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Perceptual Metrics Quality:
Comparative Study for 3D Static Meshes

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ABSTRACT

A 3D mesh can be subjected to different types of operations, such as compression, watermarking etc. Such processes lead to geometric distortions compared to the original version. In this context, quantifying the resultant modifications to the original mesh and evaluating the perceptual quality of degraded meshes become a critical issue. The perceptual 3D meshes quality is central in several applications to preserve the visual appearance of these treatments. The used metrics results have to be well correlated to the visual perception of humans. Although there are objective metrics, they do not allow the prediction of the perceptual quality, and do not include the human visual system properties. In the current work, a comparative study between the perceptual quality assessment metrics for 3D meshes was conducted. The experimental study on subjective database published by LIRIS / EPFL was used to test and to validate the results of six metrics. The results established that the Mesh Structural Distortion Measure metric achieved superior results compared to the other metrics.

KEYWORDS

3D Meshes, 3D Triangle Mesh, Human Visual System, Objective Metrics, Perceptual Quality, Quality Assessment, Static Metrics 3D, Statistical Modeling

1. INTRODUCTION

With technological advances in telecommunication, hardware design and multimedia, the use of 3D data is now well established in several industrial domains, like digital entertainment, scientific visualization, computer-aided design, architecture and many others (Rindos, Vouk, Jararweh, 2014; Gupta & Garg, 2015).

The 3D content is mostly represented by polygonal meshes, or sequences of polygonal meshes (i.e. dynamic meshes), which may be associated with colour information or texture maps. For its transmission, protection, visualization or manipulation (Chowdhuri, Chakraborty, Dey, Azar, Megeed Salem, Chaudhury & Banerjee 2014; Chowdhuri, Roy, Goswami, Azar, Dey, 2014), this 3D content is subject to a wide variety of processing operations such as compression, filtering, simplification, watermarking and so forth. These operations introduce distortions which may alter the visual quality of the 3D content; this is a critical issue, as these processing operations are often targeted at human-centered applications with viewing as the intended use.

The three-dimensional (3D) computer graphics technologies are widely used in numerous applications on the market including the medical domain, 3D gaming network, 3D virtual world in

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immersive and 3D visualization applications (Cooperstock, 2011). Furthermore, emerging products, such as the 3D televisions and 3D gaming devices open new avenues possibility for an improved user experience during the interaction with 3D environments (Abderrahim & Jeder & Bouhlel, 2013). Thus, the 3D models are becoming a popular new form of media (Daly & Brutzman, 2007).

In several application domains, 3D mesh data are conventional for digital entertainment, scientific visualization, and cultural heritage. The ability for 3D mesh visualization has been developed from desktops to mobile (Chowdhuri & Chakraborty & Dey & Azar & Abdel-Megeed & Salem & Chaudhury & Banerjee, 2014) devices as well as the web content. The 3D mesh models are usually composed of a large number of connected vertices and faces to be rendered and/or to be real-time streamed (Salehpour & Behrad, 2012). The massive number of vertices/faces provides more detailed representation of a model, which increases the visual quality. However, this causes a loss in performance due to the increased calculations. Therefore, a compromise between the visual quality graphic models and the processing time is compulsory.

In addition, an extensive range of 3D mesh processes are obliged, such as simplification, transmission, filtering, compression (Abderrahim & Techini & Bouhlel, 2013) and watermarking (Masmoudi & Bouhlel & Puech, 2012). Such processes inevitably lead distortions that alter the visual rendered data quality. This requires the measurement of the 3D graphics content quality. Assessment metrics for the 3D Mesh Visual Quality (MVQ) were comprehensively deliberated for accurately evaluates the perceptual impacts of the distortions to predict the distorted 3D data visual quality compared to the original data (El-Bendary & El-Tokhy & Shawki & Abd-El-Samie, 2012).

Consequently, several metrics for predicting the adverse effects of the visual artifacts were developed. Such metrics are based on Laplacian coordinates, types of curvature computation, geometric attributes, and conventional geometric distance. For example, the 3D models transmission of network-based applications Figure 1 (Gupta & Thakur & Garg & Garg, 2016; Cardoso & Pedrinaci & Leidig & Rupino & Leenheer, 2013) requires accurate compression that compromise between visual quality and transmission speed (Cheng & Basu, 2007).

Many applications require specified level of detail, 3D meshes and 3D optimized models such as in the medical (Ryan & Tormey & Share, 2014) applications that dedicated to surgery (El-Bendary & El-Tokhy & Kazemian, 2012; Aribi & Khalfallah & Bouhlel & Elkadri, 2012).

