A NO-REFERENCE VISUAL QUALITY METRIC FOR 3D COLOR MESHES

Zicheng Zhang[1](✉),Wei Sun[1],Xiongkuo Min[1],Tao Wang[1],Wei Lu[1],Wenhan Zhu[2],and Guangtao Zhai[1]

[1]Institute of Image Communication and Network Engineering, Shanghai Jiao Tong University, China
[2]MoE Key Lab of Artificial Intelligence, AI Institute, Shanghai Jiao Tong University, China
zzc1998@sjtu.edu.cn

2021 IEEE International Conference on Multimedia & Expo Workshops (ICMEW) | 978-1-6654-4989-2/20/$31.00 ©2021 IEEE | DOI: 10.1109/ICMEW53276.2021.9455963

ABSTRACT

To improve the viewers' quality of experience (QoE) in computer graphics applications, the visual quality assessment (VQA) of 3D meshes is becoming a popular task in the multimedia area. Since 3D meshes are quite sensitive to the processing operations like simplification and compression, many studies concerning the VQA of 3D meshes have been carried out to measure the caused degradations. However, the previous studies mostly utilize full-reference metrics and focus mainly on the geometry attributes. While in some application scenarios such as 3D reconstruction, digital entertainment, and medical modeling, the reference 3D mesh is not always available and the color information can not be ignored. Therefore, in this paper, we propose a no-reference visual quality metric for 3D color meshes, which is based on the statistical parameters and entropy estimated from the probability distributions of curvature, dihedral angles, face area, face angle, and diffuse color information. The performance of the proposed method is validated on a database specially built for VQA of 3D color meshes. Experimental results show that our metric operates stably and achieves the highest correlation with subjective judgement.

***Index Terms*—** Visual quality assessment (VQA), no-reference (NR), 3D meshes, diffuse color

1. INTRODUCTION

With the rapid development of computer graphics, the digital representation of 3D models has been widely studied and used in a wide range of application scenarios such as virtual reality (VR), medical 3D reconstruction, and video post-production [1]. Among the common digital representation forms of 3D models (mesh, voxel, point cloud), the 3D mesh is more complicated because it is a collection of vertices, edges, and faces which together define the shape of a 3D model. Additionally, except for geometry information, the 3D mesh may also contain various appearance attributes, such as color and material. Therefore, the 3D mesh is able to vividly display exquisite models while it may take up relatively large storage space. Limited by complex application environment and fixed transmission bandwidth especially on mobile devices, diverse 3D mesh encoders utilize processing operations such as compression and simplification [2], to adapt to specific needs, which inevitably cause damage to the visual quality of 3D meshes. However, in the literature, most VQA metrics designed for 3D meshes [3] [4] [5] mainly concerns about geometry information while ignoring apperance attributes. As far as we know, few works have been conducted to deal with the VQA problems for 3D meshes with diffuse colors. To solve the problem of quantifying the quality score of 3D color meshes, we can simply refer to human objects for subjective scores. But the subjective evaluation is usually expensive, time-consuming, and unstable in real-world situations. Thus it is crucial to design objective metrics for evaluating the visual quality of 3D color meshes.

In the current literature, various metrics have been designed to evaluate the visual quality of 3D meshes. The mainstream metrics can be generally categorized into two types: model-based metrics which operate directly on the 3D models [3] [4] [5] and image quality assessment (IQA) metrics which operate on the rendering snapshots of 3D models [6] [7]. The IQA metrics can effectively extract the quality features from the snapshots with the mature development of IQA methods. However, affected by diverse viewpoints and complicated animations, the IQA metrics may not be stable and precise when predicting the quality of 3D meshes. Therefore, model-based metrics are more suitable and effective for VQA of 3D meshes since the mesh model is invariant to the viewpoints. Currently speaking, most model-based metrics are full-reference (FR) models and they are inspired by similar ideas exploited in IQA methods like mean squared error (MSE) at the vertex level, distribution distance computed between feature maps and structure similarity based on geometry. Considering that the reference is not always available, some NR model-based metrics are proposed, which are mainly developed on the basis of geometry characteristics such as curvature, dihedral angle, and roughness [8] [9] [10]. Such metrics are able to predict the quality of 3D meshes only when the geometry distortions exist, and they might fail to evaluate the visual quality of 3D meshes with color distortions.

