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Full-Reference Objective Quality Metric for Three-Dimensional Deformed Models

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Three-dimensional data are generally represented by triangular meshes. The 3D data are used in several fields including remote 3D games, 3D medical application, 3D virtual worlds and 3D augmented reality application. These applications require displaying, printing or exchanging the 3D models through the network to optimize the rendering of the 3D models and 3D applications, which include different treatments, for example, smoothing, compression, remeshing, simplification, watermarking, etc. However, these processes generate distortions that affect the quality of the rendered 3D data. Thus, subjective or objective metrics are required for assessing the visual quality of the deformed models to evaluate the efficiency of the applied algorithms. In this context, we introduce a new perceptual full-reference metric that compare two 3D meshes based on their 3D content information. The proposed metric integrates the relativity and selectivity properties of the Human visual system (HVS) independent of the mesh type and connectivity (e.g. Triangular, Quadrilateral, Tetrahedron, Hexahedron), which represent a limit in the existing method, in order to capture the perceptual quantity of the distortion by the observer. The results of the proposed approach outperform the existing metrics and have a high correlation with the subjective measures. We use the two correlation coefficients

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Spearman Rank (Rs) and Pearson Rank (Rp) in order to assess the performance of the proposed metric.

Keywords: 3D Static meshes; HVS; 3D perceptual metrics; full-reference metrics.

1. Introduction

The measure of the quality after treatment is an important task in order to evaluate the efficiency of processing methods. In 3D applications, the 3D model is represented by a triangular mesh which is exposed to different types of lossy operations that introduce distortions and modifications to the geometry of the original model.[1] Several operations applied on 3D models require quality assessment such as compression,[2] simplification and watermarking.[3] After treatments, it is important to assess how much visual distortion has been introduced into the original model by a particular operation and whether this distortion degrades the quality. Visual distortion is measured subjectively (e.g. by a group of human observers) or objectively (e.g. by an algorithm executed by a computer). The subjective measures are very expensive and require a lot of time and equipment[4] to reduce the evaluation time and facilitate the procedure of the quality assessment. Many research works focus on the development of an objective and automatic measures that correlate well with the subjective measurement.

The visual quality assessment of 3D models with objective metrics is very useful in several fields of application based on 3D modeling such as image reconstruction[5] and 3D medical model processing.[6] In this field, the objective quality metrics are based on the difference between the original and deformed model.

These metrics are classified according to the availability of data:

- Full reference metrics,[7] which are used when the entire reference content is available.
- Reduced reference metrics, which are applied when only a part of the information is available.[8]
- No reference metrics, which are employed when no reference information is available.

In the literature, full reference metrics are the most used to measure the quality of 3D static models.[9] However, these metrics are destined to measure a very specific degradation.

In this context, a new objective metric is proposed in order to evaluate the perceptual quality of 3D deformed models. The proposed metric is classified in the category of “full reference” metrics. The aim of the proposed approach is to measure the quality of a deformed mesh independent to its mesh type (triangular, quadrangular) in order to solve the connectivity constraint between 3D mesh. The proposed metric is based on the relative weighted Peak Signal-to-Noise Ratio (rwPSNR) which is a 2D metric developed by Loukil *et al.*[10] This metric integrates the human visual system (HVS) properties.

To validate the obtained results, the LIRIS/EPFL database is used. This database contains four reference 3D models and 88 3D deformed models that undergo two distortion types: noise and smoothing. These distortions are applied with different strengths and at three different areas: on the whole model, on smooth areas and on rough areas. The results of the proposed method are compared to the existing metrics: RMS, Hd, GL, 3DWPM, MSDM, DAME, FMPD and SMQI.

This paper is organized as follows. In Sec. 1, the visual perception properties are defined. In Sec. 2, the objective quality metrics for 2D image and 3D models are analyzed and discussed. Then, the proposed approach to measure the quality of 3D models is described. Finally, the linear and nonlinear correlation ranks are calculated in order to validate the proposed method. Conclusion and perspectives are mentioned at the end.

2. Visual Perception

The estimation of the 3D model quality by an observer is a very complex task due to the complexity of the HVS. Several treatments can be applied on 3D models,[11] whose purpose is to reduce their sizes in order to archive or to send them via a low bandwidth network,[12] in this case, a compression scheme is applied. Also, for security reasons, watermarking algorithms are applied before sending operation.[13] Other treatment can be applied on 3D models such as re-meshing, subdivision or simplification. These different operations introduce unavoidable perturbations on the 3D model geometry.[14] The aim of the proposed metric is to develop an algorithm that evaluates the visual quality of 3D deformed models as they are seen by the HVS.[15] Several studies on objective quality measurement based on the HVS have been done. These studies analyze the behavior of the HVS and quantify the quality as perceived by the human eyes. However, these approaches are limited to compute the general structure deformation of the 3D model and consider the HVS as a black box. To overcome this problem, a new metric is presented which imitates the properties of the HVS in order to obtain a better correlation value with the subjective evaluation.

