

Quality Metric of 3D Models Using Weber's Law

^{1,2}Nessrine ELLOUMI, ^{1,3}Habiba LOUKIL HADJ KACEM, and ¹Med Salim BOUHLEL

¹Research Unit: Sciences of Electronics, Technologies of Image and Telecommunications,
Higher Institute of Biotechnology, University of Sfax, Tunisia.

²Higher Institute of Computer Science and Communication Technologies (ISITCom)
Hamman Sousse, University of Sousse, Tunisia.

³Higher Institute of Industrial Management, University of Sfax, Tunisia.

ABSTRACT

According to its causes and effects, it becomes essential to judge the quality of the model after a treatment, compared to the initial image. In fact, the quality of 3D objects becomes a paramount criterion for any treatment.

Many authors proposed descriptors to evaluate the quality or the natural appearance of images. However, it is obvious that the best correlation between the results obtained and human visual perception. We stand out against current trends by avoiding purely developing and mathematical measures, or completely inspired by the HVS (Human Visual System).

Indeed our new metric 3DrwPSNR based on the use of Weber's law that takes into account the human visual system. This law translates a logarithmic eye's perception of light. This property led us to develop a metric that takes into consideration the relative difference of models and not the absolute difference. These measurements prove there are much correlated with the human visual appreciation of the processed 3D objects.

Keywords: Perceptual quality, Static metrics 3D, Human Visual System, 3D meshes, objective metrics.

1. INTRODUCTION

In the field of 2D image processing, the search for an objective visual quality evaluation is very developed. It is the idea to replace the classic PSNR (Peak Signal to Noise Ratio) that is not correlated with human vision.

The human visual system has psychophysical properties relating to the luminous intensity and to other relatives of the spatial frequency. These properties have arisen from psychophysical experiments through which the perception of a stimulus depends on its neighbors in terms of luminance, frequency, and orientation. The results of such experiments can be described in the spatial domain (in terms of stimulus intensity) while others are represented in the frequency domain.

The first works on this subject are those of Daly with the Visible Difference Predictor [1] and Lubin with the Sarnoff Visual Discrimination Model [2]. These metrics, modeled on the low-level mechanisms of the human visual system (such as the contrast sensitivity function or the visual masking mechanism), predict the visibility of artifacts in a degraded object. Because of this pioneering work, many other metrics have been introduced such as Visual Signal to Noise Ratio (VSNR).

Recently, another class of techniques has emerged and has not directly sought to model the psychophysical properties of the human visual system but rather has relied on a simple criterion of a signal fidelity, which is assumed to be correlated with a perceived quality. Among these, the most known is the relative weighted PSNR (rwPSNR) of Loukil Hadj Kacem [4], which is based on the relativity of information in the 2D image. Therefore, we will extend this metric to evaluate the 3D objects.

2. PSYCHOPHYSICAL PHENOMENON OF THE HUMAN VISUAL SYSTEM

2.1 Perception of luminous intensity

The human observer is sensitive to a very wide range of light intensities, ranging from 0.01 cd / m² in the scotopic domain to several thousand cd / m² in the photopic vision. From a physical point of view, the luminance of an object is independent of the luminance, of a stimulus perceived by the human observer, depending on the luminance of its neighborhood. As a result, the HVS system is more sensitive to luminance contrast than the absolute value of luminance [10].

2.2 Phenomenon of Mach

The lateral connections in the various layers of the retina are the germ of a phenomenon, studied scientifically by E.Mach (1865) as we are observing two juxtaposed uniform regions of different physical luminance, for example, light gray and dark gray. Indeed, luminance increases in the clear region and decreases in the dark spot [3].

An example of a stimulus, having a linear luminous gradient that is shown in Figure 1, is perceived by the human eye as a luminance transition having an over bright band on the light side and a sublight sideband on the light side of the dark area. These are the bands of Mach. The asymmetry of the two bands can be explained by retinal logarithmic treatment.

