American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-4, Issue-4, pp-124-131
www.ajer.org
Research Paper Open Access

Evaluation of 3D segmentation methods based on a criterion of homogeneity

El Mostafa Rajaallah[1], Basma Sirbal[1], Mohcine Bouksim[1], El Hassan Essoufi[1], Taoufiq Gadi[1]
[1]*(Faculty of Science and Technology - Settat / University Hassan 1st, Morocco)*

ABSTRACT: *The majority of evaluation tools are based on a human criterion for evaluating the quality of 3D segmentation methods. An algorithm is considered efficient if it provides a better semantic segmentation as would a human being intuitively do. This evaluation is difficult to carry out because it remains dependent on the point of view of subjectivity that establishes the truth-ground and the fact that an individual may establish several semantic levels depending on the desired detail for segmentation. The metric proposed in this work evaluates the homogeneity of the faces components in the segments generated by segmentation methods, this metric is insensitive to human subjectivity and is interested in the final result of the segmentation, helps to analyze the segmentation algorithms and may also improve outcomes.*

Keywords – *Object 3D, Segmentation, Evaluation, homogeneity, Inertia*

I. INTRODUCTION

3D segmentation is part of the classification methods (clustering), which is a mathematical tool of data analysis, in order to bring together several clusters so that the elements of a cluster are as much similar as possible and that the clusters are as much dissimilar as possible.

The evaluation of segmentation methods is very important in order to select the algorithm that works best on a specific type of data. It can also be used to analyze the results of segmentation algorithms so that they can be possibly improved.

The evaluation tools of segmentation methods can be classified into five groups (Zhang et al. 2008) [1], (Vandeborre 2012) [2]:

a. Analytical methods have the disadvantage of focusing on the algorithm only (Principale, complexity ... etc.) And not the final result.
b. Subjective methods, as their name tells, are dependent on human observers in each stage of the evaluation and can't be integrated into an automated system.
c. Methods related to the user system segmentations that relies heavily on the latter and aren't generalizable.
d. The unsupervised methods are those that depend on a defined criterion, and don’t allow assessing quantitatively the segmentations.
e. Finally, supervised methods, even if they are also dependent on human operators, they are the most represented (Martin et al., 2001) [3], (Unnikrishnan et al. 2007) [4], (Benhabiles et al., 2009) [5] because they are automated and they also provide a quantitative evaluation with a metric of comparison (calculation of the difference between truth-ground’s segmentations and the segmentations obtained).

We can also include the methods based on a partial match (Moumoun et al. 2011) [6], that have a set of constraints and choices that must be made:

- ✓ Selection of a human segmentation for reference.
- ✓ The level of segmentation to use for each model.
- ✓ The choice of the shape descriptor.
- ✓ The matching algorithm.

Benhabiles and al. exposed in (Benhabiles and al. 2010) [7], a comparison study between the metric named 3DNPRI (3D Normalized Probabilistic Rand Index) and the different 3D mesh segmentation evaluation metrics. In this study, the authors stated that the 3DNPRI is better than the others in terms of features and discriminating power. The 3DNPRI belongs to the interval [-1,1], the better segmentation must have values neighboring to 1, whereas a value below zero indicates that the automatic segmentation is less expressive.

The approach proposed in our work is an automatic evaluation approach, which is a part of the empirical methods with quality. It's based on the level of homogeneity of the segments; this latter is based on the intra-classes inertia between segments (abbreviated Inertia Intra-segments).

This paper is organized as follows, first, we present the theoretical notion of Inertia intra-class, and then we will introduce our evaluation metric methods for 3D objects segmentation, the next part will be devoted to an experimental evaluation showing the performance of our metric over the 3DNPRI. Finally, a conclusion that discusses the potentials benefits and prospects of our work.

II. INTRA-CLASS INERTIA:

Definition 1:

We call inertia of a cloud $\Omega = \{\Omega_i, i = 1,. . ., n\}$ the weighted sum of the distances of the points to the center of gravity of the cloud. Therefore, if G is the center of gravity of Ω, the inertia of Ω is:

$$I = \sum_{i=1}^{n} w_i * d(\Omega_i, G)^2 \tag{1}$$

With w_i as i= 1, ..., n are the weights of Ω_i and G is the center of gravity of Ω.

For more theoretical details on this section, the reader can refer to the work of (Bisson 2001) [8].

Theorem 1:

For a partition of k classes with W_i weights.

$I_1, I_2, ..., I_k$ are the associated inertia.

