https://doi.org/10.2352/ISSN.2470-1173.2017.20.3DIPM-001

A 3D Mesh Quality Metric based on Features Fusion

Aladine Chetouani; University of Orleans – PRISME laboratory; Orleans, France

Abstract

3D mesh becomes a common tool used in several computer vision applications. The performances of these applications depend highly on its quality. In order to quantify it, several methods have been proposed in the literature. In this paper, we propose a 3D Mesh Quality Measure based on the fusion of some selected features. The goal is here to take into account the advantages of these features and thus improve the global performance. The selected features are here some 3D mesh quality metrics and a geometric attribute. The fusion step has been realized using a Support Vector Regression (SVR) model. The 3D Mesh General database has been used to evaluate our method. The obtained results, in terms of correlation with the subjective judgments, show the relevance of the proposed framework.

Introduction

Image quality area is a growing field and is a sensible notion for different applications (biometric, medical, security and so on). Indeed, the performances of computer vision applications are often sensitive to the quality of the data and thus need to have information about it. In [1], the authors propose to integrate the quality in the proposed identification system. In [2], some quality metrics have been used to detect the spoofing in images and videos.

To estimate the quality, three main approaches are proposed: Full-Reference (FR), No-Reference (NR) or Blind and Reduced-Reference (RR) approaches. Using FR metrics suppose that the original image is available. For 2D images, more than one hundred FR metrics have been listed in [3]. Blind (NR) metrics are often degradation-based and only the common degradation types are generally considered (blocking, ringing, blur) [4][5][6]. RR metrics are an alternative solution because only some features of the original image are assumed accessible. We have the same division for stereoscopic images [7][8][9].

In this paper, we focus our attention on 3D Mesh Quality Metric and we propose to take into account the performance of some attributes by combining it. These attributes are here selected experimentally. The underlying idea developed here is to benefit of the specificity of each selected descriptor to improve the efficiency of 3D mesh quality estimation process. The fusion has been here realized by Support Vector Regression (SVR) model where its inputs are the selected features, while its output represents the predicted subjective score, often so-called MOS (Mean Opinion Score).

This paper is organized as follows: In section 2, some related works are presented. The proposed method is then described in details in section 3. The obtained results and the conclusion are respectively presented in section 4 and 5.

Related Work

Different authors are interested by the estimation of the quality of 3D Meshes. Two main families are proposed in the literature: model-based and image-based. Model-based approach exploits directly the meshes. Some of them are mathematically-based, while some others are structural-based or perceptually-based. As in 2D domain, one of the first common used metrics is the RMS (Root Mean Square). Hausdorff distance is also among the most used metric. In [10, 11], the authors propose to improve the performance by measuring the smoothness based on geometric distance. However, as the PSNR (Peak Signal to Noise Ratio) in 2D, this metric is not well correlated with the subjective judgments. In order to better enhance the performance, some perceptual concepts have been considered.

In [12], the authors propose the Mesh Structural Distortion Measure (MSDM), inspired by the concept of the SSIM (Structural SIMilarity metric) [13], which is a common used 2D structural-based measure and extend it to 3D meshes. The underlying idea is to compute the local curvature, the contrast and the structure and, then combine it to obtain a single value. Such as the 2D-SSIM metric, a multi-scale version, so-called MSDM2, has been also proposed in [14]. Other interesting methods have been proposed such as the Tensor-based Perceptual Distance Measure (TPDM) [15] and the Fast Mesh Perceptual Distance (FMPD) [16].

Image-based approach uses some 2D metrics to estimate the quality of the 3D meshes [17]. The idea is to decompose the mesh into several snapshots by varying the camera view. In this case, all the 2D image quality metrics can be used such as the PSNR, SSIM [13], VIF (Visual Information Fidelity) [18], Visual Difference Predictor (VDP) [19] and so on. This approach allows overcoming some problem linked to the 3D. However, we need to develop a strategy for combining all the snapshots.

