Application of the Laplacian smoothing on 3D static models and their evaluation by the new objective quality metric 3DrwPSNR

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Abstract. Interest in 3D modeling has surged in recent years. However, efforts to improve the quality of compression and transmission are severely hampered by a lack of effective quality evaluation metrics. This is a particularly severe problem for researchers trying to improve the robustness of transmission to packet loss. Subjective measurement for evaluating error robustness present huge requirements in terms of time and resources. To solve this problem, this paper presents an objective metric for visual quality assessment of 3D static models. This full-reference metric is based on the relativity of the Human visual system. The performance of the presented approach are evaluated using a dataset of static model smoothed by the 3D Mesh Processing Platform (MEPP). The obtained results show that the proposed metric outperforms the MSDM metric value.

Keywords: Visual Quality Assessment, 3D Static Models, Objective Metric.

1 Introduction

Technological advances in the fields of telecommunications and computer graphics over the past two decades have contributed to the development of a new type of multimedia data: three-dimensional (3D) data. These objects are present due to their massive use in various fields through the development of computer graphics applications. 3D data are generally represented by a 3D mesh. This mesh has different properties and requires a large amount of information to be stored in order to obtain an accurate representation [1]. This requires processing to enable the storage, transmission and visualization of the three-dimensional models. These models are used in various applications such as augmented/virtual reality, video games, telemedicine and cinema. 3D model is a digital representation of an object made by a Computer Aided Design software or an acquisition via a 3D scanner. Different representations are possible for a 3D model after its acquisition such as mesh or point cloud data. The use of the 3D models necessities the application of an optimization processing which generate a specific deformation on the geometry of the shape. For example, to protect the 3D content a watermarking method is needed. In addition, to send 3D data over a low bandwidth network a compression schema is applied. Various processing which are specific to 3D meshes can be used in other situation such as simplification, smoothing, remeshing and subdivision.

Distortions are a critical factor in the development process of an objective metrics in order to evaluate the quality of 3D models. However, conventional measures based on geometric differences such as RMS and Hausdorff distance, used in many software programs do not match well with human visual perception [2]. This perceptual shortcoming has been the subject of the most research in the development of perceptual objective metrics for 3D deformed models.

2 State of the Art

Several method have been developed in order to process the 2D images and 3D data of static or animated 3D models such as the remeshing, watermarking, simplification, smoothing and compression algorithms. These methods are done to optimize the rendering process and data transmission through different types of network [3]. These treatments introduce various modifications on the content of the data (2D images or 3D models). Therefore, they will be misinterpreted during their visualization by the human observer. In this regard, it is essential to study the perceptual quality of 3D data to evaluate the new processing algorithms (compression, watermarking, smoothing, etc.) or transmission techniques [4]. To measure 2D or 3D quality, there are two methods: the first method consists of measurements made by observers (subjective measurements), the second is done through algorithmic processes (objective measurements).

Subjective measurements are rarely used because for each observer the quality may have a different definition according to personal criteria. Also, subjective measures require a precise environment to evaluate correctly the perceptual quality (light, screen, ...) and need time and material resources. While, objective metrics allow to integrate the behavior of the Human Visual System [5] to evaluate the quality of the 3D data, as human observers perceive it.

There are two approaches to measure 2D or 3D visual quality. The top-down approach which considers the SVH as a black box and tries to imitate the behavior of the human visual system. The bottom-up approach, which is based on the simulation and imitation of each component of the human visual system. The majority of existing metrics follow the Top-Down approach to studying the human visual system [6].

In the field of 2D image processing, the objective measures are very developed; among the most known metrics of 2D visual quality are SSIM, SNR and PSNR. These metrics do not adapt to the dynamic characteristics of the image. Indeed, the most visible distortion is found in regions with little texture. The first works on this subject is proposed by Dally with the visible Difference Predictor and Lubin with the Sarnoff Visual discrimination model [7]. These metrics predict the visibility of an artifact in a degraded image by trying to model and reproduce the low-level mechanisms of the human visual system. In 2012 Loukil et al [8] develop the relative weighted PSNR (rwPSNR) which is based on the relative weighted difference of the 2D image information. The rwPSNR metric incorporates two important properties of the human visual system: the contrast sensitivity and the visual relativity modeled by the Contrast Sensitivity Function (CSF function) and weber's law respectively. The rwPSNR gives excellent results in terms of correlation with the human visual system.