3. Perceptual Properties

Human vision is based on two mechanisms: low-level mechanisms which concern the biophysical structure of the sensory system and high-level mechanisms related to the human cognitive system.[16]

Researchers in the field of 3D modeling and computer graphics have been working to define an efficient objective metric that measure the quality of a 3D model after treatment. To develop this objective measure, it is necessary to study and determine the important perceptual properties of the human visual perception.

This task is more complex for 3D models that are represented by triangular or quadrangular meshes. State-of-the-art metrics follow the Top-down approach to study the HVS and imitate its behavior. The objective of these metrics is to maximize the correlation of predicted results with the subjective scores. The subjective evaluation of the visual quality is established and based on the psychometric experiments of the human observers.[17]

3.1. *Visual selectivity*

Visual selectivity is defined by the way that we interpret in a selective manner what we observe, depending on human attitudes. Many researchers in the field of visual perception have demonstrated that perceptual attention is selective. This makes visual selectivity an important property of the HVS.

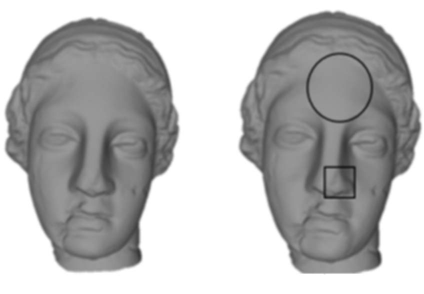
The proposed approach integrates this property through the calculation of the variance of the distances between the 3D model vertices to detect the level of detail of the distorted models. In the 3D field, the distortions generally affect the low frequency (smooth area) and high frequency (rough area). The high-frequency distortions represent the detail areas (contours and pointed area). As a result, distortions in these areas are more visible to the HVS.[18] This phenomenon is related to the visual selectivity of the human eye.

Figure 1 shows that the deformation is more visible in areas that have low variance (Fig. 1 square surface) and less visible in high variance areas (Fig. 1 circular surface). As a result, the low-frequency distortions are less visible than the high-frequency distortions.

3.2. *Visual relativity*

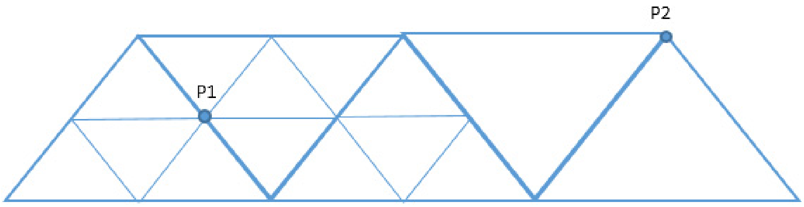
Visual relativity is an important property of psychophysics that describes the relationship between the magnitude of a physical stimulus and its perceived version. This dependence on the sensory system of the human vision is proven to be logarithmic in nature.

Human perception is considered to be a reaction to physical stimuli that follows certain quantitative dependencies, the Weber–Fechner Law (WFL) is among the most important. The WFL provides that in many cases, the perception of the human sensory system depends on the magnitude of the physical stimulus.[10]

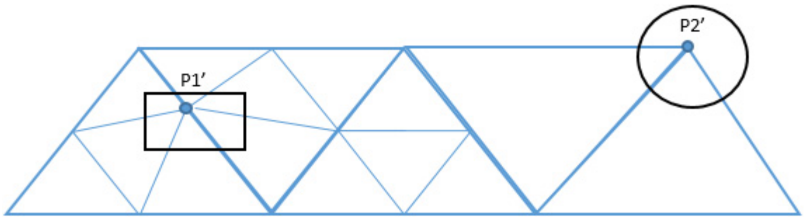


(a) (b)

Fig. 1. Venus model (a) original model, (b) model after distortion.



(a)



(b)

Fig. 2. Example of a same quantitative distortion applied into different vertex (original vertex and its deformed version). (a) represents the original mesh, (b) represents the distorted mesh.

This relationship has been validated experimentally with a wide range of sensory perceptions and is now considered one of the fundamental laws of visual psychology. Several studies are focused on the evaluation of 2D image quality based on the perception of the HVS. In 3D geometry, the difference between the position of an original vertex and its position in the distorted version does not reflect the same visual error of another vertex in the same model with the same difference.

Indeed, the same difference between two positions of the selected vertex with coordinates, respectively, of P1 [0.5, 0.4, 0.3] and P1' [0.7, 0.6, 0.5] (see Fig. 2 the square area) is numerically identical (equal to 0.2) to the difference between a pair of vertices that are in the different position of the original and deformed model P2 [10.5, 10.4, 10.3] and P2' [10.7, 10.6, 10.5] (see Fig. 2 the circle area), this difference is evaluated different by the observer.[19] In the first case, the error is quantified at 30% between P1 [0.5, 0.4, 0.3] and P1' [0.7, 0.6, 0.5]. In the second case, the error is quantifiable at 1% between the two points P2 [10.5, 10.4, 10.3] and P2' [10.7, 10.6, 10.5].