In [20], the authors conclude that each of these approaches has its advantages and drawbacks and, could be used for specific applications.

Proposed Method

As mentioned above, different metrics for 3D meshes have been proposed in the literature. In this paper, we propose to combine some of them and a standard geometric attribute in order to improve the performance. We first extract some features from the original and the degraded 3D meshes. The selected features are then used as inputs to a regression tool. The obtained output corresponds here to the predicted subjective score. These steps are presented in this section.

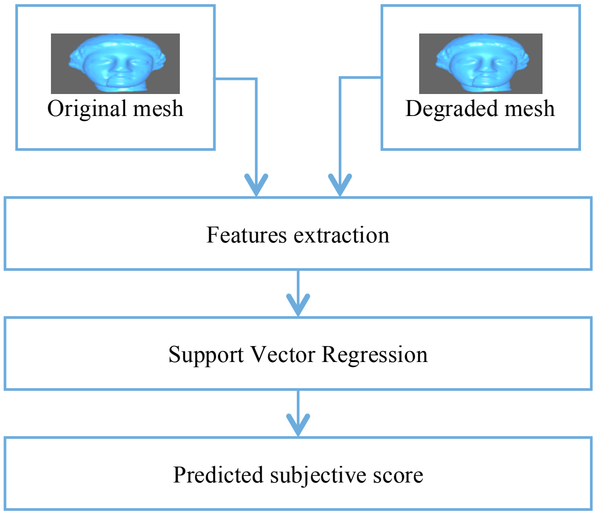

Figure 1. Flowchart of the proposed method

Selected features

Different kinds of features can be used (geometric attributes, smooth, rough and so on). In this study, we choose to use some 3D mesh metrics and one geometric attribute as features (listed in Table 1). Note that these features are experimentally used through several tests and the best combination has been selected.

Table 1: Selected Features

Features	Based on
HD	Distance
3DWPM2 [21]	Global roughness
MSDM [12]	Structural
Dame [22]	Dihedral angle
Difference of the local Normals	Geometric attributes

As mentioned above, the Hausdorff Distance (HD) is the one of the first proposed method. This distance is here used as feature and is computed between the original mesh (Mo) and its degraded version (Md) as follows:

$$\boldsymbol{HD(S_o, S_d) = \max_{p_O \in M_O} d(p_O, S_d)}$$

with

$$\boldsymbol{d(p_O, S_d) = \min_{p_d \in M_d} \|p_O - p_d\|}$$

where S_O and S_d are respectively a surface of the original and degraded meshes. $d(p_O, S_d)$ represents the distance between a point p_O to a surface S_O and a surface S_d.

Note that this metric is generally not well correlated with the subjective judgments. However, as the PSNR in 2D domain, this metric is relatively well adapted for noise degradation.

The second one, named 3DWPM2 [21], which is a rough-based measure. This method has been initially developed for watermarked meshes and is an improved version of 3DWPM1 [23]. The authors propose to estimate the roughness on smooth areas by computing the variance of the differences between both original and degraded meshes.

The third one inspired by the 2D common image quality metric SSIM (Structural Similarity Metric) [13], named MSDM [12] (Mesh Structural Distortion Measure) is a structural-based method and is obtained by combining three factors: Local curvature (L), Contrast (C) and Structural (S). The local measure is computed as follows:

$$LMSDM(a,b) = (0.4 * L(a,b)^3 + 0.4 * C(a,b)^3 + 0.2 * S(a,b)^3)^{1/3}$$

with

$$L(a,b) = \frac{\|\mu_a - \mu_b\|}{\max(\mu_a, \mu_b)} \qquad C(a,b) = \frac{\|\sigma_a - \sigma_b\|}{\max(\sigma_a, \sigma_b)}$$

$$S(a,b) = \frac{\|\sigma_a . \sigma_b - \sigma_{ab}\|}{\sigma_a . \sigma_b}$$

where a and b designate respectively the original mesh and its degraded version.