Figure 1. 3D model transmission through the network

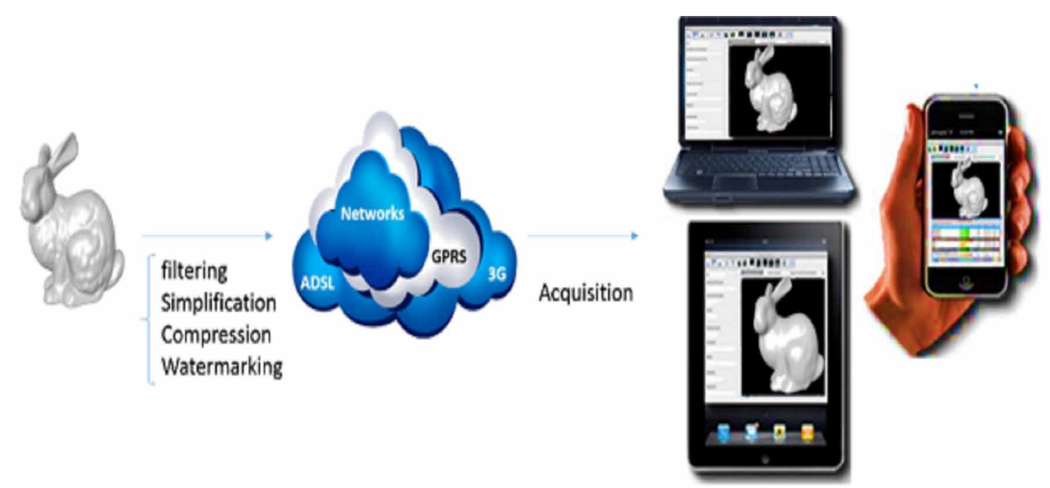
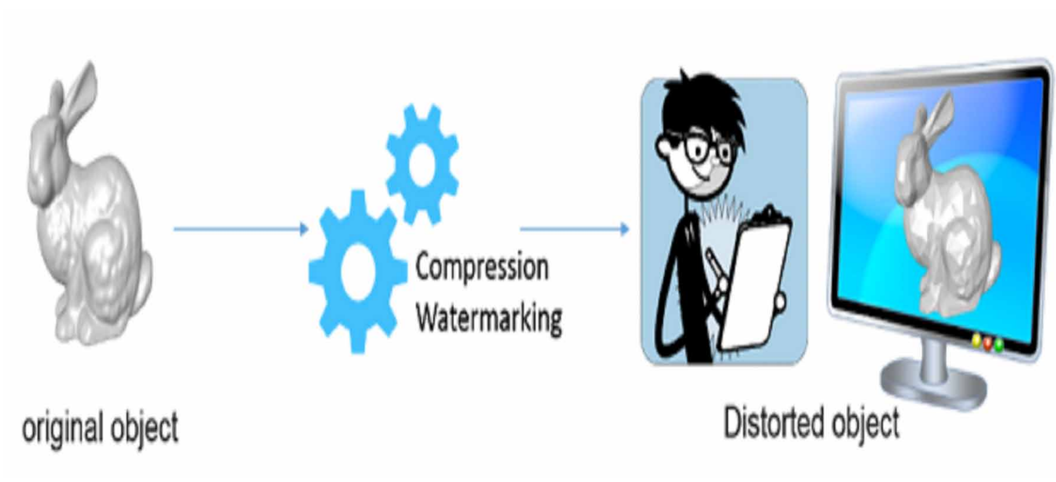


Figure 2. Quality of the received object distortion



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 introduced multiple features metric with a comparative study between the perceptual quality assessment metrics 3D meshes.

The remaining sections organization is as follows. Section 2 reports related work to the 3D mesh metrics. Section 3 highlights the six perceptual quality metrics under concern. The database used for the metrics efficiency evaluation is introduced in Section 4. In Section 5, the experimental results are illustrated. Finally, the conclusion of the current work is represented in Section 6.

2. RELATED WORK

Research and development efforts on 3D technologies have increased significantly in recently to cover the entire capture process line to the display. Today, many experts predict that imminent media applications will based on the 3D, such as in the television and the Internet to improve the objects quality for the final user. To date, there is no single acquisition process for the 3D data. Thus, the different treatment systems are based on different representations of the 3D scene that integrate different types of data. Several studies have been devoted to filtering, simplification, watermarking and compression of images and video including 3D stereo and multi-view or geometric data in 3D static or animated meshes (Abderrahim & Techini & Bouhlel, 2013).

As illustrated in Figure 2, it is significant to note that the screens (computers, televisions) play a central role in the 3D technology adoption (Triki & Kallel & Bouhlel, 2012).

This necessitates distortion less transmission to avoid rejection by the end users due to poor quality of visual fatigue. In this context, several studies have been devoted to the definition of subjective paradigms and objective measures to assess the visual quality of distorted objects. Perceptual factors have an imperative role on computer graphics research that affects the quality performance.

Typically, the 3D models MVQ metrics are inherited from IQA (Image Quality Assessment) metrics. The IQA metrics depend on the peak signal-to-noise ratio (PSNR), pixel-to-pixel differences of the luminance attributes, Structural Similarity Index (SSIM), and the Root mean square error (RMSE). Furthermore, the more complex metrics rely on the human visual system features including the multi-channel decomposition, contrast sensitivity function, contrast/luminance masking. Generally, several 3D mesh quality evaluation metrics deliberate directly the 2D (Abdmouleh & Khalfallah & Bouhlel, 2012) image metrics (Namara & Mania & Banks & Healey, 2010). Limb (Limb, 1979) concerned with fitting an objective measure to closely estimate the deficiency ratings on five test images.

However, the 3D objects quality may not be properly calculated based on the 2D quality metrics as perceived in (Rogowitz & Rushmeier, 2001) owing to the additional depth perception.