As shown in Fig. 2, the first distortion is more visible to the human eye than the second. In this case, the error is more significant. The developed approach includes the visual relativity property by the calculation of the relative difference based on the Weber–Fechner Law.

4. Related Works

4.1. *Objective 2D quality metrics*

Assessing visual quality is an important process in order to measure the quantity of deformation after a treatment.[20] For assessing 2D image quality, 2D objective metrics are used. These metrics are based on the difference between the original image, and the distorted version.[21]

These metrics are classified according to the following criteria:

- The availability of the original image, that is considered to have an efficient quality.
- The field of application, metrics adapted to specific applications, such as compression, filtering, and watermarking.
- The simulation of the HVS: Using methods that imitate the functionalities of the different components of the HVS (Bottom-up approaches), or method that treat the HVS as a global system, or "black box" (Top-down approaches).

In the field of 2D images assessment, several quality metrics are developed in order to measure the quality of 2D distorted images such as PSNR, WPSNR, rwPSNR.

4.1.1. *Peak signal-to-noise ratio*

The PSNR is a 2D metric that measures the quality of 2D images. The PSNR is calculated by the ratio between the maximum power of a signal and the power of the noise that affects the accuracy of its representation.[22] PSNR is measured in logarithmic decibel scale by

$$\text{PSNR} = 10 * \log_{10} \frac{x_{\max}^2}{\text{MSE}}, \tag{1}$$

where $x_{\max}^2$ represents the maximum value of the original signal. The MSE represents the mean square error between the original and distorted images. The MSE is defined by

$$\text{MSE} = \frac{1}{\text{MN}} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \|x_{(i,j)} - y_{(i,j)}\|^2 \tag{2}$$

where MN is the size of the original image and $x_{(i,j)}$, $y_{(i,j)}$ represent the pixels of the original and distorted image, respectively. This metric is considered as the most used quality assessment criterion in image processing. However, PSNR does not measure visual quality and thus cannot be considered a good objective measure for 2D image quality. Consequently, researchers in this field have suggested developing WPSNR and rwPSNR, that reflect human quality judgment.

4.1.2. *Weighted peak signal-to-noise ratio*

In, Ref. 23, a weighted PSNR metric called WPSNR which integrates the contrast sensitivity function (CSF) by adding the local variance of pixel intensity was introduced. The weighted PSNR distortion for an image is defined as

$$\text{WPSNR} = 10 * \log_{10} \left\{ \frac{(M * N) * x_{\max}^2}{\sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left(\frac{\left| x_{(i,j)} - y_{(i,j)} \right|}{1 + \text{var}(y_{(i,j)})} \right)^2} \right\} \tag{3}$$

where $\mathrm{var}(y_{(i,j)})$ represents the local variance of the pixel (i,j). $x_{(i,j)}$ represents the intensity of pixels in the original image and $y_{(i,j)}$ the pixels in the distorted image. $(M * N)$ is the size of images. This metric has a good correlation result to measure the distortion on the gray-scale 2D images.[24]

4.1.3. *Relative weighted peak signal-to-noise ratio*

The rwPSNR is an extension of the PSNR metric.[10] rwPSNR metric is a relative weighted PSNR that measures the visual quality of 2D images. To compute rwPSNR, a new definition of the MSE noted rwMSE "relative weighted Mean Square Error" which takes into account the variance and the intensity of the image is defined as follows:

$$rw\mathrm{MSE} = \frac{1}{\mathrm{MN}} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left\{ \frac{2 * \left| \frac{(x_{(i,j)} - y_{(i,j)})}{(x_{(i,j)} + y_{(i,j)})} \right|}{1 + \mathrm{var}(y_{(i,j)})} \right\}^2, \tag{4}$$

where $x_{(i,j)}$ and $y_{(i,j)}$ are the original image and the distorted image, respectively. $\mathrm{var}(y_{(i,j)})$ is the local variance of the distorted image. The rwPSNR is computed using the following aspects:

$$rw\mathrm{PSNR} = 10 * \log_{10} \frac{x_{\max}^2}{rw\mathrm{MSE}}. \tag{5}$$

4.2. *Objective quality measures of 3D models*

The estimation of perceptual quality is an important process in assessing the quality of 3D models after treatment. The goal of perceptual quality metrics is to accurately judge the visual quality of a 3D model with respect to human perception.[25]

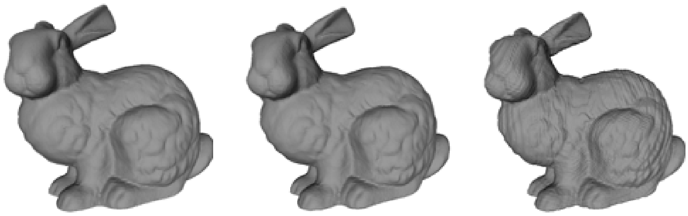
There are two classes of HVS metrics such as Top-down and Bottom-up approaches.