The global measure is finally given by follows:

$$MSDM(a,b) = \left(\frac{1}{n}\sum_{j=1}^{n} LMSDM(a_j, b_j)^3\right)^{1/3}$$

The fourth one, named Dame [22], is based on the estimation of Dihedral angles. The idea developed by the author is to measure the variations of this angle for all edges of the mesh. They also integrate masking weight based on the smoothness and a visibility weight. This metric is computed as follows:

$$Dame = \frac{1}{n_e} \sum_{n_e} \|\alpha_O(\mathrm{i}) - \alpha_d(\mathrm{i})\| m_i . w_i$$

where ne represents the number of edges. $\boldsymbol{\alpha_O(i)}$ and $\boldsymbol{\alpha_d(i)}$are respectively the dihedral angles of the original and degraded meshes. mi is the masking weight, while wi is the visibility weight.

The last one is the sum of the difference between the local normal of the original mesh and its degraded version. This geometric attribute has been commonly used in 3D Mesh domain.

Regression Step

Once the selected features are extracted from the original mesh and its degraded version, a Support Vector Machine for Regression [24], generally called Support Vector Regression (SVR), has been used to combine it. This method has been widely used in pattern recognition with a certain success. Note that this kind of machine learning can be also used for classification problem with only few differences (cost function). The goal is here to find a function with a certain deviation (not exceeds a certain fixed value (ε)) according to the training set. In our case, the training data is composed of an input vector, which corresponds here to the selected features and its corresponding target, which corresponds here to the subjective score. A Gaussian function has been used to define the kernel function. In order to generalize our results, a 4-fold cross validation method was applied (75% for the training step and 25% for the testing step).

Evaluation and Results

In order to evaluate our method, the General Mesh database [25] has been used. This dataset is composed of 88 meshes derived from 4 original meshes as presented in Fig. 2 (22 meshes per original mesh). Noise and smoothing are the considered degradation types. Four degradation locations are chosen to insert the considered degradation types with different strengths: whole mesh, smooth areas, rough areas and intermediate areas. The authors define this last one as the regions between smooth and rough areas. For each of the degraded mesh, the mean subjective score, obtained from 12 observers, is provided.

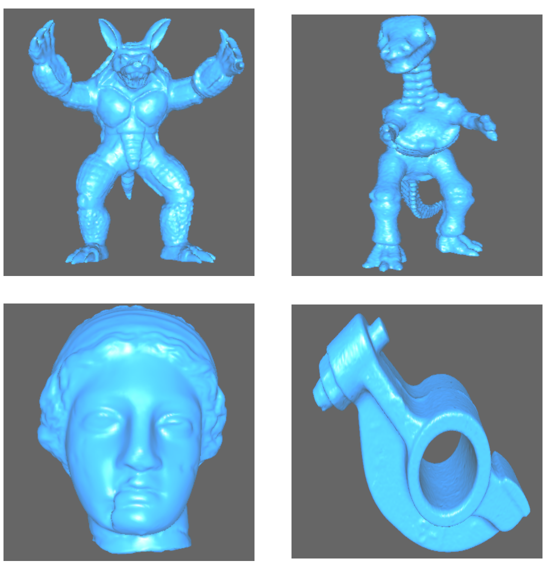

Figure 2. Sample of 3D meshes of the General Mesh Database.

The more common criteria generally computed to evaluate the performance of a given quality metric have been here used: Pearson Linear Correlation Coefficient (PCC) and Spearman Rank Correlation Coefficient (SROCC). The PCC value is often used to measure the prediction accuracy and it's computed using the true values (or using the values obtained after applied the logistic function), while the SROCC is used to measure the prediction monotonicity and it's computed using the rank.

Our method has been also compared to some other metrics, which are considered as the state-of-the-art (see Table 2).