In the field of 3D metrics, researchers can use two alternatives: either they use an existing 2D perceptual quality metric (2D image-based metrics) or they develop a 3D model-based metrics that exploit the geometry of 3D models to assess quality [9]. To measure the quality of a 3D model two types of metrics can be used: geometric metrics or HVS metrics.

Geometric metrics are based on the calculation of the Euclidean distances between the vertices of the reference mesh and the mesh to be compared (deformed mesh). The well-known metrics are the RMS that measure a distance between two surfaces in 3D space [10] and the Hausdorff distance (Hd) that measure the geometric distance between two surfaces [11]. Hd distance is defined using the minimum Euclidean distance of a point p between a continuous surface S and another surface S'.

These geometric metrics are based on the mathematical Euclidean distances. However, they do not reflect the correct quality perceived by humans [12]. However, the HVS metrics are based on the calculation of the deformation quantities in 3D deformed model by incorporating the visual properties of the HVS. Among the SVH metrics, we cite the 3DWPM, GL, MSDM, FMPD and DAME.

In 2007 Corsini et al. developed the 3DWPM (3D Watermarking Perception Metric) metric based on the calculation of the distance between two meshes relying on the surface roughness [13]. This approach measures the distance between two meshes $M1$ and $M2$. Karni and Gotsman propose a metric called Geometric Laplacian (GL) based on the roughness of the model. The limitation of this metric is that the compared models must have the same connectivity. To overcame this limitation Sorkine et al proposed a different version of GL1 called GL2 that proposes a small change in the value of α (α = 0.15) [14].

In 2009 Lavoué et al proposed a structural mesh distortion measure (MSDM) [15] that was inspired from the 2D image quality measure SSIM (the Structural Similarity Index) developed by Wang and Al [16]. MSDM is based on the difference of the average curvature amplitudes to measure the perceptual quality between two 3D meshes. In 2011, Lavoué et al improved the MSDM metric by incorporating a multiscale analysis MSDM2 [17]. MSDM and MSDM2 are based only on the curvature magnitude statistics since they take into account the structure of the 3D model.

Wang et al. proposed a reduced reference metric named Fast Mesh Perceptual Distance (FMPD) [18]. It is based on the calculation of global roughness between two 3D models. This approach uses a roughness descriptor derived from the Gaussian curvature. The FMPD metric incorporates a power function to capture the spatial masking effect on the surfaces of the 3D deformed mesh.

Váša and Rus developed a metric named Dihedral Angle Mesh Error (DAME) that measures the perceptual quality of a deformed 3D model [19]. This approach is based on the calculation of the dihedral angle on each pair of neighboring triangles in the processed mesh.

In this paper, a new 3D HVS quality metrics for measuring the degradation of the three-dimensional geometric model is presented. The proposed approach is tested on a corpus, which contain seven 3D models having different geometric properties. The obtained results are summarized and compared with another state of the art metric in the experiments section.

