A Comparative Study of the 3D Quality Metrics: Application to Masking Database

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Abstract. High definition and 3D telemedicine offer a compelling mechanism to achieve a sense of immersion and contribute to an enhanced quality of use. 3D mesh perceptual quality is crucial for many applications. Although there exist some objective metrics for measuring distances between meshes, they do not integrate the characteristics of the human visual system and thus are unable to predict the visual quality.

Keywords: Perceptual quality · Static metrics 3D · 3D meshes · Objective metrics · Quality assessment · 3D triangle mesh · Human visual system · Statistical modeling

1 Introduction

Many applications require a specified level of detail, 3D meshes and 3D optimized models such as in the medical applications that dedicated to surgery. 3D models are widely used including networked 3D games, 3D virtual and immersive worlds and telemedicine 3D information technology to facilitate certain procedures [1]. Telemedicine cover different medical practices, such as viewing or sharing remote data (medical imaging, patient records, etc.) [2, 3]. Telemedicine applies to all areas of medicine, specialized or not [4]. For example Teleconsultation, Tele radiology, and medical hotline (see Fig. 1).

Today, this innovative approach grows and opens new perspectives in the organization of care. It has several advantages: helps develop home care, to improve monitoring of patients and prevent complications, limits the movements (especially for elderly or disabled patients), facilitates access to care in areas of difficult access, and facilitates consultation between general practitioners and specialists.

Furthermore, 3D models are appear as a new media trend, such as 3D screen and 3D devices gaming, these engines open up new perspectives in terms of interaction with the 3D world.

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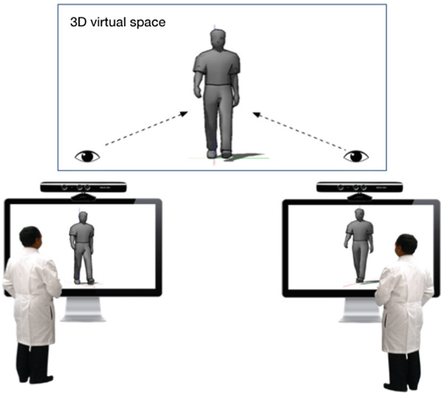

Fig. 1. 3D technology for advanced telemedicine

Many applications required rendering and/or streaming in real time 3D mesh models, these objects are generally composed of a set of vertices, which are, connect to form meshes. This high number of vertices/faces represents the 3D model in a detailed way to increase the visual quality. In addition, 3D applications require a high level-of-detail (LOD) when they process 3D models for optimization and fast rendering. These treatment (Watermarking, simplification or compression) apply on 3D objects requires quality assessments because they cause certain distortion on the 3D models (see Fig. 2).

Fig. 2. Bunny model with two type of distortion (simplification and smoothing)

In the literature, many researchers conducted to extend the 2D objective quality metrics to integrated 3D properties [5, 6]. 3D objects can be viewed from different types of screens.

In addition, these models can be used in different application, which makes the appearance of 3D models dependent properties of the material, texture and lighting used by the application [7, 8].

Moreover, many operations that applied on the 3D model, such as simplification, makes handle changes when they reduce the number of vertices this treatment can delete for example many faces, which represent an important level of details.

In this context, it is important to evaluate the visual quality introduced by the operations performed on the mesh based on the metrics for measuring quality 3D meshes. The current work presents a comparative study between existing approaches for assessing quality assurance. Then their application on a database that contains 26 models distorted with a masking effect.

We introduce our work by describing multiple features approach for assessing quality assurance. The database used for assessment efficiency of measures and experimental results in Sect. 3. Finally, the conclusion represented in Sect. 4.

2 Related Work

2.1 Geometric-Distance-Based Metrics

These metrics based on the calculation of the distance between the two vertices. The simplest estimation of similarity provided by the root mean square Root Mean Square (RMS).

$$RMS(A,B) = \sqrt{\sum_{i=1}^{n} ||ai| - bi||^2} \tag{1}$$

This metric calculates the Euclidean distance between two point A and B, which share the same connectivity ai and bi [9]. Hausdorff Distance (Hd) is the most popular and metric which compare objects with different connectivity. It calculates the similarity between two vertices with the calculation of the distance. The distance between A and B computed as:

$$\begin{aligned} dist(a,B) &= min_{b \in B}(||a-b||) \\ \mathrm{D(A,B)} &= max_{a \in A}(dist(a,\ B)) \end{aligned} \tag{2}$$

If the result is not symmetric, the Hd distance is computed by taking the maximum of the distance between A and B and the distance between B and A. (see Fig. 3).

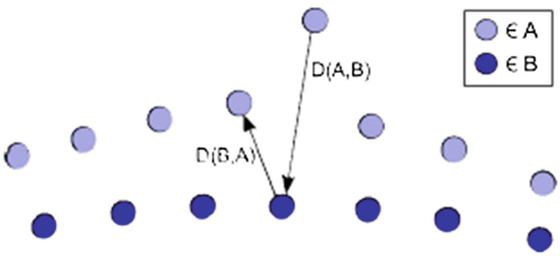

Fig. 3. The Hausdorff distance.