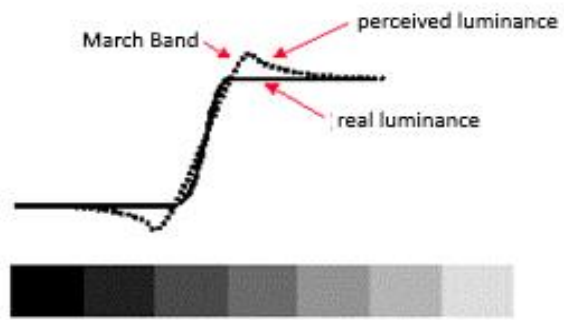


Figure. 1. Mach bands, subjective distribution of luminance

2.3 Weber's Law

The classical psychophysics of Fechner is primarily concerned with the determination of absolute and relative sensory thresholds beyond the logarithmic law, stated by Fechner, over the differential thresholds and according to which there exists a logarithmic relationship between the sensations felt and the physical intensity of different stimulations. His successors deepened their research in experimental procedures. Currently, the applications of psychophysics are very numerous in the fields of detection, discrimination, recognition, and identification. In fact, Weber law regards the sensitivity of the human eye to luminance as a logarithmic function [9]. He develops a quantitative description of the relationship between stimulus intensity and discrimination, which is known as Weber law [2].

Weber's law expresses that there exists a constant k such that:

$$\frac{\Delta x_i}{x_i} = k \quad (1)$$

Where Δx_i is the difference in luminance between the stimulus and its neighborhood, and x_i is the luminance of the stimulus.

If $\frac{\Delta x_i}{x_i} < k$ the distortion is not perceptible then the distortion is perceptible if $\frac{\Delta x_i}{x_i} > k$.

3. THE EVOLUTION OF THE PSNR QUALITY METRICS

3.1 Peak Signal to Noise Ratio (PSNR)

The PSNR is a measure of distortion, used in the digital image, especially in image compression [8]. It is a matter of quantifying the performance of the encoders by measuring the reconstruction quality of the compressed image with respect to the original image.

The PSNR defined by:

$$PSNR = 10 * \log_{10} \frac{x_{\max}^2}{MSE} \quad (2)$$

Where x_{\max}^2 is the signal dynamics (the maximum possible value for a pixel). In the standard case of an image where the components of a pixel are coded on 8 bits, $x_{\max} = 255$.

MSE is the mean squared error defined for two images x and y of size $M * N$ as:

$$MSE = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left(x_{(i,j)} - y_{(i,j)} \right)^2 \quad (3)$$

If the PSNR is useful for measuring the proximity of the compressed image with reference to the original at the signal level, it does not take into account visual reconstruction quality and cannot be considered as an objective measure of the visual quality of the image.

3.2 relative Peak Signal to Noise Ratio (rPSNR)

The basic idea of the relative PSNR (rPSNR) based on the evaluation of a pixel with respect to the relative difference with its value in the original image. Thus, an error between two pixels of two images cannot translate the same error between two pixels of two others images, having the same intensity difference.

Indeed, if the intensity difference 10 between two pixels of values 30 and 40, is numerically equivalent to that between a pair of pixels of values 130 and 140. However, visually, the perception differs. In the first case, the error is quantified at 100% (30-40). In the second case, it is a mistake quantifiable at 10% (130-140) [6-7].

The rPSNR formula defined as follows:

$$rPSNR = 10 * \log_{10} \frac{x_{\max}^2}{rMSE} \quad (4)$$

Where:

$$rMSE = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left(2 * \frac{\left(x_{(i,j)} - y_{(i,j)} \right)}{\left(x_{(i,j)} + y_{(i,j)} \right)} \right)^2 \quad (5)$$

The rPSNR parameter measures the relative deviation between the pixels of the original image x and the degraded image y . This parameter varies from zero to infinity. It is smaller if distortions between two images x and y are important. It is infinite if both images are identical. M and N represent the size of the image.

3.3 relative weighted Peak Signal to Noise Ratio (rwPSNR)

Among the most popular 2D metrics, we quote the PSNR. This metric does not adapt to the dynamic characteristics of the image. Most visible distortions are found in the regions with little texture. The visibility of these distortions is always relative to the variance: since the distortion is visible, the variance is small and conversely. Then, the variance of the image must always be taken into account [3].

The rwPSNR is an extension of the PSNR metric. The rwPSNR is a relative weighted PSNR of the gray level of the 2D image. The difference between the two stimuli was approximately proportional to the intensity of the stimuli. To calculate the rwPSNR, we must first calculate the rwMSE (relative weighted Mean Square Error).

The rwMSE is given as:

$$rwMSE = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left(2 * \frac{\left(\frac{|x(i,j) - y(i,j)|}{x(i,j) + y(i,j)} \right)^2}{1 + \text{var}(y)} \right)^2 \quad (6)$$

Let $x = \{i = 1, \dots, M; j = 1, \dots, N\}$ and $y = \{i = 1, \dots, M; j = 1, \dots, N\}$ be the original image and the test image, respectively. The $\text{var}(y)$ is the variance of the test image, the sensitivity of the HVS to the errors may be different with respect to different intensities [5].