3 Proposed Approach

In order to measure the quantity of a distortion of a 3D deformed model acquired by different means (modeled by a CAD tool or given from 3D scanners). The developed approach represent a full reference metric which measure the quantity of deformation in a 3D deformed model based on its reference version. The proposed approach is largely inspired from the 2D rwPSNR image metric proposed by Loukil et al. [8], which considers that the human visual system is highly sensitive to visual relativity between two pixels. The 2D rwPSNR metric, incorporate the relative difference between the original pixels and the distorted version weighted by the variance of the image gray levels. This approach have a good correlation with the subjective scores [20]. This research work aims to extending this metric in order to evaluate the Laplacian smoothing processing applied on 3D models. In 3D representation, the distortion of a 3D model depends on the visual relativity of the affected area with respect to its original version. In this context, this metric is based on the calculation of the relative weighted differences between the information content of two 3D models in order to measure the perceptual quality of the processed 3D model compared to its reference version. The 3DrwPSNR integrates the visual properties of the HVS to detect the distortions in a 3D deformed model [21]. The main idea of the proposed metric is based on the fact that a distance between two vertices is judged from the relative difference of these positions in the 3D space. To compute the final 3DrwPSNR value, the calculation of the 3D weighted relative root mean square error (3DrwRMSE) between the vertices within the original model and its distorted version is needed. The 3DrwMSE is defined by equation 1:

$$3DrwMSE = \frac{1}{M}\sum_{j=0}^{M-1}\left(\frac{2*\left|\frac{x_j-y_j}{(x_j+y_j)}\right|}{1+var(y_j)}\right)^2 \qquad (1)$$

M represent the number of 3D point. x and y are respectively the point cloud within the 3D original model and the 3D deformed model. The variance $var(y_j)$ represent the variance of the distance between all the vertices of the deformed model. The quotient $2*\left|\frac{x_j-y_j}{(x_j+y_j)}\right|$ mesure the relative difference between the position of a point in the original model and the distorted version. The 3DrwPSNR value is calculated as follows:

$$3DrwPSNR = 10 * log_{10}\frac{dx_{max}^2}{3DrwMSE} \qquad (2)$$

The 3DrwPSNR measures the weighted relative error between an original model x and a degraded model y where dx_{max}^2 is the maximum distance of all vertices within the original model.

4 Experiments

In order to test the effectiveness of the proposed metrics a Laplacian smoothing processing is applied with three different strength on a corpus containing seven 3D models "Bunny, Hand, Head, Skull, Duck, Beethoven, Brain" acquired from different tool. The selected models of the used corpus are chosen considering different properties: mesh topology, number and points, number of faces. The first model "Bunny of Stanford" is composed of 2503 points and 4968 faces with unstructured mesh topology. The second model "Hand" is composed of 41122 points and 41120 faces with structured mesh topology. The third model "Head" is composed of 475 points and 442 faces with semi-structured mesh topology. The fourth model "Skull" is composed of 40062 points and 39288 faces with structured mesh topology. The fifth model "Duck" is composed of 8590 points and 8588 faces with structured mesh topology. The sixth model "Beethoven" is composed of 2655 points and 8588 faces with semi-structured mesh topology. The seventh model "Brain" is composed of 18844 points and 36752 faces with semi-structured mesh topology. The Laplacian smoothing processing is applied on the original version of the corpus models with different Laplacian smoothing strength using the 3D Mesh Processing Platform tool (MEPP).

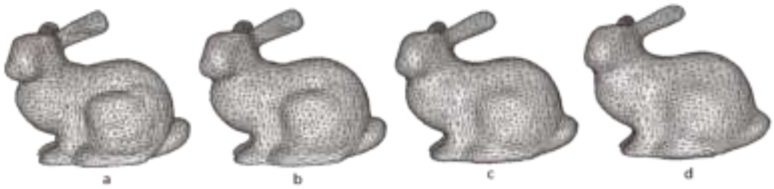

Figure 1: Laplacian smoothing processing applied on the Bunny

Figure 1 present the "Bunny" model respectively, (a) Reference "Bunny" model, (b) "Bunny" model distorted by smoothing strength = 0.10, (c) "Bunny" model distorted by smoothing strength = 0.15, (d) "Bunny" model distorted by smoothing strength = 0.25.

Table 1. The evaluation of the Laplacian smoothing processing on Bunny model.

Model	**Metrics**	**strength = 0.10**	**strength = 0.15**	**strength = 0.25**
Bunny	**3DrwPSNR**	**6.16**	**8.80**	**12.94**
	MSDM	0,33	0,54	0,60

Figure 2: Laplacian smoothing processing applied on the Hand

Figure 2 present the " Hand" model respectively, (a) Reference " Hand" model, (b) "Hand" model distorted by smoothing strength = 0.10, (c) "Hand" model distorted by smoothing strength = 0.30, (d) "Hand" model distorted by smoothing strength = 0.50.