Karni and Gotsman combined the geometric distance root-mean-square (RMS) of the vertices with the RMS of corresponding vertices Laplacian coordinates. Pan et al. (Yixin & Cheng & Basu, 2005) used the crucial factors determining the display quality, namely the texture resolution and wireframe resolution to model a perceptual metric. Statistical data from a 3D quality were collected to assess the metric using evaluation experiment. The proposed quantitative method proved its efficiency to closely fit to the subjective ratings by human observers. Other studies use structure-based approaches to evaluate the mesh visual quality. In his work Lavoué proposed a metric called mesh structural distortion measure (MSDM). This metric applied on the curvature analysis of the mesh geometry. First a local structural distortion measure is calculated based on three functions: curvature, contrast and structure comparison. Then the MSDM is calculated using the local structural distortion measure. After that, Lavoué proposed another metric called MSDM2 in order to improve MSDM and overcome some limitations of the MSDM. In fact, the MSDM2 computes a fast projection and curvature interpolation, while MSDM needs an implicit correspondence between vertices. Moreover, the MSDM2 is multi-scale and symmetric. The visual distortion measure is calculated as follow: first, the local roughness is defined in each vertex of the original mesh and the distorted mesh as well. Then a fast matching is applied, after that the metric compute the local distortion measure resulting in the global distortion score.

3. PERCEPTUAL QUALITY METRICS

3.1. The Perceptual Quality 3D Meshes

It is essential to study the perceptual quality of visual data in order to notify new algorithms of compression, watermarking or transmission techniques.

For measuring the quality of digital images, there are both methods: the first method consists in measurements made by observers (subjective measures), the second uses or algorithmic processes (objective measures).

In subjective measures, for each observer, quality can have a different definition of personal criteria. However, the objective metrics permit to analyze the behavior of the Human Visual System (Hemanth, Balas, &Anitha, 2014) and quantify the quality as perceived by observers (El-Bendary, El-Tokhy, Shawki, & Abd-El-Samie, 2012). In fact, the HVS is based on two mechanisms which we must exploit in the development of metrics: low-level mechanisms that affect the biophysical structure of the sensory system and high-level mechanisms related to human cognitive system.

3.2. Objective Measures of Quality Meshes

To ensure proper assessment of the visual quality of the mesh after the treatment, it is necessary to estimate its visual quality. The mean of the perceptual quality metrics is to judge the quality of a mesh based on human perception characteristics (Escribano-Barreno, & García-Muñoz, 2016).

For this purpose, we find different approaches such as the top-down approach which considers the HVS as a black box and tries to imitate the behavior of the system from the perspective of inputs / outputs and the bottom-up approach which is based on simulation and imitation of each component of HVS.

In fact, to develop a 3D metrics (Triki, Kallel, &Bouhlel, 2012), researchers can follow two alternatives: on the one hand they can use existing metrics of perceptual quality 2D images (Nandi, Ashour, Chakraborty, &Dey, 2015 ; Cho, Prost, & Jung, 2007 ; Wang, Lavoué, &Baskurt, 2011) on two-dimensional projections of 3D meshes (metric- based images and videos), on the other hand they can use develop metrics based-models that exploit the term mesh geometry and connectivity signal to evaluate the quality (Abderrahim, Techini, & Bouhlel, 2013).

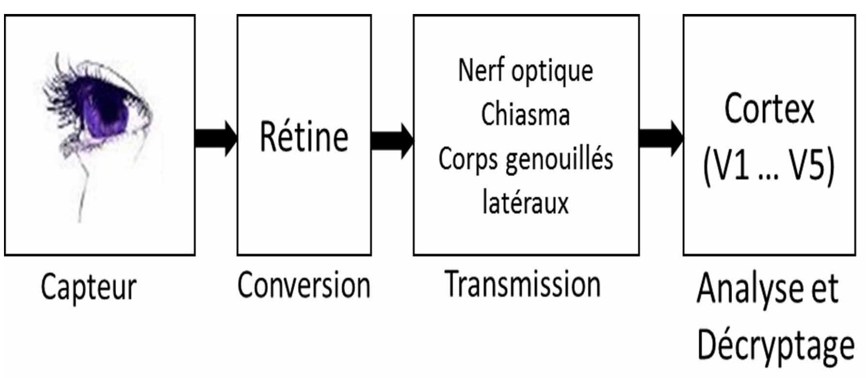
We can find other classification of the quality metrics in order to qualify the 3D meshes, in fact we find:

- **Metrics "Full – Reference":** which is generic, the original model is available in full, in this case we will try to quantify the existing difference between the original image and the degraded version.
- **Metrics to "Reduced Reference":** The original image is available in its entirety, but is represented by a vector containing a reduced set of attributes. In this case, this type of metric predicts the perceptual quality of distorted images with only partial information about the reference images. This method is useful in a number of applications such as in real-time visual communication systems.
- **Metrics "No–Reference":** In many situations, the original un-distorted 3D meshes might not exist or be very hard to obtain. On the other hand, it is very easy for human observers to assess image quality without using any reference image. In recent years, the No-reference 3D meshes quality assessment has attracted the attention of more and more researchers. Due to the limited understanding of HVS, most, if not all, of the existing No-reference assessment algorithms focus on distortion measurement, in which the quality metric is described by the extent to which the image has probably been distorted. No matter whether explicitly or implicitly, the general flow of these algorithms can be summarized as follows: first we find some discriminative local feature; second we use local feature to model local distortion metric; also to get an overall distortion metric we do the average local distortion metric over the whole image, finally, we use the overall distortion metric to predict image quality score which is consistent with human perception. Finding suitable local feature and modeling the local distortion metric are two key steps within the whole algorithm.

