REGION-BASED OBJECTIVE EVALUATION OF POLYGONAL MESH SEGMENTATION METHODS

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Abstract: In this paper, we propose a new region-based objective evaluation approach of polygonal mesh segmentation algorithms. This approach is derived from 2D-images segmentation similarity measures. We quantify an evaluation criterion relatively to each type of segmented mesh-regions, based on a mesh classification method into convex, concave and planar regions. We apply this approach on eight well-selected existing algorithms conducted by a heterogeneous ground-truth. We present and discuss the evaluation results of these techniques by taking into account the corresponding objects' classes in every type of region. This provides better understanding as to the strengths and weaknesses of each technique in function of each mesh-regions type. That aims to make a better choice concerning the segmentation algorithms for different applications.

1 INTRODUCTION

The evaluation of segmentation methods is an area of recent research for 3D polygonal meshes segmentation. Until now, few researchers have addressed this problem. Recent works (Benhabiles et al., 2009; Chen et al., 2009) proposed ground-truths and quantitative 3D measures for an objective evaluation drawing from 2D evaluation measures. However, these measures evaluate only the obtained results quality for the whole given image and they cannot be adapted to assess the consistency of a segmentation method in relation to each type of segmented mesh region.

Adjudging objectively and quantitatively the quality of segmentation for each type of segmented region is the main inspiration of this paper. We propose three quality measures that quantify the similarity of each type of region of the ground-truth relatively to the segmentation obtained by an automatic algorithm. Section 2 synthesizes related works. We present our evaluation approach in section 3. In section 4, we describe the process of segmented regions classification. Section 5 details the three objective metrics for each type of region. In section 6, we apply our three measures on eight well-selected existing algorithms and then we analyze their evaluation results. Finally, we conclude.

2 RELATED WORK

Attene et al. (Attene et al., 2006a) emphasized the difficulty of evaluating the segmentation quality given the different contexts of use. They conducted a comparative study of segmentation algorithms in which they have proposed several evaluation criteria, namely type of segmentation, complexity, sensitivity to pose, etc. These criteria are very important, but they are not sufficient to quantify the evaluation of the segmentation towards the human visual perception. Recently, Benhabiles et al. (Benhabiles et al., 2009) have proposed an objective evaluation approach of 3D mesh segmentation algorithms which is based on two measures of consistency error (local and global). They tested the proposed measures on two recent 3D mesh segmentation algorithms. These measures are based on a ground truth corpus containing some various 3D objects models with their manual segmentations produced by human observers. However, this corpus contains a limited set of 3D models that are manually segmented. In the same context, Chen et al. (Chen et al., 2009) have proposed a benchmark which contains a comparative study of seven 3D mesh segmentation algorithms. They tested these algorithms on a large base of 3D mesh models. They introduced four quantitative evaluation criteria.

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However, their proposed criteria reflect an overall evaluation of the mesh segmentation. In fact, these criteria evaluate only the quality of the obtained results for a given image without taking into account the evaluation against each type of segmented region.

Our work offers an analysis of the quality of segmentation in relation to each type of segmented regions (convex, concave or planar). This evaluation provides a better understanding of the use of certain criteria during the mesh segmentation process. It also measures the performance of a segmentation method relatively to the type of segmented 3D object regions.

3 FRAMEWORK OF OUR APPROACH

Our approach is inspired from 2D-images segmentation evaluation method (Amri and Zagrouba, 2006). In fact, Amri and Zagrouba (Amri and Zagrouba, 2006) have defined two measures for the evaluation of regions segmentation algorithms which we have generalized for 3D-mesh segmentation evaluation.

First of all, having the ground truth of an image, our approach begins by classifying the regions constituting the ground truth into three classes: convex, concave and planar. This classification is based on the computation of the principal curvatures of each segmented mesh region. Then, the automatic segmentation quality is objectively evaluated relatively to the different region types. To do this, three similarity measures are proposed which each measure is relative to a region type (Figure1).

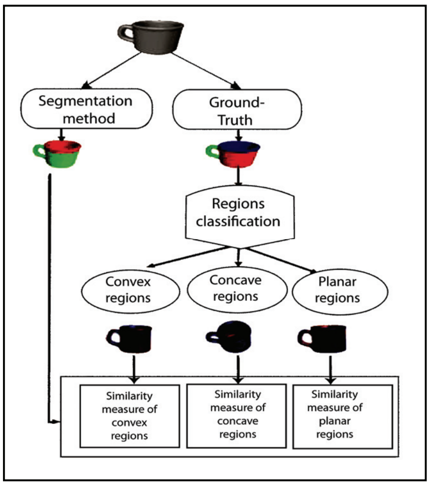

Figure 1: Framework of our approach.