Table 2. The evaluation of the Laplacian smoothing processing on Hand model.

Model	Metrics	strength = 0.10	strength = 0.30	strength = 0.50
Hand	**3DrwPSNR**	**118,23**	**108,85**	**104,56**
	MSDM	0,08	0,12	0,15

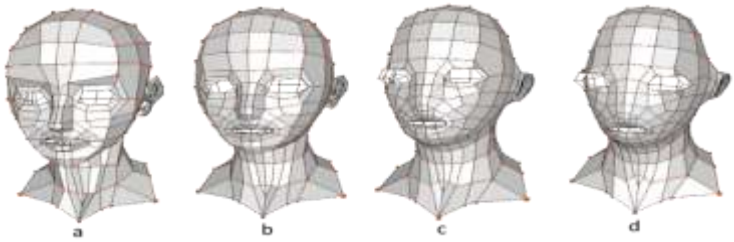

Figure 3: Laplacian smoothing processing applied on the Head

Figure 3 present the "Head" model respectively, (a) Reference "Head" model, (b) "Head" model distorted by smoothing strength = 0.15, (c) "Head" model distorted by smoothing strength = 0.35, (d) "Head" model distorted by smoothing strength = 0.50.

Table 3. The evaluation of the Laplacian smoothing processing on Head model.

Model	Metrics	strength = 0.15	strength = 0.35	strength = 0.50
Head	**3DrwPSNR**	**21.69**	**21.46**	**19,29**
	MSDM	0,49	0,66	0,68

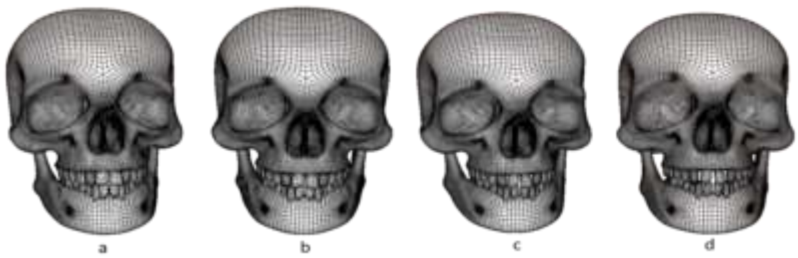

Figure 4: Laplacian smoothing processing applied on the Skull

Figure 4 present the "Skull" model respectively, (a) Reference "Skull" model, (b) "Skull" model distorted by smoothing strength = 0.10, (c) "Skull" model distorted by smoothing strength = 0.30, (d) "Skull" model distorted by smoothing strength = 0.50.

Table 4. The evaluation of the Laplacian smoothing processing on Skull model.

Model	Metrics	strength = 0.10	strength = 0.30	strength = 0.50
Skull	**3DrwPSNR**	**70,56**	**69,75**	**54,21**
	MSDM	0,14	0,26	0,34

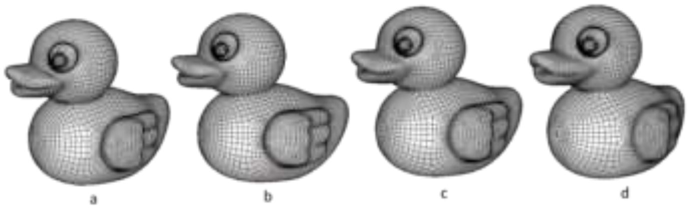

Figure 5: Laplacian smoothing processing applied on the Duck

Figure 5 present the "Duck" model respectively, (a) Reference "Duck" model, (b) "Duck" model distorted by smoothing strength = 0.15, (c) "Duck" model distorted by smoothing strength = 0.20, (d) "Duck" model distorted by smoothing strength = 0.30.

Table 5. The evaluation of the Laplacian smoothing processing on Duck model.