- The top-down metrics consider the HVS as a black box and try to imitate its behavior.
- The bottom-up metrics are based on the simulation and imitation of HVS component.

To evaluate the visual quality of 3D models, two alternatives are defined: the adaptation of existing perceptual quality metrics of 2D images (image-based metrics), or the development of model-based metrics that use the mesh in terms of geometry and connectivity.

To measure a simple error between two 3D meshes, geometric metrics are used such as Root Mean Squared error (RMS) and Hausdorff distance (Hd).[26] However, those metrics have a poor correlation with the human perception.

Figure 3 presents an original model and two watermarked versions, deformed by two different watermarking algorithms. The versions of Bunny model watermarked by the first method have better perceptual quality than the second model



(a) (b) (c)

Fig. 3. Bunny model (a) original mesh size, (b) RMS $= 1.42 * 10^3$, (c) RMS $= 1.42 * 10^3$.

watermarked by the second method. The RMS error provides exactly the same geometric error value for both versions of the deformed models with respect to the reference model. This example shows the limitation of the geometric metrics that are not able to correctly judge the perceived quality of degraded models.

Over the last decade, several perceptual metrics have been developed to improve the correlation of objective measures with subjective measures. In this context, Karni and Gotsman[27] introduced the GL measurement (Geometric Laplacian). This metric measure compares the roughness of surfaces between two 3D models. GL was later on improved by Sorkine *et al.*[28] to the new version called GL2.

Among the Reduced Reference methods, Corsini *et al.*[29] proposed the 3DWPM (3D Watermarking Perception Metric) based on surface roughness. This measure is dedicated to the perceptual evaluation of the static model quality after watermarking process.

Another reduced reference measure is proposed by Wang *et al.*[30] named Fast Mesh Perceptual Distance (FMPD) which is based on the calculation of global roughness between two 3D models. This approach uses a roughness descriptor derived from the Laplacian of Gaussian curvature. The FMPD metric incorporates a power function to capture the spatial masking effect on the mesh surfaces.

Vasa and Skala[31] developed a metric named Dihedral Angle Mesh Error (DAME) that measures the perceptual quality of a deformed 3D model compared to its original version. This approach is based on the calculation of the dihedral angle on each pair of neighboring triangles in the processed mesh.

In 2006, an extension of the SSIM index proposed for 2D images quality assessment is developed by Lavoué called structural distortion metric Mesh Structural Distortion Measure (MSDM).[32] The MSDM metric is based on the computation of the amplitude curvatures of mesh surfaces. In 2011, Lavoué proposed an improvement of MSDM called MSDM2[33] that integrates the multiscale principle. This metric does not take into account the mesh connectivity.

Recently, a full reference metric for measuring the quality of the 3D static model is proposed by Nouri *et al.*[34] called Saliency-based Mesh Quality Index (SMQI). This metric is based on the visual saliency that captures perceptually important regions on which the human visual attention is focalized. This metric is very much used to measure the masking effect which is applied on a 3D static models.[35]

To overcome the problem of the mesh type and connectivity, a new full reference metric based on visual perception is presented. The principal novelties of this paper rely on several key points: (1) A matching operation step is used to check the correspondence between the set of 3D reference and deformed point from the input mesh. (2) A combination of visual relativity and selectivity properties of the HVS for the full-reference quality assessment of 3D static meshes. (3) Performance comparison study of existing 3D metrics based on the Spearman correlation coefficient (Rs) and the Pearson Linear Correlation Coefficient (Rp).

5. Proposed Metric (3DrwPSNR)

To measure the quality of 3D model, three types of metrics can be used: Full-reference metric, half-reference metric and no-reference metric. In this paper, a new full-reference perceptual metric for assessing the visual quality of 3D models is proposed. This metric named "three-dimensional relative weighted Peak Signal-to-Noise Ratio" (3DrwPSNR) integrates human visual properties to capture distortions which are significant for human perception. The proposed metric is largely inspired from the 2D image metric rwPSNR proposed in Ref. 10, who consider that the HVS is very sensitive to the relative weighted difference between two 2D images. The integration of visual relativity produced better results in terms of correlation with the subjective scores. Therefore, this proposed metric is based on calculation of the relative differences between the vertices of the 3D original and distorted models. The measure of visual distortion must depend on visual relativity of vertices in relation to their neighborhoods. Also, the perception of the 3D model deformation depends on its level of detail and the viewing conditions (viewing distance...). Therefore, a simple geometric metric may only be suitable for simple distances, which is a clear limitation of all existing 3D geometric metrics.