Table 2. List of the compared 3D Mesh Image Quality Metric

Metrics	Metrics
HD	GL1 [10]
RMS	GL2 [11]
MSDM [12]	DWPM2 [21]
Dame [22]	DWPM1 [23]

It's important to remember that we have used a 4-fold cross validation method to evaluate our method (section 3.2). As the used database is composed of 4 different meshes, each subset corresponds thus to a given mesh. So, the 3D meshes using during the learning step is different from that of the testing step.

In Table 3, we present the global performance (i.e. whatever the degradation type). Our metric acquires the best result in terms of correlation with the subjective judgments. Indeed, its PCC and SROCC values are respectively equal to 0.9229 and 0.9113, which are higher than the compared metric. The Dame and the MSDM metrics have obtained respectively the second best PCC (0.8414) and the second best SROCC (0.8379) values. Note that the difference between the best and the second is high.

Table 3. Global Performance

Metric	PCC	SROCC
MSDM	0.8333	0.8379
HD	0.3445	0.2921
Dame	0.8414	0.8179
GL1	0.3684	0.4082
GL2	0.6021	0.5706
RMS	0.3179	0.3645
DWPM2	0.5220	0.4975
DWPM1	0.6556	0.7188
Our method	0.9228	0.9113

Table 4. PCC and SROCC values obtained for each subset

Metric	Armadillo		Venus		Dyno		Rocker	
	PCC	SROCC	PCC	SROCC	PCC	SROCC	PCC	SROCC
GL2	0.7646	0.7775	0.8771	0.9097	0.3530	0.3055	0.4137	0.2897
DWPM2	0.6606	0.7413	0.4197	0.3477	0.4606	0.5235	0.5472	0.3775
MSDM	0.8274	0.8475	0.8747	0.8758	0.7655	0.7301	0.8655	0.8984
Dame	0.7682	0.5720	0.8155	0.8566	0.9021	0.9232	0.8798	0.9198
Our method	0.9017	0.8295	0.9595	0.9582	0.9156	0.9232	0.9144	0.9345

We show in Table 4 the obtained correlation values for each mesh (i.e. each subset). As we can easily see, our metric achieved the best results and all the correlation values of our metric are superior to 0.9, except for the Armadillo mesh where its SROCC is equal to 0.8295. The best performance has been obtained for the 3D Venus mesh. We can also note that the performances of our method are relatively similar for all the 3D meshes, while the performances of the other metrics vary highly from a mesh to another. For example, the PCC value for the GL2 metric of the 3D Venus and the 3D Dyno meshes are respectively equal to 0.8771 and 0.3530.

We also evaluate the performance of our method according to the degradation type. Tables 5 and 6 present respectively the obtained PCC and SROCC values for the noise and the smooth distortions.

According to the obtained results, we can note that the best performances for the compared metrics are obtained for noise degradation, except the MSDM metric. As the SSIM 2D metric, this metric can well estimate the quality of smooth meshes. We can also see that these correlation values not exceed 0.80 for the smooth degradation, which is not high. Our metric obtained the best metric for the noise degradation (0.9229) and the second best metric for the smooth degradation (0.7144). For this last one, the MSDM obtained the best result (0.7263). Moreover, the RMS (0.8202) and HD (0.6816) metrics obtained better PCC value than the MSDM (0.5356) metric for the noise degradation.

Table 5. Obtained PCC values according to the degradation type

Metric	Degradation type	
	Noise	Smooth
MSDM	0.5356	0.7263
HD	0.6816	0.5277
Dame	0.6580	0.6181
GL1	0.8212	0.6753
GL2	0.8221	0.6536
RMS	0.8202	0.6900
DWPM2	0.8982	0.6269
DWPM1	0.8219	0.5011
Our method	0.9229	0.7144

To better show the distribution of the obtained scores, we also display in Fig. 3 the MOS versus predicted MOS. This plot depicts the correlation of the predicted scores versus its corresponding subjective judgments for the used mesh database. Note that the scatter of this distribution is smaller, which indicates that our system predict well the subjective scores.