3.3. The Human Visual System

Over the last 30 years, there have been many efforts to design objective image distortion models by taking advantage of the human visual system (HVS) features. Vision Researchers have gained considerable insight into the operation of the HVS which is a complex sensory system and not yet fully mastered. Nevertheless, it may be considered an information transcription system turned into usable data by the brain Figure 3. The primary visual cortex (area V1) is the cortical area which receives most of the visual signals from the retina (Abderrahim, Techini, & Bouhlel, 2013). Its neurons are arranged in channels, which are known to be locally responsive in space, frequency, and orientation. A part from V1, over 20 other cortical areas have been discovered. These areas are likely to be involved in higher level processing of visual data.

Figure 3. Human Visual System: simplified



A conversion step can capture the received information and decoded into signals by the brain.

It is the role of the eye that converts light energy into sensory signals and then transmits them to the visual cortex via the optic nerves and geniculate nucleus. The visual cortex decrypts and processes the information. To better understand the flow of information and operation of the HVS, we recall the essential elements that are involved in the process of gathering and processing of visual in-formation (Capture, conversion, transmission and processing of information). In fact, the eye which is an optical system whose primary role is to converge the light signals to the conversion zone and transmit the decoded form in the brain. It comprises several important elements including the cornea which focus to the light rays received to the retina (Shnayderman, Gusev, & Eskicioglu, 2004). Then, the iris which adapts the light intensity by varying its opening. In addition, the crystalline which allows to redirect the light flow to the retina where it's arranged into photoreceptor cells (Cones and rods). Moreover, the retina converts the light signal captured by the receiving photocells into electrical signals which are then transmitted to the visual cortex via the optic nerve. Finally, the optic nerve transports information from the retina to the visual cortex, through the chiasm and lateral geniculation body. The direction Information goes through from the right eye and the left eye, chiasm's role is to transmit the information received to the lateral geniculation body. The major role of the visual cortex is the decrypting (or decoding) and the analyzing of the received signals.

3.4. The Human Visual System and the Perception of Visual Quality

Some of the most important properties which we need to consider when developing a HVS based quality model include are the sensitivity to contrast changes rather than luminance changes (approximated by Weber's Law at photopic light levels), the varying sensitivity to stimulus at different spatial frequencies. This can be modeled by the Contrast Sensitivity Function (CSF), which estimates the visibility threshold for stimulus at different spatial frequencies. However, the shape and threshold of the CSF is dependent up on the type of stimulus used. This function can be viewed as a band pass filter with a frequency response reaching the highest value at about 4 cycles per degree of visual angle and decreasing very fast with increasing spatial frequency. Besides the masking, which refers to our reduced ability to detect a stimulus on a spatially or temporally complex background is an important property of our HVS. Thus errors are less visible along strong edges, in textured areas, or immediately following a scene change. The amount of masking caused by a background depends not only on the background's contrast, but also on the level of uncertainty created by the background. Areas of high uncertainty induce higher masking than areas of the same contrast with lower uncertainty. The higher level perceptual factors, such as attention, eye movements and our different objection ability to different types of coding artifact must be considered to develop a HVS metric quality, because we only possess high visual acuity over a small area of viewing (the fovea), and our acuity drops or rapidly in the periphery. Some areas of images are also more important to us (e.g. eyes, lips in videophone scene), and distortions in these important regions are more objectionable than distortions in background regions.

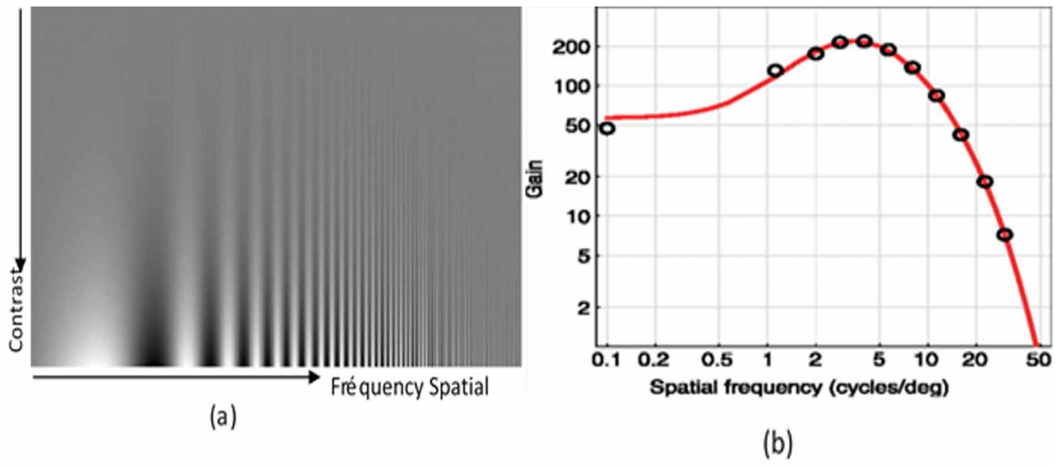
Most of the existing metrics follow the approach Top – Down to study the human visual system and imitate its behavior.

The existing metrics has for objective to maximize the correlation of the results (profits) of prediction with the subjective scores. The subjective evaluation of the meshing quality is established by means of observers through psychometric experiments. Many databases were developed to have measures of the real structure of the 3D meshes perceptual quality. There are two important properties of the HVS that we have to consider in order to measure the perceptual quality of the 3D meshing (Hirai, Tsumura, Nakaguchi, Miyake, & Tominaga, 2010).