The 3DrwPSNR metric is based on the fact that a distance between two vertices is judged from the relative difference of these two positions.

The proposed approach is computed, as shown in Fig. 4. First, a matching operation is defined between each point of the reference mesh and the deformed mesh. Then, the relative distance for each reference point and its distorted version is

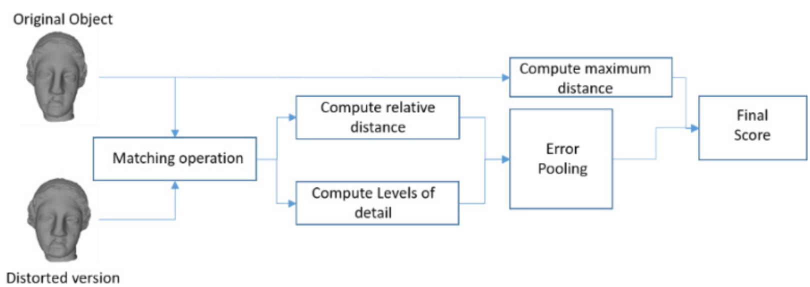


Fig. 4. Block diagram of the proposed perceptual metrics.

measured. In parallel, the level of detail of the 3D model is calculated. Next, the global error using the mean square error formula is measured. Finally, the perceptual distance between the two objects is evaluated using the logarithmic function between the maximum distance and the mean error of distance. In the following section, we present the technical details and the motivation for each step of the proposed metric.

The matching operation phase contains four steps as follows:

Step 1. Orthogonal projection of the input point cloud (deformed mesh) PC_{def} on the point cloud of the reference mesh PC_{ref}.

In order to match the input 3D deformed point cloud (PC_{def}) with the point cloud of the reference mesh (PC_{ref}), a projection step of a 3D point P from the deformed point cloud PC_{def} onto the surface of the input triangle mesh (P_1, P_2, P_3) is required (Fig. 5). This step generates a set of projected points P_{proj}.

The normal N_f of the triangle (P_1,P_2,P_3) is calculated using the following equation:

$$N_f = P_1P_2 \times P_1P_3, \tag{6}$$

where N_f represents the normal of the triangle mesh. $P_i i = 1, 2, 3$ represent the point of the triangle mesh. The angle, α between the normal N_f and PP_{proj} is calculated the following.

The angle, α between the normal N_f and PP_1 is calculated as follows:

$$\cos_\alpha = \frac{PP_1.N_f}{|PP_1||N_f|}. \tag{7}$$

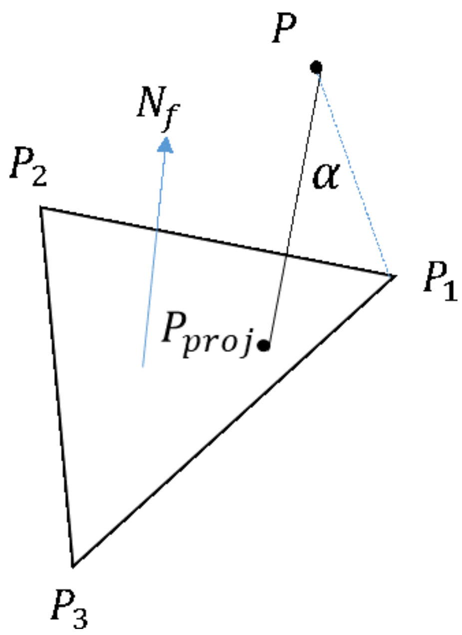


Fig. 5. Projection of the point P on the selected triangle mesh (P_1, P_2, P_3).

The length of the vector PP_{proj} is defined using the following equation:

$$|PP_{\text{proj}}| = |PP_1| \cos \alpha. \tag{8}$$

The vector PP_{proj} is determined as follows:

$$PP_{\text{proj}} = -|PP_{\text{proj}}| \frac{N_f}{|N_f|}. \tag{9}$$

Since the direction of the vector PP_{proj} is opposite to N_f, the negative sign is used. Here P_{proj} is defined by

$$P_{\text{proj}} = P + PP_{\text{proj}}. \tag{10}$$

After the projection step, the corresponding triangle mesh of each projected point P_{proj} is defined.

Step 2. Find the triangle mesh corresponding to the projected point.

In order to find the triangle mesh corresponding to the projected point, P_{proj}, the coordinates of the point P_{proj} are calculated as follows:

$$T\text{Area}P_1P_2P_3 = \frac{\overline{P_1P_2} \times \overline{P_1P_3}}{2}, \tag{11}$$

$$\alpha = \frac{\overline{BP_2} \times \overline{BP_3}}{2T\text{Area}P_1P_2P_3}, \tag{12}$$

$$\beta = \frac{\overline{BP_3} \times \overline{BP_1}}{2T\text{Area}P_1P_2P_3}, \tag{13}$$

$$\gamma = 1 - \alpha - \beta, \tag{14}$$

where α, β and γ are the coordinates of the point P_{proj} in the triangle (P_1, P_2, P_3).