The Hausdorff distance can be defined as:

$$H(A; B) = \max(D(A; B); D(B; A)) \tag{3}$$

These metrics fail to correlate with the human visual system because they compute a geometric distance between two faces [10].

To estimate the perceived quality of 3D objects several metrics was proposed. We can categorize these measurement as roughness-based and structure-based [11]. These metrics integrated different properties of perception to estimate the perceived quality.

2.2 Roughness-Based Metrics

Many metrics developed to measure the quality of 3D shapes by calculate the difference between the original objects and its distorted version based on roughness faces.

These solutions include the properties of the human visual system to calculate the noise related to the roughness or smoothing of the details of a surface.

One of the important perceptual property is the roughness. We can detect the distortion on smooth surfaces easily but it's difficult to determine the distortion on the rough region of the 3D model [12]. This effect related to the masking effect, which can hide some detail (see Fig. 4).

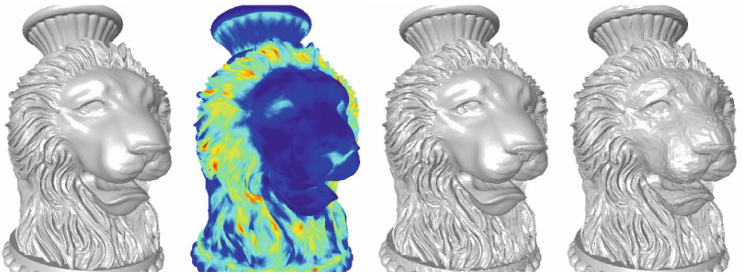

Fig. 4. Roughness map of LION.

Karni propose a new compression approach [13]. To evaluate his roughness-based metrics approach. This metric calculates the geometric laplacian of a vertices v_i.

$$GL(vi) = vi - \frac{\sum_{j \in n(i)} l_{ij}^{-1} vj}{\sum_{j \in n(i)} l_{ij}^{-1}} \tag{4}$$

Where n (i) is the set of neighbors of vertices i, and Lij is the geometric distance between two vertices i and j. The norm of laplician difference between two models M1 and M2 is combined with the norm of the geometric distance between two models where v is the vertices set of M.

$$||M^1 - M^2|| = \frac{1}{2n}\left(||v^1 - v^2|| + ||GL(v^1) - GL(v^2)||\right) \quad (5)$$

This metric has limitation is that the compared models as the RMS approach. Also, Wu and al propose a simplification algorithm to calculate the dihedral angles of the adjacent faces of the 3D models, where they have a greater dihedral angles they find the rough surface [14]. This type of metric have well result with the watermarked models.

Recently, watermarking of 3D objects the attracted attention of researchers owing to the increased diffusion of such objects in several areas of applications, such as in medical, mechanical engineer, design, and entertainment. The 3D Watermarking Perception Metric (3DWPM) is employed to predict the quality of watermarked 3D mesh as perceived by human subjects. Corsini et al. [15] have developed a new quality metric entitled the 3DWPM based on the calculation of the difference in roughness between two 3D meshes. This 3DWPM distance measured between two vertices M1 and M2 are meshes defined by:

$$3DWPM(M_1, M_2) = \log\left(\frac{\rho(M_2) - \rho(M_1)}{\rho(M_1)} + k\right) - \log(k) \quad (6)$$

where, ρ(M1) and ρ(M2) measure the overall roughness of the two meshes, and k is a constant numerical stability. Two variants of 3DWPM were developed using two different roughness descriptors. 3DWPM1 is the first descriptor roughness is inspired by Wu et al. [17]. The roughness value is calculated through the measurement of the dihedral angles between the normal of the facets in a neighborhood. Normal facets on a smooth surface do not strongly vary. However, on textured areas (roughness), normal rough varies more meaningful [18]. A Multi-scale analysis of these entities is considered in [19] to evaluate dihedral angles using the direct vicinity (1 ring) and the extended neighborhood (1 ring, 2 rings, etc.). The second roughness measurement adopted by Corsini et al. for 3DWPM2 is based on estimating the roughness of surfaces [20]. This approach was based on the comparison of a mesh and smoothed version of the same mesh. Smooth regions correspond to small differences, while the rough areas have more significant differences.

The roughness-based metrics correlate very well with the Human visual system when we have a watermarking distortion. Lavoué develop a new approach called local roughness measure. This metric is able to calculate the difference between different parts in a rough or smooth object. His approach based on the curvature analysis of local windows of 3D meshes in depending of the connectivity between faces [21]. This measure provides a local roughness estimation, it can be used to design a future quality metric or hide artifacts.

2.3 Structural Distortion-Based Metrics

The Human visual system is very good at extracting the structural information. Lavoué et al. propose a structural measure (MSDM) [22].