3.4.1. Contrast Sensitivity Function

The spatial frequency sensitivity of the HVS is simulated by a wavelet contrast sensitivity function (CSF) derived from Daly's CSF. This function estimates the visibility threshold for stimulus at

Figure 4. The spectral properties of the HVS: (a) - Graph illustrating Campbell- Robson con-trast sensitivity (CSF), (b) - curve of HVS sensitivity as a function of spatial Frequency



different spatial frequencies. However, the shape and threshold of the CSF is dependent upon the type of stimulus used (Ninassi, Meur, Le Callet, & Barba, 2008).

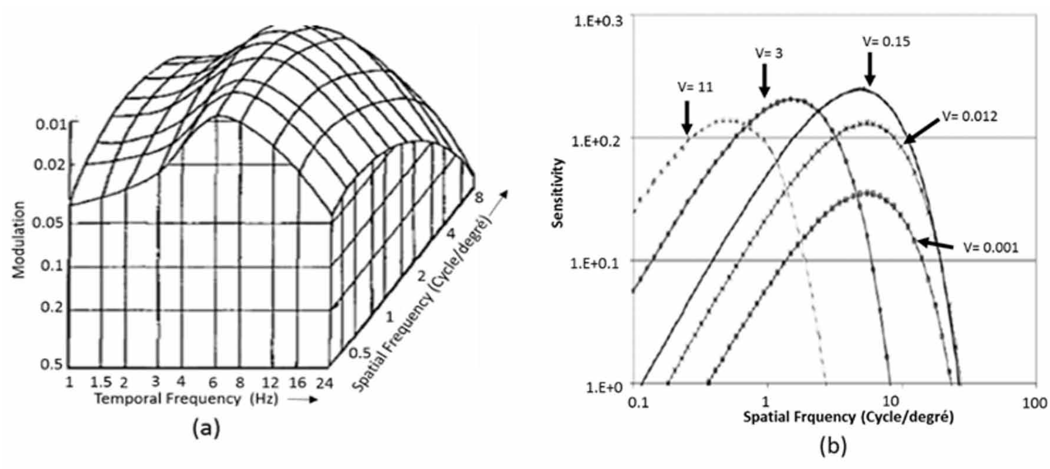
Figure 4 (a) shows that the pixel intensity is modulated by a horizontal sine function. When the spatial frequency of the pixel increases in a logarithmical way (on the horizontal axis), the contrast increases from top to bottom. Although the change contrast is the same for all frequencies, we observe that the bars appear to be highest in the middle of the image following the shape of the sensitivity function in Figure 4 (b). This effect is not made by the image; it's rather made by the property of frequency selectivity of the human vision system.

In the context of dynamic visual content (2D videos, dynamic meshes, etc.), the CSF must be modulated by stimuli speed. This is due to the variability of the contrast sensitivity depending on the speed of the stimulus movement. Since 1977, Kelly has presented an experimental study for modulating the function of contrast sensitivity affected by the test conditions (see Figure 5 (a)). In 1998, Daly has developed a dynamic model of CSF through a time function of CSF tends to move to lower frequencies. These studies were performed for achromatic data. Other studies have integrated color effect on the CSF: The contrast sensitivity Figure 5 (b). With increasing speed, the CSF curve tends to shift towards low frequencies. These studies were realized to achromatic data (Ninassi, Meur, Le Callet, Barba, 2008).

3.4.2. The Masking Effect

Masking, which refers to our reduced ability to detect a stimulus on a spatially or temporally complex background or it's the effect of modification of the component bordures visibility in a multimedia content (masked signal) by the presence of another component (masking signal). Thus errors are less visible along strong edges, in textured areas, or immediately following a scene change. The amount of masking caused by a background depends not only on the background's contrast, but also on the level of uncertainty created by the background. The magnitude of this effect is measured by the change of the masked signal visibility with or without the presence of the masking signal (Fernandez-Maloigne, Larabi, &Bringier, Richard, 2005). In fact, areas of high uncertainty (e.g. complex areas of a scene) induce higher masking than areas of the same contrast with lower uncertainty. In conclusion, masking effects (Kelly, 1977). include both contrast masking and entropy masking. Entropy masking allows to consider the modification of the visibility threshold due to the semi-local complexity of an image. The contrast masking is connected to the change of the surface visibility as a function of

Figure 5. Kelly Illustration (a) - for the presentation of the combination of the effect of spatial and temporal frequency on contrast sensitivity, and (b) - the CSF illustration depending on the speed. The time function of CSF in (b) is calculated from an empirical equation. The speeds V are measured in degree / second



the contrast values. The spatial masking effect is often linked to the concept of surface roughness for 3D meshes (Daly, 1998).

3.5. Geometric Metrics

The geometric metrics are based on the calculation of distances between peaks of the reference mesh and the mesh to compare. These geometric measurements are namely the RMS (distance calculated by the square root of the mean square error) and the Hausdorff distance (Hd) (Karni & Gotsman, 2000).