Therefore, the expression of our relative weighted peak signal to noise ratio (rwPSNR) is given by:

$$rwPSNR = 10 * \log_{10} \frac{x_{\max}^2}{rwMSE} \quad (7)$$

4. OVERVIEW OF OUR APPROACH

In multimedia applications, 3D models are represented by meshes [7]. Many 3D applications need operations for rendering 3D models (i.e., transmission, simplification, compression, watermarking or smoothing), which can introduce distortion to the 3D shape; these operations degraded its perceptual quality.

A static mesh can be defined by two kinds of information: the 3D geometry information (vertices) and the connectivity information, which describes the adjacent relationship between vertices (faces).

Our proposed metric, the 3D object quality is to calculate the distortion of vertices, because the distortion generally exists on them.

In this paper, we will introduce our approach, which is inspired by the rwPSNR metric of Loukil Hadj Kacem [4] who consider that the human visual system is highly adapted to relative information and the contrast sensitivity function. Hence, our measure entitled three dimensions relative weighted Peak Signal to Noise Ratio (3Drwpsnr) relies on differences, computed by taking into consideration the relativity between two vertices.

The 3DrwPSNR is calculated as follows:

$$3DrwPSNR = 10 * \log_{10} \frac{x_{\max}^2}{3DrwMSE} \quad (8)$$

Where 3DrwMSE presents the three dimensions relative weighted mean square error, which is calculated as follows:

$$3DrwMSE = \frac{1}{M} \sum_{j=0}^{M-1} \left(2 * \frac{\left| \frac{(x_j - y_j)}{(x_j + y_j)} \right|}{1 + \text{var}(y)} \right)^2 \quad (9)$$

The rwPSNR based on the difference between the content of the original model and its distorted version; it takes these models as two matrixes.

For this reason, we consider the 3D object as a matrix. Therefore, to calculate the 3DrwPSNR for the 3D object we must calculate the 3DrwMSE for a 3D object. Where M is the number of vertices. x and y are the original object and distorted object respectively.

The $\text{var}(y)$ is the distorted object variance. This new metric is applicated on the 3D object to evaluate its quality.

The quotient $2 * \left| \frac{(x_j - y_j)}{(x_j + y_j)} \right|$ represents the relative difference between two vertices. The results of our 3D

object are illustrated in the following section.

5. RESULT AND DISCUSSION

In order to evaluate the performance of our proposed metric, we use a database, containing twelve models with a different type of meshes, which are derived from three reference models. These models are compared through using our proposed metric 3DrwPSNR.

The first object constitutes eight vertices. The first distortion attacks one vertex, we obtain a 3DrwPSNR = 3,96 While the second distortion attacks vertices, we got 3Drwpsnr = 3,59 so, the 3DrwPSNR approves the quality of the object. The second object constitutes 310 vertices. We obtain 3DrwPSNR = 147,36 for a distortion of one vertex. Then the 3Drwpsnr becomes 113,16 for a distortion of eight vertices. The third object constitutes 11908 vertices. We obtain 3DrwPSNR = 217,74 for a distortion of one vertex. Then the 3Drwpsnr becomes 212,21 for a distortion of eight vertices. Hence 3DrwPSNR decreases when distortion increase.

Also, we applied 3DrPSNR on the same model with the same level of distortion. Tables 1,2 and 3 contain the experiment results. We observe that the 3DrPSNR of cube d, which has more distortion than cube c, has a better value. So we approve that 3DrwPSNR has a good result and it correlates very well with the subjective measures than the 3DrPSNR.

We consider that the problem lies with the model's cube and shuttle and it is disappeared with trumpet object. This is related to the total number of vertexes compared to the number of distorted vertexes. The success of our 3Drwpsnr metric is due to the integration of the variance that measures the distribution of vertex values.

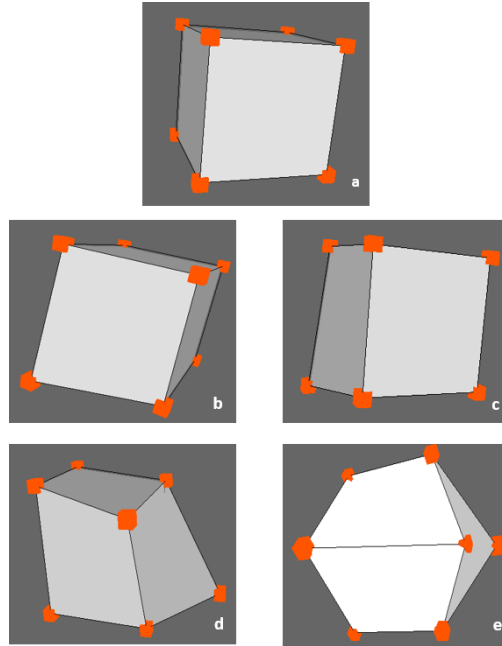


Figure.2. (a) reference cube model, (b) one vertex distorted, (c) two vertex distorted, (d) five vertex distorted, (e) eight vertex distorted.