Model	Metrics	strength = 0.15	strength = 0.20	strength = 0.30
Duck	**3DrwPSNR**	**41.06**	**39.21**	**35.55**
	MSDM	0,17	0,32	0,41

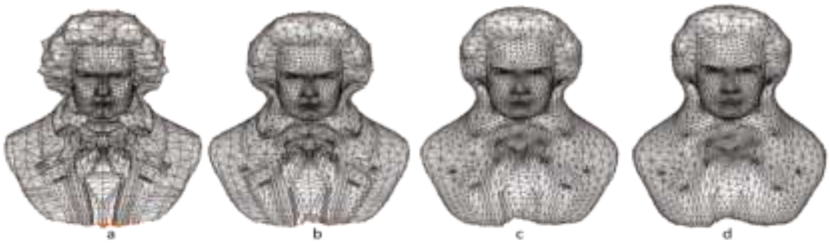

Figure 6: Laplacian smoothing processing applied on the Beethoven

Figure 6 present the "Beethoven" model respectively, (a) Reference " Beethoven" model, (b) "Beethoven" model distorted by smoothing strength = 0.20, (c) " Beethoven" model distorted by smoothing strength = 0.25, (d) "Beethoven" model distorted by smoothing strength = 0.30.

Table 6. The evaluation of the Laplacian smoothing processing on Beethoven model.

Model	Metrics	strength = 0.20	strength = 0.25	strength = 0.30
Beethoven	**3DrwPSNR**	**34.75**	**30.55**	**25.34**
	MSDM	0,47	0,67	0,73

Figure 7: Laplacian smoothing processing applied on the Brain

Figure 7 present the "Brain " model respectively, (a) Reference " Brain" model, (b) "Brain" model distorted by smoothing strength = 0.15, (c) "Brain" model distorted by smoothing strength = 0.25, (d) "Brain" model distorted by smoothing strength = 0.35.

Table 7. The evaluation of the Laplacian smoothing processing on Brain model.

Model	**Metrics**	**strength = 0.15**	**strength = 0.25**	**strength = 0.35**
Brain	**3DrwPSNR**	**28.79**	**17.56**	**13.55**
	MSDM	0,59	0,74	0,77

The above tables (1, 2, 3, 4, 5, 6, and 7) highlights the results of the proposed metrics "3DrwPSNR" on a heterogeneous corpus that contain seven 3D reference model with different properties. In this paper, we have applied the Laplacian smoothing processing with different strength on the whole of the reference model. These results are compared with the value of the HVS metric MSDM. When the smoothing strength increase the quality of the model degrades relatively to the amount of the deformation. The 3DrwPSNR values decrease proportionally as the quality degrades. More the deformation is visible the value of the proposed metric decreases. The obtained results prove that the 3DrwPSNR metric is very efficient to evaluate the visual quality of 3D models after the application of the Laplacian smoothing processing. Regarding the mesh topology of the tested models, the 3DrwPSNR give a good result with the structural or semi-structured mesh such as Hand, Skull, Duck, Beethoven and Brain.

5 Conclusion

Several methods for estimating the visual quality of 3D static models are used by the 3D Processing platform in order to evaluate the 3D processing method. There are two families of 3D metrics: geometric methods and methods that incorporate properties of the human visual system (HVS metrics). These methods are classified into three categories: metrics with reference (full reference), metrics without reference (no reference) and metrics with reduced reference (reduced reference). This paper focuses on a study of some methods for the perceptual quality of 2D images and 3D static models and the evaluation of the Laplacian smoothing processing using proposed perceptual quality metric (3DrwPSNR) which measure the quality of a deformed model taking into account the limitations of the human visual system. In order to evaluate the efficiency of the developed approach, a database which contain seven models with different geometric properties is used. The obtained results are compared with the MSDM metric. The highlited results prove that the 3DrwPSNR is very efficient to mesure the quantity of distortion of a 3D deformed model. In the future work, we will apply other type of processing on this database such as Uniform Noise and Gaussian Noise.

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