Table 6. Obtained SROCC values according to the degradation type

Metric	Degradation type	
	Noise	Smooth
MSDM	0.5297	0.6167
HD	0.6378	0.6471
Dame	0.5962	0.5000
GL1	0.7413	0.5958
GL2	0.7413	0.5875
RMS	0.7273	0.6208
DWPM2	0.8131	0.5746
DWPM1	0.7601	0.5584
Our method	0.9073	0.6875

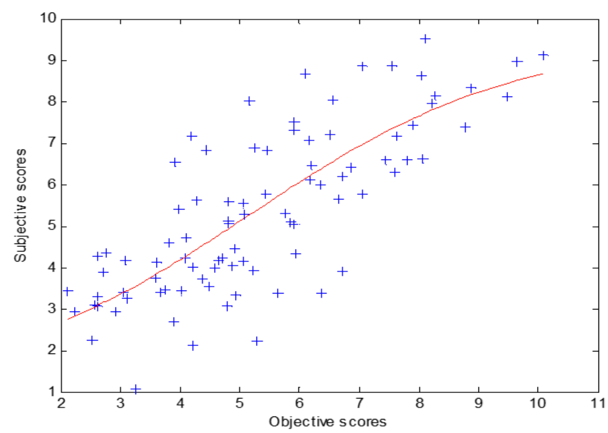

Figure 3. MOS vs Objective scores.

Conclusion

In this paper, a 3D mesh quality metric based on features fusion has been proposed. The selected features are here some 3D mesh quality metrics and a geometric attribute. The underlying idea is to consider the benefits of each of them in order to better predict the subjective score. Our method has been evaluated in terms of correlation with the subjective judgments using the whole General Mesh Database and also by comparing its performance with the state-of-the-art for different degradation types. The obtained results show the relevance of the proposed approach.

References

[1] J. Fierrez-Aguilar, Y. Chen, J. Ortega-Garcia and A. K. Jain., "Incorporating image quality in multi-algorithm fingerprint verification", International Conference on Biometrics (ICB), Springer LNCS-3832, pp. 213-2207, 2006

[2] J. Galbally and S. Marcel, “Face Anti-spoofing Based on General Image Quality Assessment”, International Conference on Pattern Recognition, pp. 1173-1178, 2014

[3] M. Pedersen and J. Y. Hardeberg, “ Survey of full-reference image quality metrics,” Høgskolen i Gjøviks rapportserie ISSN: 1890-520X, 2009

[4] Z. Wang, A.C. Bovik and B.L. Evans, “Blind measurement of blocking artefacts in images,” IEEE International Conference on Image Processing, Vol. 3, pp. 981-984, 2000

[5] H. R. Sheikh, A. C. Bovik, and L. K. Cormack, “No- Reference Quality Assessment Using Natural Scene Statistics: JPEG2000,” IEEE Transactions on Image Processing, Vol. 14, no. 12, 2005

[6] A. Chetouani, G. Mostafaoui and A. Beghdadi, “A New Free Reference Image Quality Index Based on Perceptual Blur Estimation”, Pacific-Rim Conference on Multimedia, pp. 1185-1196, 2009

[7] A. Chetouani, “Full reference image quality metric for stereo images based on Cyclopean image computation and neural fusion”, Visual Communications and Image Processing, pp. 109-112, 2014

[8] W. Zhou, G. Jiang, M. Yu, F. Shao and Z. Peng, “Reduced-reference stereoscopic image quality assessment based on view and disparity zero-watermarks”, Signal Processing: Image Communication, Volume 29, Issue 1, pp. 167-176, 2014

