close to the others except that the fuzzy clustering approach obviously outperforms the others on the segmentation of the rear limbs. Morever, since we did not provide boundary smoothing, the boundaries between adjacent segments from our method are more jaggy than the others.

V. Concluding Remarks and Future Works

In this paper, we have proposed a simple iterative salient-based part-type 3D mesh segmentation method and proposing the following contributions:

1) A simple and effective protrusion degree estimation scheme for part protrusion estimation.
2) A fast low time-complexity, $O(m^2)$, algorithm for initial feature selection (m is the number of features).
3) A novel controlled region growing method using gauss mapping.

Compared with [8], [10], the new method has a more intuitive approach to part protrusion quantisation and is more computation efficient by eliminating the need of an integration over geodesic distances.

Moreover, with the advent of our novel opposite feature selection method, the time complexity of initial feature calculation has significantly reduced from $O(C_2^m \times n^2 \log n)$ to $O(m^2)$ provided that the number of features is m.

With the novel region growing control scheme considering both surface area and guass area, the region grows faster in the flat area but is slower in curved region. As a result, the segmented result matches with human vision.

From our experiment, we have shown that our new method has very good computation efficient and is able to yield competitive part-type segmentation results.

However, in this work, we do not address the issue of boundary smoothing. Thus, the boundary is apparently more jaggy than the others. In the future work, we may encourage the successors to deal with these issues and perform more tests by the benchmarks [18] to further proof the reliability of our method.

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