Table 1. The results are obtained by our metric 3DrwPSNR and applied on the cube model.

	Cube b	Cube c	Cube d	Cube e
3DrwPSNR	3,96	3,87	3,64	3,60
3DrPSNR	3,01	0,41	2,31	2,00

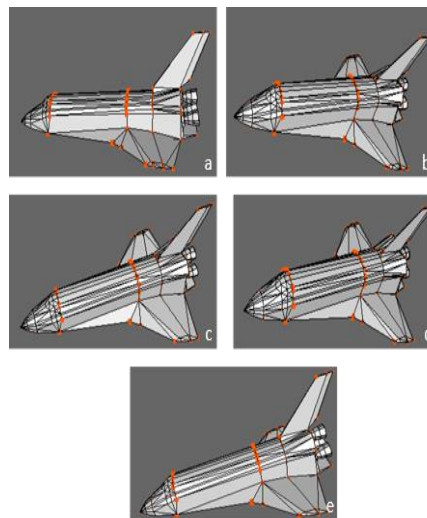


Figure. 3. (a) reference shuttle mesh, (b) one vertex distorted, (c) two vertex distorted, (d) five vertex distorted, (e) eight vertex distorted.

Table 2. The results are obtained by our metric and applied on shuttle model.

	shuttle b	shuttle c	shuttle d	shuttle e
3DrwPSNR	147,36	118,95	115,36	113,16
3DrPSNR	42,06	13,89	104,46	102,25

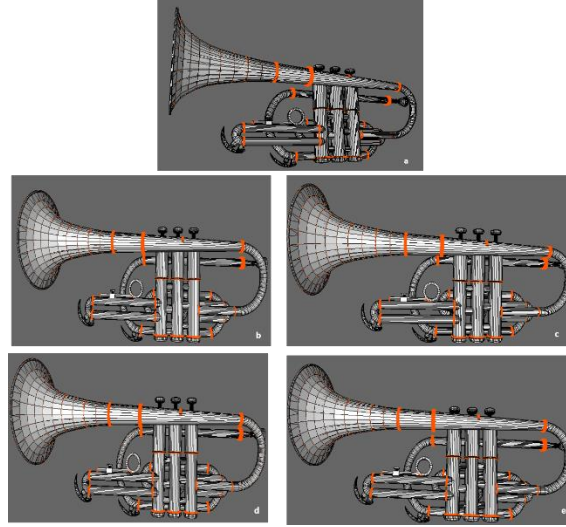


Figure 4. (a) reference Trumpet mesh, (b) one vertex distorted, (c) two vertex distorted, (d) five vertex distorted, (e) eight vertex distorted.

Table 3. The results are obtained by our metric and applied on Trumpet model.

	Trumpet b	Trumpet c	Trumpet d	Trumpet e
3DrwPSNR	217,74	214,16	213,09	212,21
3DrPSNR	145,45	141,868	140,795	139,92

The result obtained from our metric indicates that when the total number of vertices is high compared to the number of distorted vertexes and according to Weber's law the properties of the HVS cannot distinguish the distortion and this is validated by our metric.

On the other hand, if we compare two objects, we notice that the distortion of one vertex does not affect two objects in the same way and this is relative to the total number of vertices in each object .

Indeed, when we apply 3DrwPSNR on the cube model with a distortion of one vertex we obtain 3,96 but on shuttle model, we obtain 147,36 and this is approved by the HVS.

The distortion cube is too clear by the observer but looking at the shuttle and trumpet models the distortion is not distinguished despite the same number of vertex distortion applied to them. These resultants are approved by the subjective evaluation (figure 2, 3 and 4).

6. CONCLUSION

In this paper, we propose a new metric for measuring the visual quality of 3D model based on the relative difference between the two 3D models introduced by Weber's law.

Our experimental results on the 3D model with a different level of distortion indicate that our new metric correlates significantly with the HVS under different level distortions of the 3D model. We think success is due to its strong ability to measure distortion occurred after the degradation process.

In the future, more experiments that are extensive needed to fully validate our 3DrwPSNR.

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