The intra-class inertia of the partition is :

$$I = \sum_{i=1}^{n} W_i * I_i \tag{2}$$

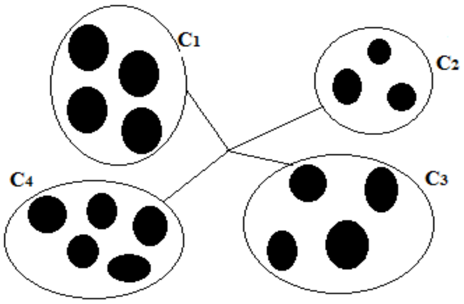

Fig. 1 : Example of clustering

Property 1:

The inertia of a cluster measures the concentration of the points of the cluster around the center of gravity. The more this inertia is low, the more the dispersion of the points around the center of gravity is lower.

Property 2:

A class is homogeneous if and only if its Intra-class inertia is low.

Property 3:

Comparing two partitions of k classes, the best is the one with the lowest inertia.

In the following we will outline our approach exploiting the properties of the intra-class inertia to evaluate the quality (homogeneity) of 3D object segmentation.

III. OUR EVALUATION APPROACH

In this section we detail our evaluation approach of segmentation based on the homogeneity measured by inertia intra-segments, the segmentation that has the lowest score is considered as homogeneous.

3.1. Construction of the point cloud

In our approach we consider that each segment is represented by a point cloud reflecting the coordinates of its faces. The coordinates of a face are its two principal curvatures k1 and k2 (Koenderink et al. 1992) [9], refer to Fig. 2.

The choice of the principal curvatures as coordinates for the faces is motivated by the fact that the homogeneity we seek reflects the shape of the faces that are parts of the segments.

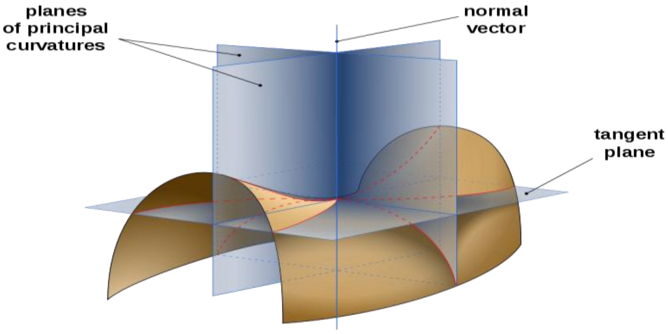

Fig. 2: principal curvatures on a surface

3.2. Estimated curvatures of a triangular mesh

The Approximation of the curvature of the faces of a triangular mesh is based on the vertices and adjacent faces. Chen and Schmitt (1992) [10], Taubin (1995) [11] & Dong and Wang (2005) [12] presented simple methods to estimate the principal curvatures of a face of a triangular mesh. We used circular arcs to approximate the curvature of a vertex by building a ring around it (Fig. 3), and then we estimate the curvature of the triangle based on the curvature of the three points that compose it.

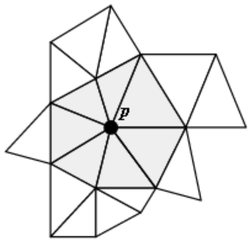

Fig. 3 : A point p and its neighborhood (a ring), composed of triangles of dark color

3.3. The face's weights

3.3.1. Categorization of faces

Based only on a local force of a face in a segment to define its weight has the disadvantage of ignoring the discriminatory power of this face, assume that the face belongs to a category of faces (refer to Table 1) which is not present in the other segments, so that this face should have a high weight in his segment.

Table 1: Categorization (Koenderink et al., 1992) of a 3D surface in function of the value of the shape index

Type of surface	Interval of shape index
Convex ellipsoid	[0, 3/16]
Convex cylinder	]3/16, 5/16]
Hyperboloid	]5/16, 11/16]
Concave cylinder	]11/16, 13/16]
Concave	]13/16, 1]

The shape index defined by:

$$SI = \frac{1}{2} - \frac{1}{\pi} \operatorname{arctg}\left(\frac{k_1 + k_2}{k_1 - k_2}\right) \qquad (3)$$

With k_1 and k2 being the principal curvatures of the surface.

Note: It is well known that the shape index is not defined for flat surfaces, where we have the equality $k_1 = k_2 = 0$.