3.5.1. The Root Mean Square Error

The RMS is considered to be a simple measure to evaluate a distance between two surfaces in 3D space. Let d(p,S') measuring the minimum distance between a point P belonging to the surface S and the surface S', which expressed by:

$$d\left(p,S'\right)=\min_{p'\in S'}\left\|p-p'\right\|_2 \tag{1}$$

where, $\| p- p' \|_2$ appointed the Euclidean norm. Thus, the mean square error between the two continuous surfaces S and S0 denoted dRMS is defined as:

$$d_{RMS}\left(S,S'\right)=\sqrt{\frac{1}{|S|}\int_{P\in S} d\left(p,S'\right)^2 dS} \tag{2}$$

where, | S | measure the area of surface S. Generally, the RMS distance is non-symmetric, where it is possible to set a symmetrical distance MRMS (Maximum Root Mean Squared Error) as:

$$\mathrm{MRMS}\left(\mathrm{S},\mathrm{S}'\right)=\max\left(\mathrm{d}_{\mathrm{RMS}}\left(\mathrm{S},\mathrm{S}'\right),\mathrm{d}_{\mathrm{RMS}}\left(\mathrm{S}',\mathrm{S}\right)\right) \tag{3}$$

3.5.2. Hausdorff Distance

The Hausdorff distance is a measure of geometric distance between surfaces. It is defined by using the minimum Euclidean distance between a point *p* on a continuous surface *S* and another surface denoted $S^{'}$ (Lavoué & Gelasca & Baskurt &.Ebrahimi, 2006). This distance *d* is calculated by:

$$d\left(p, S'\right) = \min_{p' \in S'} \left\| p - p' \right\|_2 \tag{4}$$

The Hd between two surfaces *S* and $S^{'}$ is then calculated by:

$$d\left(S, S'\right) = \max_{p \in S'} \left(p \ \ , S'\right) \tag{5}$$

The Hausdorff symmetrical distance can be defined as:

$$Hd\left(S, S'\right) = \max\left(d\left(S, S'\right), d\left(S', S\right)\right) \tag{6}$$

Cignoni proposed approximations of the Hausdorff measure and MRMS measure to compare two discretized 3D mesh surfaces. This approach was based on the sample surfaces and the distances calculation of each point of a grid to the surface of the second mesh. These geometric measurements reduced the complexity; however, they do not reflect the mesh quality perceived by humans.

3.6. Metrics Integrating Visual Perception Properties (SVH)

3.6.1. 3D Watermarking Perception Metric

Recently, watermarking of 3D objects attracted attention of researchers owing to the increased diffusion of such objects in several areas of applications, such as in medical, mechanical engineer, design, entertainment and cultural Heritage. The 3D Watermarking Perception Metric (3D WPM) is employed to predict the quality of watermarked 3D mesh as perceived by human subjects. Corsini (Corsini & Larabi & Lavoué & Petřík & Váša & Wang, 2013) 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 M1 and M2 are meshes defined by:

$$3DWPM\left(M_1, M_2\right) = \log\left(\frac{\rho(M_2 - \rho\left(M_1\right)}{\rho\left(M_1\right)} + k\right) - \log\left(k\right) \tag{7}$$

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. (Torkhani & Wang & Chassery, 2013). 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 vary more meaningful. (Chowdhuri & Roy & Goswami & Azar & Dey, N. 2014).

A Multi-scale analysis of these entities is considered in (Wu & Hu & Tai & Sun, 2001) 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 (Abouelaziz & Omari & Hassouni & Cherifi, 2015). This approach was based on the comparison of a mesh and smoothed versions of the same mesh. Smooth regions correspond to small differences, while the rough areas have more significant differences.

3.6.2. The Mesh Structural Distortion Measure

Metric MSDM (Mesh Structural Distortion Measure) uses the amplitude of the average curvature of the 3D mesh surface to quantify the perceptual distortion. This metric has been improved recently under the name MSDM2 by integrating multi-scale analysis (Lavoué, 2011).

Lavoué et al. (Lavoué & Gelasca & Dupont & Baskurt & Ebrahimi, 2006) introduced a structured distortion measurement called the MSDM that inspired by the quality measurement of 2D pictures SSIM (Structural Similarity index) introduced by Wang et al. (Wang & Bovik & Sheikh & Simoncelli, 2004). The MSDM measurement is based on the statistical difference of the average curvature amplitudes to measure the perceptual difference of two meshes. The mean curvatures (CMsi) are calculated for each summit si as the average of the minimum and maximum curvatures:

$$\mathrm{CMsi} = \frac{\left|Cmin, si\right| + \left|Cmax, si\right|}{2} \tag{8}$$

The amplitudes of minimum and maximum curvatures (| Cmin, si | and |Cmax, si |) are deducted from the values of the curvature tensor.