4 CLASSIFICATION PROCESS

The aspect of convex, concave or planar regions prove to be an important criterion to separate the majority of the caracterisitc features of meshes. Thus, we started our approach by a classification process which allows identifying automatically the type of each region of the 3D-image reference (convex, concave or palnar). Indeed, they exist in the literature several methods to classify the different regions of a 3D mesh; these methods are based on different topological and geometrical properties of the mesh. We opted for the classification of regions according to the values of mean and Gaussian curvatures due to its accuracy, consistency and simplicity of its implementation. For this goal, we have applied the work of Meyer et al. (Meyer et al., 2002), using averaging Voronoi cell and the mixed Finite-Element/Finite-Volume method. We have calculated the mean curvature (1) and the Gaussian curvature (3) following the below equations.

$$C_m(x_i) = \frac{1}{2A} \sum_{j \in N_1(i)} (\cot\alpha_{ij} + \cot\beta_{ij})(x_i - x_j) \tag{1}$$

Where A *is* the Voronoi area region in the vertex x_i :

$$A = \frac{1}{8} \sum_{j \in N_1(i)} (\cot\alpha_{ij} + \cot\beta_{ij}) \left\| x_i - x_j \right\|^2 \tag{2}$$

Where α_{ij} and β_{ij} are the angles of the side (x_i, x_j) and $N_1(i)$ is the 1-ring neighbours around vertex x_i. Calculating the Gaussian curvature is remanded to use equation (3):

$$C_g(x_i) = \frac{1}{A}(2\pi - \sum_{j=1}^{f} \theta_j) \tag{3}$$

Where f is the number of adjacent faces to the vertex x_i and θ_j is the angle of the face j in x_i.

After estimating the curvatures values for region vertices, we deduced the curvature values for the whole region of a segmented object. We repeat this curvature calculation, in the same way, for all regions of the same mesh and then for all ground-truth segmented models. The mean and Gaussian curvature values can be positive, negative or null. Finally, according to the curvature estimation done in the previous step, we can deduce which region is convex and which is concave from which that is planar. The first class presents the convex regions with positive both mean curvature and Gaussian curvature. The second is concave regions with positive Gaussian curvature and negative mean curvature. The last class is the class of planar regions having almost null or negative Gaussian curvature.

5 SIMILARITY METRICS

The next step of our approach is to develop a metric of an objective quantitative evaluation relatively to each region type.

Given a set of n images, $I = \{I_k / 1 \le k \le n\}$, we associated relatively to each image I_k a set of automatic segmented regions $Seg_k = \{R_k^1 \dots R_k^{N_k}\}$, and a set of manual segmented regions $Ref_k = \{r_k^1 \dots r_k^{M_k}\}$. Where N is the number of regions of the automatically segmented mesh and M is the number of regions of the manually segmented mesh.

After the classification step, we obtained three regions classes $Ref_k^{cnv} = \{r_k^j / r_k^j \text{ convex}\}$, $Ref_k^{cnc} = \{r_k^j / r_k^j \text{ concave}\}$ and $Ref_k^{pln} = \{r_k^j / r_k^j \text{ planar}\}$, where $Ref_k = Ref_k^{cnv} \cup Ref_k^{cnc} \cup Ref_k^{pln}$.

For each image I_k, a similarity table T_k is calculated (4), where each element $T_k(i, j)$ is defined as:

$$T_k(i,j) = \frac{1}{2}\left(\frac{card(R_k^i \cap r_k^j)}{card(R_k^i)} + \frac{card(R_k^i \cap r_k^j)}{card(r_k^j)}\right) \quad (4)$$

We define then three similarity measures associated respectively to convex, concave and planar regions (5). Each of these measures evaluates the faculty of an algorithm to segment each type of zones ($type = convex, concave, planar$).

$$Z_{type}^{n} = \frac{\sum_{k=1}^{n}\left(\sum_{j=1/r_k^j \in Ref_k^{type}}^{M_k} \max_{1 \le i \le N_k}(T_k(i,j))\right)}{\sum_{k=1}^{n} M_k^{type}} \quad (5)$$

6 EXPERIMENTS

To validate our evaluation approach, we have firstly selected a corpus of 3D mesh models. Indeed, our data set contains globally 42 models, regrouped in six classes (varied objects, Human, Animals, Hand, CAD and Bust), containing each one seven models. We selected this set of meshes and its corresponding ground-truth (figure2) from the benchmark (Chen et al., 2009). We have selected secondly eight 3D mesh segmentation methods (Table1). To make our choice, we have mainly focused on recent works. Moreover, we favoured approaches that adopt a semantic segmentation (part segmentation methods).