The position of the point B is calculated as follows:

$$B = \alpha P_3 + \beta P_1 + \gamma P_2. \tag{15}$$

Step 3. Check if the projected point P_{proj} is in the triangle.

To check if the projected point P_{proj} is inside the triangle mesh (see Fig. 6), the following restrictions are met:

$$\begin{aligned}
&0 \leq \alpha \leq 1,\\
&0 \leq \beta \leq 1,\\
&0 \leq \gamma \leq 1,\\
&\alpha + \beta + \gamma = 1.
\end{aligned}$$

If α, β, γ are outside those ranges, or if the sum of $\alpha + \beta + \gamma \neq 1$, the point P is not inside the triangle. If one of α, β, γ is 0, and the other two coordinates are between 0 and 1, the point P_{proj} is on the edge of the triangle.

If one of α, β, γ is 1 and the other two are 0, the point P_{proj} is exactly at the point P_i of the triangle.

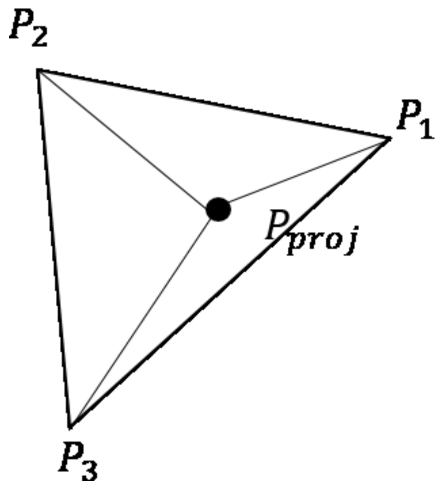


Fig. 6. Coordinates of the point P_{proj} on the selected triangle (P_1, P_2, P_3).

Step 4. Determination of the point $\boldsymbol{P_i}\{\boldsymbol{i} = 1, 2, 3\}$ in the PC_{ref} corresponding to the point P in the PC_{def}

After the matching of the projected point P_{proj} with the selected triangle mesh (P_1, P_2, P_3) is checked, the determination of the nearest point $P_i\{i = 1, 2, 3\}$ to the projected point P_{proj} on the selected triangle mesh (P_1, P_2, P_3) is needed (see Fig. 7). In order to find the corresponding point P_i in PC_{ref} with the projected point P_{proj} that represent the point P of the PC_{def}, The nearest point $P_i\{i = 1, 2, 3\}$ is selected by the calculation of the minimum distance using the following equation:

$$\begin{aligned}&\text{Mindist}(\{P_1P_2P_3\}, P\text{proj})\\&\quad = \min(\sqrt{|P\text{proj} - P_1|_2}, \sqrt{|P\text{proj} - P_2|_2}, \sqrt{|P\text{proj} - P_3|_2}).\end{aligned}$$

To calculate the 3DrwPSNR value for a 3D deformed model, the 3DrwMSE is defined as follows:

$$\text{3DrwMSE} = \frac{1}{M}\sum_{j=0}^{M-1}\left(\frac{2 * \left|\frac{|x_j - y_j|_2}{(x_j + y_j)}\right|}{1 + \text{var}(y_j)}\right)^2, \tag{16}$$

where M is the number of point. x and y are the original and the distorted model, respectively. The $\text{var}(y_j)$ represents the variance between all vertices. The quotient $2 * ||x_j - y_j|_2/(x_j + y_j)|$ represents the relative distance between the two positions of the same vertices in the original and distorted object. The 3DrwPSNR score is calculated as follows:

$$\text{3DrwPSNR} = 10 * \log_{10}\frac{dx_{\max}^2}{\text{3DrwMSE}}. \tag{17}$$

The 3DrwPSNR measures the relative weighted difference between the vertices of the original model X and the deformed model, Y where $dx_{\max}^2$ represents the

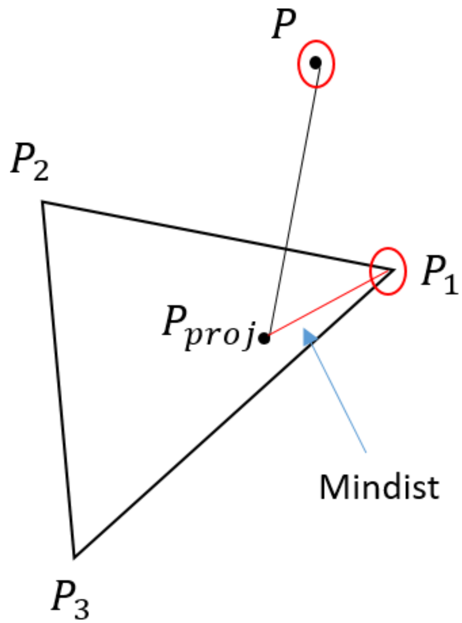


Fig. 7. Determination of the nearest point P_i to the projected point Pproj.

maximum distance between all the vertices of the original model. The results of the 3DrwPSNR are illustrated in following section.