[9] F. Shao, S. Gu, G. Jang and M. Yu, “A Novel No-Reference Stereoscopic Image Quality Assessment Method”, Symposium on Photonics and Optoelectronics pp. 1-4, 2012

[10] Karni, Z., Gotsman, C., “Spectral compression of mesh geometry”, ACM Siggraph, pp 279–286, 2000

[11] O. Sorkine, D. Cohen-Or and S. Toldeo, “High-pass quantization for mesh encoding”, Eurographics Symposium on Geometry Processing, pp. 42–51, 2003

[12] G. Lavoue, E. Drelie Gelasca, F. Dupont, A. Baskurt and T. Ebrahimi, “Perceptually driven 3D distance metrics with application to watermarking”, SPIE, vol. 6312, pp. 63,120L 63,120L–12. SPIE, 2006

[13] Z. Wang, A. Bovik, H. Sheikh and E. Simoncelli, “Image quality assessment: From error visibility to structural similarity”, IEEE Transactions on Image Processing 13(4), 600–612, 2004

[14] G. Lavoué, “A Multiscale Metric for 3D Mesh Visual Quality Assessment”, Computer Graphics Forum 30(5), 1427–1437, 2011

[15] F. Torkhani, K. Wang, J.M. Chassery, “A Curvature Tensor Distance for Mesh Visual Quality Assessment”, International Conference on Computer Vision and Graphics, 2012

[16] K. Wang, F. Torkhani and A. Montanvert, “A Fast Roughness-Based Approach to the Assessment of 3D Mesh Visual Quality”, Computers & Graphics, 2012

[17] LavouéChaker G. Lavoué, M.C. Larabi and L. Vasa, “On the Efficiency of Image Metrics for Evaluating the Visual Quality of 3D Models”, IEEE Transactions on Visualization and Computer Graphics, 2013

[18] H.R. Sheikh and A.C Bovik, “Image information and visual quality”, IEEE Transactions on Image Processing, Vol.15, pp. 430-444, 2006

[19] S. Daly, “The Visible Differences Predictor: An Algorithm for the Assessment of Image Fidelity”, A.B. Watson (ed.) Digital Images and Human Vision, pp. 179–206. MIT Press, 1993

[20] G. Lavoué and R. Mantiuk, “Quality Assessment in Computer Graphics”, Chapter in Visual Signal Quality Assessment – Quality of Experience (QoE). Deng, C., Ma, L., Lin, W., Ngan, K.N. (Editors), Springer, 2015

[21] E. D. Gelasca, T. Ebrahimi, M. Corsini and M. Barni, “Objective evaluation of the perceptual quality of 3D watermarking”, IEEE International Conference on Image Processing, pp. 241–244, 2015

[22] L. Vasa and J. Rus, “Dihedral Angle Mesh Error: a fast perception correlated distortion measure for fixed connectivity triangle meshes”, Computer Graphics Forum 31(5), 2012

[23] M. Corsini, E. D. Gelasca, T. Ebrahimi, M. Barni, “Watermarked 3-D Mesh Quality Assessment”, IEEE Transactions on Multimedia 9(2), pp. 247–256, 2007

[24] http://asi.insa-rouen.fr/enseignants/~arakoto/toolbox/

[25] G. Lavoue, E. Drelie Gelasca, F. Dupont, A. Baskurt and T. Ebrahimi, “Perceptually driven 3D distance metrics with application to watermarking”, SPIE.Vol 6312. SPIE, 63120L-63120L-12, 2006

Author Biography

Aladine Chetouani received the master’s degree in computer science from the University Pierre and Marie CURIE, France, in 2005, and the Ph.D. degree in image processing from the University of Paris 13, France, in 2010. From 2010 to 2011, he was a Post-Doctoral Researcher with the L2TI Laboratory, Paris 13 University. He is currently a Teacher and a Researcher with the Laboratory PRISME. His present interests are in image quality, perceptual analysis, visual attention, and image processing for cultural heritage.