This approach uses the curvature analysis of 3D mesh [23]. It calculates the distortion of 3D mesh by two local windows x and y. Is measured as:

$$LMSDM(x,y) = (\alpha * L(x,y)^a + \beta * C(x,y)^a + \gamma * S(x,y)^a)^{\frac{1}{a}} \tag{7}$$

Where, α, β are defined as 0.4, and 0.2, respectively, L: represent the curvature comparison, C: contrast comparison, and S: structure comparison which are computed as:

$$L(x,y) = \frac{||\mu_x - \mu_y||}{MAX(\mu_x, \mu_y)} \tag{8}$$

$$\mathrm{C}(x,\mathrm{y}) = \frac{||\sigma_\mathrm{x} - \sigma_\mathrm{y}||}{\mathrm{MAX}(\sigma_x, \sigma_y)} \tag{9}$$

$$S(x,y) = \frac{||\sigma_x\sigma_y - \sigma_x\sigma_y||}{\sigma_x\sigma_y} \tag{10}$$

Where μx is the mean, σx is the standard deviation, and σxy is the covariance of the curvature on local windows x and y.

Then the MSDM is measured as:

$$MSDM(x,y) = (\frac{1}{n_w}\sum_{i=1}^{n_w} LMSDM(x_i, y_i)^a)^{\frac{1}{a}} \in [0,1] \tag{11}$$

Where X and Y are the compared meshes, xi and y_i are the corresponding local windows of the meshes, and n_w is the number of local windows. a is selected as 3 by the authors, for Eqs. 7 and 11. This metric correlates very well with the Human visual system [24].

3 Experimental Results and Discussion

For evaluating the performance of an objective metric we need to calculate, the correlation between the objective metric and the mean opinion scores (MOS).

There are two coefficients fluently used: the Pearson linear correlation coefficient (rp) that used to measure the accuracy of the prediction (measures the linear dependence between the objective measurement and subjective scores) and the Spearman rank-order correlation (rs) used to measure the prediction monotony as it measures how the relationship between objective and subjective scores can be described by a monotonic function. In order to evaluate the quality assessment of 3D meshes, we compared existing metrics detailed in Sect. 2 using the LIRIS Masking Database. This database contains 26 models. (4 reference meshes: Armadillo, Bimba, Dyno and Lion, and 24 distorted models). The local noise addition is the only type of distortion applied. The specific objective of this database is to test the capability of mesh visual quality metrics in capturing the visual masking effect. Eleven observers participated in the subjective evaluation. This database was created at the University of Lyon, France. Figure 5 shows some models from the LIRIS Masking Database and their distorted versions.

Fig. 5. LIRIS masking database and their distorted versions. (a) Reference meshes. (b) Distorted meshes with noise addition.

Table 1. Correlation coefficients r_p and r_s (%) of different objective metrics on LIRIS masking database.

Metrics	Models							
	Armadillo		Lion		Bimba		Dyno	
	r_s	r_p	r_s	r_p	r_s	r_p	r_s	r_p
HD	48.6	37.7	71.4	25.1	25.7	7.5	48.6	31.1
RMS	65.6	44.6	71.4	23.8	71.4	21.8	71.4	50.3
3DWPM1	58.0	41.8	20.0	9.7	20.0	8.4	66.7	45.3
3DWPM2	48.6	37.9	38.3	22.0	37.1	14.4	71.4	50.1
GL1	65.7	44.4	37.1	22.4	20.0	19.8	71.4	50.0
GL2	65.7	44.2	20.0	21.6	20.0	18.0	60.0	49.8
MSDM	**88.6**	**72.2**	**94.3**	**78.0**	42.9	33.9	**100.0**	**91.7**
MSDM2	81.1	70.6	91.8	100	95.6	100	93.5	90.3

Regarding the LIRIS masking database (Table 1), MSDM produce the highest score for Dyno model (rs = 100.0%, rp = 91.7%) and also for Lion model (rs = 94.3%, rp = 78.0%), in addition MSDM prove a good results for Armadillo model (rs = 88.6%, rp = 72.2%) and fair scores for Bimba model comparing to the other metrics cited in Table 1. Moreover, we can conclude that MSDM is a good detector of visual masking effect as proven by the results.

Generally, the results obtained in Table 1 prove that the metric based on curvature amplitude provides superior results compared to those based on surface roughness. The comparison results obtained from metrics prove that the MSDM metric is closer to the subjective results because it does not take into account the connectivity constraint between two 3D meshes.

Consequently, the experimental comparative study establishes that the results of the MSDM metric are quite effective and provide noble performance to predict the results of which are well correlated with the subjective scores. However, this metric is still limited due to its needs to an implicit correspondence between the tops of two 3D meshes. Thus, proposing an innovative quality assessment metric using perceptually 3D mesh surface attributes can be considered in the future work.

4 Conclusion

The rise of the use of 3D graphic models highlight the importance of assessing the visual quality of 3D objects. In this context, we can evaluate the visual quality of the 3D models by using subjective measurements or an objective evaluation that done through the metrics. The different treatments applied to 3D models also affect the visual quality of 3D models. Given these distortions, it is necessary to develop objective measures that reflect perceptual quality. The measures that integrate the properties of the human visual system that are possibly the masking effect and the contrast sensitivity function gives good results for the measurement of the perceived quality.

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