6. Experiments

To measure the performance of an objective metric, it is common to evaluate its correlation with the human judgment (subjective score). In the literature, researchers use two correlation coefficients for calculating the correlation between the objective measures and the subjective measures: Pearson linear correlation (Rp) and Spearman nonlinear correlation (Rs). The linear correlation (Rp) evaluates the degree of linear dependence between the objective measures established by the objective metric and the subjective scores. The nonlinear correlation (Rs) compares the ranks of subjective scores with the objective results of the perceptual quality measures.

To validate the results of the 3DrwPSNR metric, the LIRIS/EPFL General-Purpose database, which has been widely selected for testing the 3D quality metrics performance, is used. This database contains 88 models (Table 1), generated from four reference models (Armadillo, Dinosaur, Venus, and RockerArm).[32] Two types of distortion (noise addition and smoothing) are applied to this database with different strength in four areas: uniformly (over the whole object), smooth regions, rough regions, and intermediate regions.

Table 1. LIRIS/EPFL general-purpose database description.

	Reference model	Deformed model	Noise degradation	Smooth degradation	Vertices number
Armadillo	1	21	12	9	40 002
Dinosaur	1	21	12	9	42 146
Venus	1	21	12	9	49 666
RockerARM	1	21	12	9	40 177

These distortions are intended to simulate the artifacts produced by conventional geometric processing operations (smoothing, compression, watermarking, filtering, etc.).

Twelve observers participated in the subjective measures; they were asked to provide a score reflecting the perceived level of quality between 0 (identical to the original) and 10 (the worst case). The Mean Opinion Score (MOS) obtained is used to evaluate the performance of the 3DrwPSNR metric.

The 12 subjects were selected from a pool of students from the Swiss Federal Institute of Technology (Lausanne, Switzerland) and from the University Claude Bernard of Lyon (France). They viewed the 3D models from comfortable sitting distances, and interaction was allowed (rotation, scaling, translation). The subjective evaluation takes on average 20 s per model (for 88 models, it can take 30 min)[3] otherwise the proposed approach takes at least 6 s for assessing the visual quality of the 3D input deformed model (For 88 models its take 8 min).

In this regard, the use of the 3D objective measure saves 70% of time compared to the subjective evaluation which require a preparing time for the establishment of the evaluation conditions such as the evaluation room, the lighting and the screen setting.

Among the objective measures, there are some metrics which are based on the mathematic measurement such as RMS and Hd. These metrics fail to predict the perceptual quality of a 3D deformed model because they don't integrate the visual perception properties. Geometric metrics have a low correlation with the subjective scores comparing to the HVS metrics (MSDM, 3DWPM, DAME, FMPD, SMQI) which have a high correlation with the subjective measures (Table 2) and this is due to the integration of the different properties of the HVS.

The proposed metric 3DrwPSNR presents a good Pearson and Spearman correlations over the whole objects of this database, with $\mathrm{Rs} = 85,6\%$ compared to other existing metrics. We note that this metric gives more importance to the regions where noise is more visible. This is due to the integration of the perceptual properties of the HVS. The 3DrwPSNR outperform existing metrics with the highest score for Armadillo model with $\mathrm{Rp} = 79,9\%$ and Dinosaur model with ($\mathrm{Rs} = 87,5\%$, $\mathrm{Rp} = 89,0\%$). For Venus and RockerArm, the 3DrwPSNR presents a good correlation value comparing to the SMQI metric. The 3DrwPSNR metric is the second metric which produce a good results on the Whole LIRIS/EPFL General-purpose database.

The proposed metric 3DrwPSNR provides competitive results compared to metrics that are based on surface roughness. The results obtained in Table 2 prove that the 3DrwPSNR metric is closer to the subjective results.

Table 2. Spearman (Rs) and Pearson (Rp) correlation values (%) between MOS and metrics values for the LIRIS/EPFL general-purpose database.