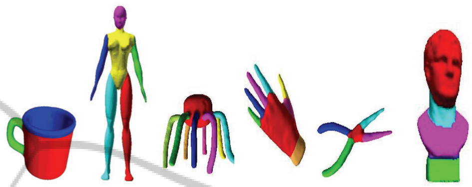

Figure 2: Some ground-truth segmented models.

Table 1: The selected regions segmentation methods.

		Segmentation Methods	Notation
Local shape properties methods	Surface-patch segmentation methods	Region Growing: Lavoué et al., 2005	RG
		Fitting Primitives: Attene et al., 2006	Fit Prim
	Part segmentation methods	K-Means: Shlafman et al., 2002	K-Median
		Random walks: Lai et al., 2008	Rand Walks
Non-local shape properties methods		Shape Diameter Function: Shapira et al., 2008	Shape Diam
		Core Extraction: Katz et al., 2005	Core Extra
		Normalized cuts: Golovinskiy et al., 2008	Norm Cuts
		Randomized cuts: Golovinskiy et al., 2008	Rand Cuts

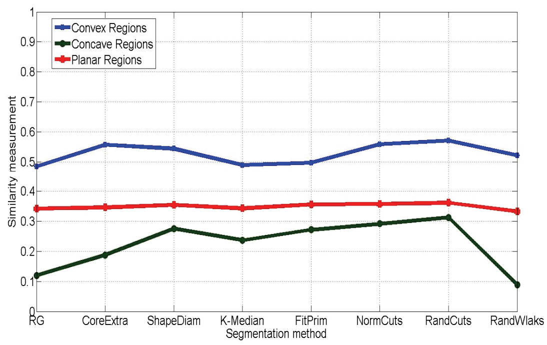

Figure 3: Segmentation evaluation according to the three similarity measurements.

Figure 3 illustrates the three proposed similarity measures (eq. 5). For a given segmented method, a high value of a similarity measure of convex regions

(respectively concave and planar) indicates a good fit of the method in question for the segmentation of convex regions (respectively concave and planar).
Our experimental results have shown that the segmentation techniques adopting non-local shape properties (Rand Cuts, Norm Cuts, Core Extra and Shape Diameter) are better than those based on the local shape properties. We note in particular that Rand Cuts is the best method to segment convex, concave and planar regions. Nevertheless, segmentation by Rand Walks is the least suited for the segmentation of planar and concave regions. The RG method is however the less good for segmenting convex regions.

The results concerning the evaluation of the convex and concave regions segmentation present the quality measures the most dispersed ($variance_{cnv}$= 0.00119277, $variance_{cnc}$= 0.0087033). This is explained by the variety of the convex and the concave forms, which can be segmented in different ways by methods using various criteria. However, planar regions segmentation methods evaluation present the similarity measures the most closest ($variance_{pln}$= 9.6161E-05). Indeed, the planar regions have the same geometric shape to be segmented in nearly the same way and it helps to have very similar results.

Moreover, our results concerning planar regions show the performance of some algorithms that are frequently used in CAD (Computer Aided Design) in the segmentation of such regions. For example, the method Fit Prim, which is composed of geometric primitives, such as CAD models, is the best suited for the segmentation of this type of object (Attene et al., 2006b).

Thus, the criteria used in each method in the segmentation process have an influence on the quality of segmented regions. Indeed, each method uses some criteria to guide the segmentation process where the type of extracted regions depends on the adopted criteria. Therefore, through the classification phase done before the application of the evaluation metric, our approach provides better understanding of the use of these criteria in the mesh segmentation process. This allows providing a better comparison of the strengths and the weaknesses of each technique in the segmentation of each type of the mesh regions. For that reason, we thought to evaluate the performance of a segmentation method on each regions type of the image and not on the entire image. Furthermore, this approach may help in making the better choice of the segmentation algorithm that is the most adapted to each 3D image zone and this can be in applications such as: watermarking, compression, medical imaging, etc.

7 CONCLUSIONS

This paper proposes a new approach of objective quantitative evaluation of 3D mesh segmentation. For this purpose, we have firstly selected a corpus of various 3D models and their ground-truth. We have adopted secondly a method for the classification of segmented regions of each ground-truth object according to the values of its principal curvatures. Then, we have proposed three similarity measures for the evaluation of the segmentation quality for every region type (convex, concave or planar). To validate our approach, we have selected eight recent segmentation algorithms on heterogeneous images.

In terms of improving our results, there are a number of interesting directions to explore. Currently, we are working to fusion the compared methods permitting to combine the results of the best selected algorithms for each type of region. We also plan to perform experiments with larger corpus in terms of number of images to establish a complete comprehensive study for an objective evaluation of the 3D meshes segmentation.

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