The used curvature tensor approximation was introduced on a spatial neighborhood defined by the geodesic disc resulting from the projection of a sphere of radius h on the surface of the mesh. The mean and standard deviation of the mean curvature in a spatial window w containing n vertices, denoted respectively μw and σw are defined as:

$$\mu_w = \frac{1}{n}\sum_{si \in w} CMsi \tag{9}$$

$$\sigma_w = \sqrt{\frac{1}{n}\sum_{si \in w}\left(CMsi - \mu_w\right)^2} \tag{10}$$

The covariance between the curvatures of two windows w1 and w2 of the meshes compare M1 and M2 is defined as:

$$\sigma_{w_1 w_2} = \frac{\sigma_{w_1 w_2}^{w_1} + \sigma_{w_1 w_2}^{w_2}}{2} \tag{11}$$

defines the covariance calculated on the window w1:

$$\sigma_{w_1 w_2}^{w_1} = \frac{1}{n}\sum_{S_{1i} \in w_1} \left(\left(CM_{S_{1i}}^{w_1}\right) - \mu_{w_1}\right) * \left(\left(CM_{S2i}^{w_2}\right) - \mu_{w_2}\right) \tag{12}$$

where, S2i is the nearest summit on S1i and the covariance on w2 window is calculated in the same way. To calculate the overall distance between two meshes, the MSDM based on local distances that noted MSDML is given by:

$$MSDML = \left(\alpha * L\left(s\right)^{a} + \beta * C\left(s\right)^{a} + \gamma * M\left(s\right)^{a}\right)^{\frac{1}{a}} \tag{13}$$

with α, β, γ and a are scalars for combining different quantities. The parameters L, C, M represent the differences of curvature, contrasts and structures; respectively that measured by:

$$L\left(s\right) = \frac{\left\|\mu_{w1} - \mu_{w2}\right\|}{MAX\left(\mu_{w1}, \mu_{w2}\right)} \tag{14}$$

$$C\left(w1, w2\right) = \frac{\left\|\sigma_{w1} - \sigma_{w2}\right\|}{MAX\left(\sigma_{w1}, \sigma_{w2}\right)} \tag{15}$$

$$M\left(w1, w2\right) = \frac{\left\|\sigma_{w1}\sigma_{w2} - \sigma_{w1}\sigma_{w2}\right\|}{\sigma_{w1}\sigma_{w2}} \tag{16}$$

Measuring overall perceptual distance MSDM is calculated by:

$$MSDM = \left(\frac{1}{W}\sum_{j=1}^{W} MSDML_{j}^{a}\right)^{\frac{1}{a}} \tag{17}$$

here, w is the number of local windows on the mesh surfaces. An improved version of MSDM is named MSDM2 that based on integrating a multi-scale analysis. The MSDM2 compares two meshes that do not share the same connectivity through a matching step using the tree data structure implemented in the AABB CGAL (Alliez & Tayeb & Wormser, 2012).

We note that to establish a measure of perceptual distance symmetrical, MSDM2 calculate the averages of two unidirectional distances, namely M1 to M2 and of M2 to M1; respectively. MSDM and MSDM2 are based only on statistics on the curvature amplitudes.

4. METHODOLOGY

In the current work, the general behavior of the perceptual quality metrics and their performance was compared and tested for six existing metrics on a general-purpose database published by LIRIS/EPFL. The basic data in this database contains 88 models, namely 4 Reference meshes: Armadillo, Dinosaur, Venus and Rockerarm as well as 84 distorted models (Lavoué & Gelasca & Dupont & Baskurt & Ebrahimi, 1998).

Figure 6. Some models from the LIRIS / EPFL general-purpose database and their distorted versions: a) reference meshes, and b) the corresponding distorted meshes

Two types of distortion are applied: a noise and a smoothing either locally or globally on the reference grid. Twelve observers participate in the subjective evaluation. Figure 6 illustrated some models of the LIRIS / EPFL database and their distorted versions. The distorted meshes in Figure 6 (b) represented from left to right the Armadillo with overall noise, Rockerarm with noise in smooth areas, Dinosaur with global smoothing, and Venus with noise in rough areas.

In the current work, the performance of six metrics, namely the RMS (Cignoni & Rocchini & Scopigno, 1998.), Hd (Aspert & Santa Cruz & Ebrahimi, 2002), 3DWPM1, 3DWPM2 (Corsini & Gelasca & Ebrahimi & Barni, 2007), MSDM and MSDM 2 (Lavoué & Gelasca & Dupont & Baskurt & Ebrahimi, 2006) in terms of correlation with the MOS (mean opinion scores) is evaluated.

The classical method for evaluating the performance of the MVQ is to measure the correlation between the perceptual distances or similarities produced by the metric and the opinion of the average scores (MOS) produced by the subjects. Usually, two types of correlation coefficients commonly used are taken into account, namely 1) the linear correlation coefficient (Pearson Rp) that used to measure the accuracy of the prediction (measures the linear dependence between the objective measurement and subjective scores), and 2) order Spearman rank correlation coefficient (Rs) used to measure the prediction monotony (Váša & Skala, 2011) as it measures how the relationship between objective and subjective scores can be described by a monotonic function.

5. EXPERIMENTAL RESULTS AND DISCUSSION

The values of Rp (PLCC) and Rs (SROCC) visual quality metric studied on the considered database are reported in Table 1.

Table 1 demonstrates that the MSDM has best values of the Rp for the three models, namely Armadillo (75.30%), Dyno (78.13%) and Rockerarm (85.53%). Furthermore, the MSDM achieves good results with the four models of the basic general purpose data LIRIS / EPFL (Rp > rs 70.35% and > 67.45%). Figure 7 and Figure 8 illustrate the same results obtained in Table 1 by representing the Pearson correlation coefficient (Rp) and the Spearman Correlation Coefficient (Rs); respectively.