3.3.2. Weighting function concept

In the information retrieval field a weighting function assigns each term "t" in a document "d" with a value "W". The weight of "t" is calculated on the basis of two criteria: The local force "LF" and its global force "GF" in a corpus.

$$W = F(LF(t,d), GF(t,CO)) \qquad (4)$$

The local force of a term in a document LF (t, d) measures the importance of the term in the document, while the global force GF (t, CO) measures its importance in a corpus. A high value of LF must participate in the maximization of W, while a high value of GF must participate in the minimization of W.

To consider the discriminatory power of a term (Salton and McGill 1983) [13] propose to report the frequency of the term to the frequency of the documents containing that term. They used the relative frequency of term-document (term-document frequency TDF), calculated as follows:

$$W(i,j) = TDF[i,j] = \frac{\log(TF + 1)}{\log(DF + 1)} \qquad (5)$$

With TF = Number of occurrences of the term "t_i" / number of terms of the document j.

DF = Number of documents containing the term 't' / total number of documents. (Gerorge GARDARI 1999) [14] presents more examples of the benefits of the proposition of (Salton and McGill 1983).

3.3.3. Weights of faces.

In our context we have faces and segments of a 3D mesh "M". The local force of a face "f" will be measured according to the local force of its belonging category. The local force of a category is calculated on the basis of the relative area of the faces in that category in its segment "Seg".

if "S_c" is the cumulated area of all surfaces of the faces of a category "C" that belongs to a segment "Seg" of an area S_{seg}, then the relative weight of a face "f" in "C" is the ratio: S_f / S_c, with S_f being the area of the face "f". The relative weight of the category "C" in "Seg" is: S_c / S_{seg}.

The relative weight of the face "f" in the segment "Seg" is:

$$FP = S_c/S_{seg} * S_f/S_c = S_f/S_{seg} \qquad (6)$$

The local force of the face "f" in the segment "Seg" is:

$$LF = \log(FP + 1) \qquad (7)$$

The global force of the face « f » is:

$$GF = \log(CP + 1) \qquad (8)$$

With CP = The cumulated area of all segments containing the faces of the same category "C" of the face "f" / the total area of the mesh "M".

Therefore the weighting coefficient of the face "f" in the segment "Seg" is:

$$W(f, Seg) = \log(FP + 1)/\log(CP + 1) \qquad (9)$$

3.4. Intra-segments inertia

3.4.1. Intra-segments inertia formulation

In our evaluation approach for segmentation methods, the segmentation that has the lowest score of the intra-segments inertia is considered the most homogeneous. Inertia intra-segments (our metric) of segmentation is defined by:

$$I = \sum_{s} W_s * I_s \tag{10}$$

With I_s being the inertia of segments "s" and W_s being weights of the segment defined by the relative areas of those segments according to the surface area of the object.

The inertia of the segment is defined by:

$$I_s = \sum_{f} W(f,s) * \ d(f, G_s)^2 \tag{11}$$

With G_s being the gravity center of the point cloud representing the segment.

3.4.2. The Tchebychev distance

The distance we have adopted in our approach is the Tchebychev distance, this measurement of the distance is appropriate, when we consider two objects as being "different" from the moment they are different in one dimension. Tchebychev distance is calculated as:

For two vectors X = (x_1, x_1,…, x_n) and Y = (y_1, y_2,..., y_n) of a vector space, the distance is defined by :

$$d(X, Y) = \max_{1 \le i \le n} |x_i - y_i| \tag{12}$$

IV. EXPERIMENTAL RESULTSTest database

The Benchmark "3D Segmentation Benchmark" proposed by [7], was created as part of the project "3D Models and Dynamic models Representation And Segmentation". The aim of this benchmark is to provide an automatic tool for the evaluation, analysis and comparison of automatic 3D mesh segmentation algorithms. In this work, we used this database to show the performance of our evaluation tool for 3D segmentation methods.

Fig. 4 : Models from the Benchmark

4.2. Performance obtained

To compare two segmentations, we must have the same number of segments, the most homogeneous is the one with the lowest inertia intra-segments I_w.

In our case, we have adopted the same number of segments recommended by the online evaluation tool of the metric 3DNPRI, the table below presents the objects of the Benchmark, which we used for our tests, with the adopted number of segments.