	Armadillo		Dinosaur		Venus		RockerArm		Whole Corpus	
	Rs	Rp	Rs	Rp	Rs	Rp	Rs	Rp	Rs	Rp
Hd	69.5	30.2	30.9	22.6	1.6	0.8	18.1	5.5	13.8	1.3
RMS	62.7	32.2	0.3	0	90.1	77.3	7.3	3.0	26.8	7.9
GL1	70.2	43.7	15.5	3.2	92	80.2	14.2	8.4	33.1	12.6
GL2	77.8	55.5	30.6	12.5	91.0	77.6	29.0	17.1	39.3	18.0
3DWPM1	65.8	35.7	62.7	35.7	71.6	46.6	87.5	53.2	69.3	38.3
3DWPM2	74.1	43.1	52.4	19.9	34.8	16.4	37.8	29.9	49.0	24.6
FMPD	75.4	83.2	89.6	88.9	87.5	83.9	88.8	84.7	81.9	83.5
MSDM	84.8	70	73	56.8	87.6	72.3	89.8	75	73.9	56.4
MSDM 2	81.6	72.8	85.9	73.5	89.3	76.5	89.6	76.1	80.4	66.2
DAME	60.3	76.3	92.8	88.9	91.0	83.9	85.0	80.1	76.6	75.2
SMQI	77.5	74.3	84.8	80.3	91.6	90.0	91.8	92.6	84.6	84.3
3DrwPSNR	80.2	**79.9**	**87.5**	**89.0**	85.0	77.4	89.8	86.8	**85.6**	70.3

Table 3. Spearman and Pearson correlation between subjective score and objective value for the LIRIS/EPFL General-purpose database per distortion type.

	Armadillo		Dinosaur		Venus		RockerArm		
	Rs	Rp	Rs	Rp	Rs	Rp	Rs	Rp	
Hd	Noise	76.8	48.8	83.4	73.9	76.9	61.2	84.6	84.2
	Smooth	70.3	29	56.3	18.2	79.9	51.2	63.0	40.7
RMS	Noise	89.6	84.4	93.4	86.8	**89.6**	87.3	95.6	94.7
	Smooth	69.7	50.7	72.1	26.9	**89.1**	68.8	83.0	75.3
3DWPM2	Noise	89.0	73.6	90.9	59.0	80.2	58.4	**96.8**	**95.6**
	Smooth	64.4	30.3	48.0	11.0	87.9	70.5	75.4	44.1
MSDM	Noise	84.1	72.8	90.1	79.9	85.2	77.4	75.8	70.6
	Smooth	**78.2**	51.6	67.3	24.1	86.7	62.3	**91.5**	80.9
3DrwPSNR	Noise	**91.3**	**91.3**	**94.2**	**91.1**	87.3	**92.3**	93.8	91.05
	Smooth	69.7	**68.4**	**76.6**	**64.9**	87.5	85.7	**85.7**	**83.3**

In Table 3, we have presented the Spearman and Pearson ranks between subjective scores and the objective values of the state-of-the-art metrics for the LIRIS/EPFL General-purpose database per distortion. We have classified this database on two classes of distortion (Noise and smooth). These values are calculated on 21 distorted models contains 9 smoothed versions and 12 noisy versions; taken into account the original model. When considering the results per model and per distortion type, we conclude that each metric leads to quite the best correlation, whatever the on all the database model. When considering only smooth distortion, the linear correlation (Rp) shows that the proposed approach outperforms the other metrics regarding all object from the general purpose database with Armadillo $\mathrm{Rp} = 68.4\%$, Venus $\mathrm{Rp} = 68.1\%$, Dinosaur $\mathrm{Rp} = 85.7\%$ and RockerArm with $\mathrm{Rp} = 83.3\%$. Hence, the nonlinear correlation (Rp) values of 3DrwPSNR are competitive regarding other metrics.

When considering the noise distortion, the proposed metric provides a high Pearson correlation values with Armadillo Rp = 91.3%, Venus Rp = 92.3%, Dinosaur Rp = 91.1% and RockerArm with Rp = 91.05% compared with the other metrics.

Although 3DrwPSNR provides a good Spearman rank results with Armadillo Rs = 91.3% and Dinosaur Rs = 94.2%.

7. Conclusion

In this paper, a new full reference objective metric is proposed in order to measure the visual quality of static 3D models. The developed method integrates the principle of visual relativity and visual selectivity. The major limitation of the state-of-the-art metrics is the connectivity constraint between two meshes. To solve this problem, the proposed approach measures the relative distance independently of vertex connectivity. Therefore, a matching operation between the 3D points of the reference model and its distorted version is implemented to ensure a better correspondence. Experimental results show that the objective metrics that integrate the HVS have a better correlation with subjective scores, and this is proven by the results of linear and nonlinear correlation applied to the LIRIS/EPFL General-Purpose database.

In the future work, we opt to apply 3DrwPSNR to other database which have other distortion types such as compression, watermarking. Also, we aim to integrate the masking effect which presents a perceptual factor for the quality evaluation of the 3D deformed models.

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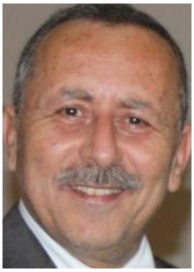

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