Generally, the results obtained in Table 1 along with Figure 7 and Figure 8 established that the metric based on curvature amplitude provides superior results compared to those based on surface roughness. The comparison results obtained from both the MSDM and MSDM2 metrics prove that the

Table 1. Linear correlations (Rp) and no-linear (Rs) (%) of various objective metrics with subjective scores from the database usage- general

Object Metrics	ARMADILLO		VENUS		DINOSAUR		ROCKERARM	
	Rp	Rs	Rp	Rs	Rp	Rs	Rp	Rs
Hd	56,95	95,00	8,57	96,00	7,46	99,00	7,98	104,0
RMS	59,15	**79,00**	79,79	81,00	47,27	84,00	42,02	90,00
3DWPM2	57,08	89,00	51,81	96,00	53,21	90,00	50,76	91,00
3DWPM1	60,08	78,00	49,36	87,00	45,89	86,00	52,98	75,00
MSDM2	68,03	76,00	54,81	78,00	40,51	77,00	85,16	83,00
MSDM	**75,30**	69,00	62,31	75,00	**78,13**	84,00	**85,53**	83,00

Figure 7. Pearson correlation coefficient

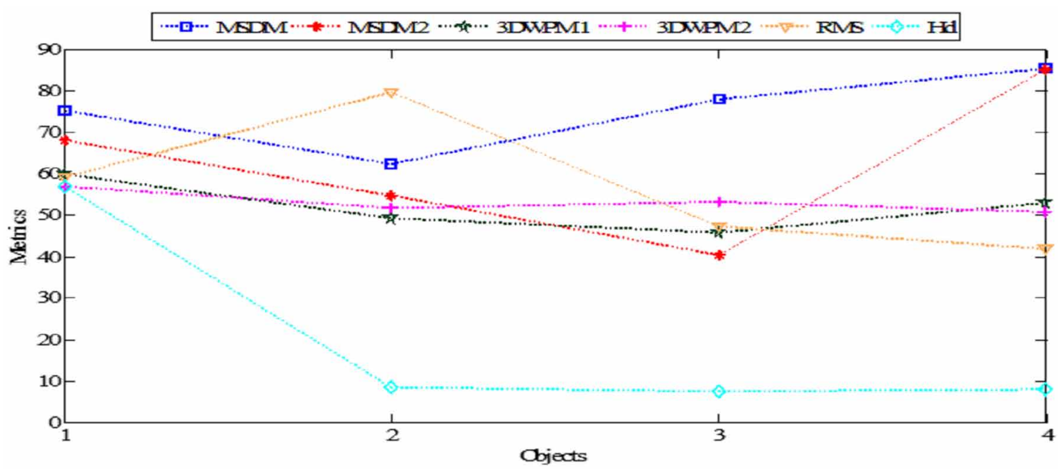
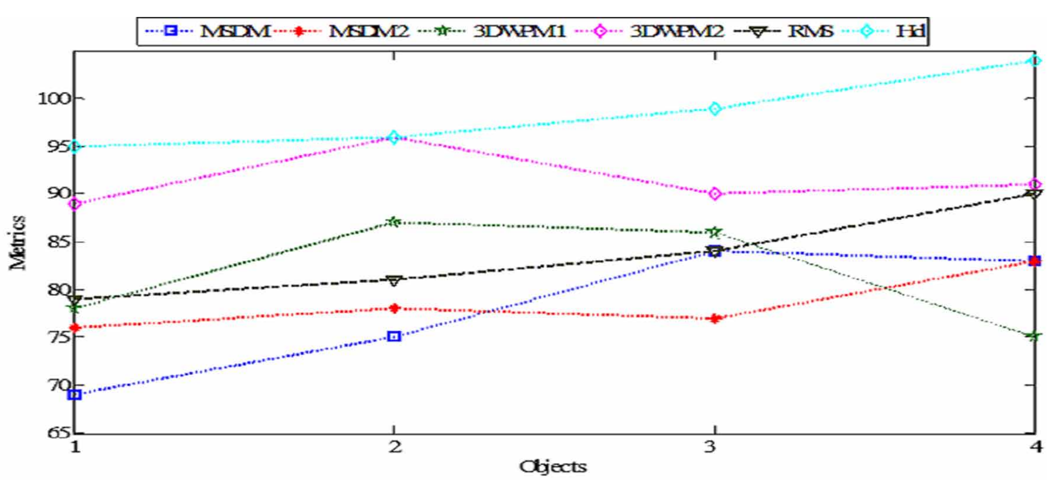


Figure 8. Spearman correlation coefficient



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 the subjective scores of the MVQ. 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. It is recommended to implement simple as well as fast execution time metric in the future. Moreover, since watermarking is essential for several applications (Dey & Samanta &Yang & Chaudhri, 2013; Dey & Pal & Das, 2012; Banerjee & Chakraborty & Pal & Dey & Ray, 2015), thus developing quality assessment metrics for watermarking of 3D objects can be considered as a future scope.

6. CONCLUSION

This work presented a comparative study between the geometric metric and metric-based on HVS, which have not the same quality assessment criterion perceptual static 3D meshes. A comparative study was conducted to evaluate the performance of existing objective metrics.

The experimental results established that the MSDM metric can be considered the most efficient metric. However, it is not yet on an exact metric that takes into account all the human visual system properties.

Future work includes further investigation to find more revealing measures of the surround influences on masking effect. In particular, the measures must be able to avoid an overestimation of the masking effect on the neighborhood of strong edges with high contrast. Furthermore, more studies have to be done on the way to take into account the contrast sensitivity. Finally, we will try to extend the proposed metric for dynamic meshes.

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