Table 2: number of segments for each object in the base

object	Number of segments	object	Number of segments
Alien	8	Fish	10
Armadillo	9	Hand1	7
Baby	14	Hand2	12
Bimba	13	Hand3	15
Boy	10	Hand4	6
Bunny	5	Homer	8
Camel	6	Horse1	9
Chair1	8	Horse2	7
Chair2	8	Maxplanck	7
Cow	7	Octopus	9
Dinopet	7	Robot	11
Dolphin	8	Table1	5
Eagle	7	Table2	4
Egea	9	Vaselion	7

Table 3 shows the performance of the inertia intra-segments by classes of objects (**Homogeneity is inversely proportional to the intra-segments inertia**), of two variants of the segmentation method based on spectral clustering technique (Rajaallah et al. 2014) [15], the first alternative is without surface information in the adjacency matrix for faces and the second variant is with surface information for details you can refer to the pages from 22 to 25 of [15].

Table 3 : Inertia Intra-segments for the classes of the test base

Class / Method	Animal	Bust	Furniture	Hand	Human
Spectral clustering 1	47,86	31,06	9,91	6,01	43,63
Spectral clustering 2	45,50	$31{,}21_2$	9,90	5,90	44,75

We can observe, in comparison with the results obtained by the 3DNPRI (refer to Table 4); there are three categories of results:

a. For the classes “Animal” and "Bust" our metric has kept the same ranking given by the metric 3DNPRI for both of the tested methods: Regarding the class “Animal” the second method is ranked first, for the class "Bust" the first method is ranked first.
b. For the class "Furniture", our metric recorded nearly equality between the two methods contrariwise the metric 3DNPRI that considered that the spectral Clustering 1 is the first.
c. For the class "Hand", 3DNPRI recorded equality between the two methods, our metric archived nearly equality.
d. Regarding the class "Human”, our metric has ranked the first method in the first position contrariwise the metric 3DNPRI that considered that the second method is the first.

The table below shows the performance obtained by the 3DNPRI:

Table 4: Performance obtained by the 3DNPRI

Class / Method	Animal	Bust	Furniture	Hand	Human
Spectral clustering 1	0,50	0,15	0,78	0,57	0,51
Spectral clustering 2	0,53	0,14	0,70	0,57	0,58

Considering that our metric is interested in the quality of the segmentation, so our metric is able to detect the segmentations with semantic similarity, achieved nearly the same score of intra-segments inertia for the object "hand4" because both methods have been segmented almost in the same way (refer to Fig. 5).

Note: For the figures below, the Spectral Clustering 1 in the left.

Fig. 5: Intra-segments inertia of the object « hand4 »

Our metric recorded the same score (equal 10,2) of intra-segments inertia for the object "table2" from the class "Furniture" (refer to Fig. 6).

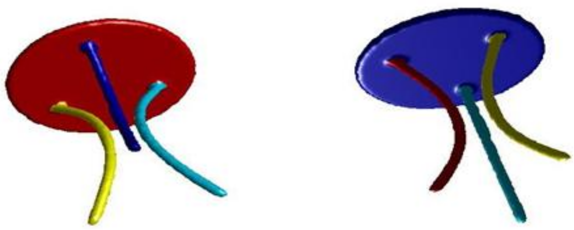

Fig. 6: Segmentation of the object « table2 »

To show the efficiency of our approach, the figure below shows three segmentations of the object "chair1" from the class "Furniture" with their inertia intra-segments scores. The segmentation above is the truth-ground plus two variants of spectral clustering segmentation down below.

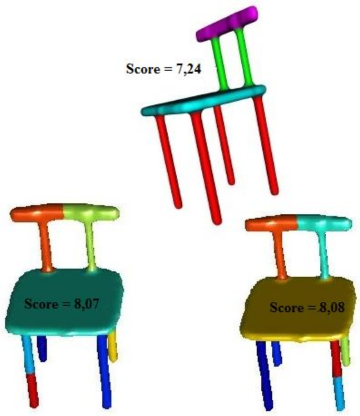

Fig. 7: Inertia intra-segments for three variants of segmentations

The scores of our metric, show its efficiency and its high sensitivity to the homogeneity of the segments that compose a 3D object; we can see that the two segmentations below have very similar scores reflecting very neighboring segmentation logic. Concerning the truth-ground of the object "chair1" the score obtained distinguishes the quality of this segmentation with an excellent uniformity of the segmentation.

For the class "Human", our metric gave the first position to "Spectral Clustering 1", Table 5 present the scores obtained for the objects of this class.

Table 5: Intra-segments Inertia for objects of the class « Human »

Method Object	Spectral clustering 1	Spectral clustering 2
alien	181,0000	187,0000
baby	0,1720	0,1670
boy	9,6900	9,3200
homer	19,3000	19,0000
robot	8,0100	8,2500

The score for the subject "alien" is very large compared to the scores of other objects of the class "Human" , with a difference of “6” between the two methods, this is due to the quality of homogeneity of segments in the segmentation of the object (refer to Fig. 8), where we can find that the chest, arms, forearms and most of the head in the same segment, also for the "Spectral Clustering 2" method we have the hand in the same segment, the last method separated one ear of the "alien" from head.

Fig. 8: Segmentation of the object « alien »

The "Spectral Clustering 1" method separated the left hand of "alien" from the forearm, which participated in the score obtained by this method, because the hand contains much more undulations than the ear, we can conclude that the metric proposed in this work is capable of indicating the heterogeneity of segmentation.

V. CONCLUSION

It is important to evaluate the segmentation methods for several reasons: first we can classify the segmentation methods, distinguish the method that gives the best results, and then analyze the results of the methods to possibly improve it.

The evaluation metric proposed in this work is one of the empirical tools with quality, that judge the quality of segmentations obtained according to a predefined criterion and is interested in the final result of the segmentation. It guarantees an independent quantitative assessment of the individuality of human segmentations that may change from one person to another. The proposed metric is able to recognize and indicate the best segmentation among other segmentations of the same object.

As prospects of this work, we will work on improving the proposed metric so that it can compare segmentations that don’t have the same number of segments.

REFERENCES

[1] H. Zhang, J. E. Fritts, and A. Sally. Goldman, Image segmentation evaluation: A survey of unsupervised methods, *Computer Vision and Image Understanding*, 2008, 110 :260–280.

[2] J-P Vandeborre, Contributions to the research and analysis of 3D models, *Computer Vision and Pattern Recognition*. University of Science and Technology of Lille - Lille I, France, 2012. <tel-00834372>.

[3] D. Martin, C. Fowlkes, D. Tal and J. Malik, A database of human segmented natural images and its application to evaluating algorithms and measuring ecological statistics, *International Conference in Computer Vision 2*, 2001, 416–423.

[4] R. Unnikrishnan, C. Pantofaru, et M. Hebert, Toward objective evaluation of image segmentation algorithms, *IEEE Transaction on pattern analysis and machine intelligence, 29(6)*, 2007, 929–944.

[5] H. Benhabiles, G. Lavoué and J.P. Vandeborre, A new similarity metric for 3D mesh segmentation evaluation using a corpus of truth-ground, *AFIG 22*, Arles (France), 2009.

[6] L. Moumoun, M. Chahhou, M. El Far, T. Gadi and R. Benslimane, Indexing of 3D objects based on partial analogy of segments, Review of Mediterranean Telecommunications (RMT), vol. 2, July 2011, 93-98.

[7] H. Benhabiles, J. P. Vandeborre, G. Lavoué and M. Daoudi, A comparative study of existing metrics for 3D-mesh segmentation evaluation, *Visual Computer International Journal of Computer Graphics, Springer Editions, vol. 26(12)*, December 2010, 1451-1466.

[8] G. Bisson, Catégorisation et textes, *Atelier Applications, Apprentissage et Acquisition de Connaissances à partir de Textes électroniques (A3CTE)*, University Paris1. 28 June 2001.

[9] J. Koenderink et J. V. D. Andrea. Surface shape and curvature scales. *Image and Vision Computing, vol. 10, no. 8*, October 1992, 557-564.

[10] X. Chen and F. Schmitt, Intrinsic surface properties from surface triangulation, *ENT*, Paris (France), (1992).

[11] G. Taubin,. Surface from a Polyhedral Approximation, *the Fifth International Conference on Computer Vision*, 199, 902-907.

[12] D. Chen-shi and W. Guo-zhao, Curvature estimation on triangular mesh. *Journal of Zhejiang University SCIENCE*, 2005, 6A(Suppl. I):128-136.

[13] G. Salton and M. McGill, Introduction to Modern Information Retrieval, *New-York, Mcgraw-Hill*, 1983.

[14] G. GARDARIN, Internet / intranet et bases de données, *Edition Eyrolles*, 1999, 89-90, ISBN 2-212-09069-2.

[15] E. Rajaallah, O. Herouane, L. Moumoun and T. Gadi, 3D Segmentation by spectral clustering using shape index, Journal of Computer Science and Information Technology (American Research Institute for Policy Development), Vol. 02, NO. 3 & 4, December 2014, 15-33.