This work was supported in part by the National Science Foundation of China (No.61831015, 61771305, 61927809 and U1908210), the National Key R&D Program of China (No.2019YFB1405900).

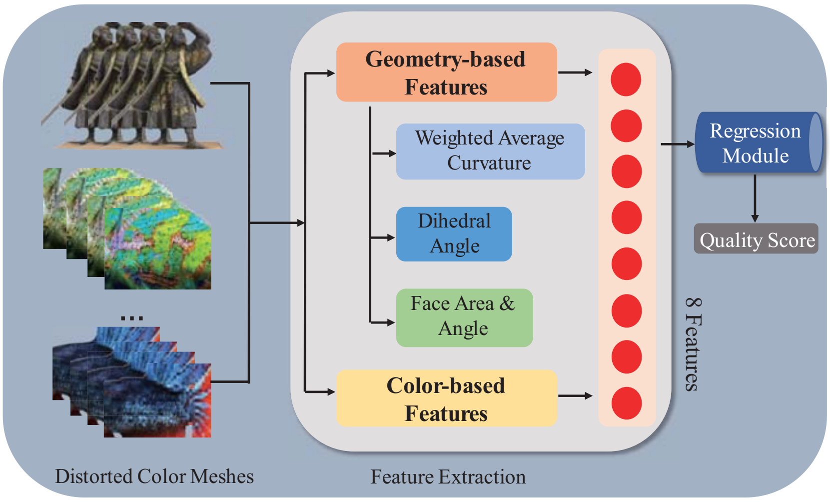

Fig. 1. Framework of the proposed method.

To address the VQA problems of 3D color meshes, this paper proposes an NR metric that operates directly on the models. Different groups of features are extracted from both geometry and color information by analyzing the corresponding probability distributions of different attributes. Then the features are collected and integrated into quality scores using the support vector regression (SVR) model. To demonstrate the accuracy and stability of the proposed metric on the color mesh distortion measure (CMDM) database [11], several representative IQA metrics along with model-based metrics are selected as competitors. Experimental results show that the proposed metric achieves the highest correlation with the subjective scores.

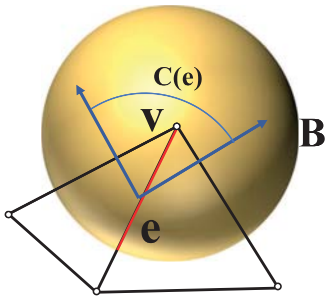

Fig. 2. Example of the variables corresponding to the curvature calculation, where the red line indicates $|e \cap B|$ and $C(e)$ indicates the curvature contribution of e.

2. PROPOSED METHOD

The framework of our proposed method is presented in Fig. 1, which includes a feature extraction module and a regression module. Specifically, the features are mainly extracted from the geometry and color information. The geometry-based features are extracted from attributes such as curvature, dihedral angle, face area, and face angle while the color-based features are extracted from the LAB color channels. Furthermore, the features are computed directly from the origin 3D mesh model rather than the 2D snapshots captured from the screen. Finally, the extracted features are integrated into a visual quality score through the support vector regression (SVR) model.

2.1. Geometry-based Features

2.1.1. Curvature

Curvature has always been a critical attribute in numerous studies concerning 3D VQA issues due to its strong correlation with representative visual characteristics like roughness or smoothness. So far, various curvature definitions have been introduced for 3D meshes [12] [13], among which the average curvature is proven to be able to stably describe the local structural information of 3D meshes. Thus in this section, a weighted average curvature method introduced in [13] is adopted to measure the roughness of embedded surfaces in 3D meshes. Additionally, by further analyzing the probability distribution of the weighted average curvature, the overall surface situation of 3D meshes can be obtained. For each vertex in the mesh, the weighted average curvature is calculated by averaging the curvature contributions over a certain region B around the vertex, which can be given as:

$$\mathbf{M}(\mathbf{v}) = \frac{1}{|B|}\sum_{e\in E} C(e)|e\cap B| \cdot \bar{e}\bar{e}^t, \tag{1}$$

where $M(v)$ represents the weighted average curvature for vertex v, region B is a sphere region centered at v and its radius is 1/100 of the bounding box of the 3D mesh, $|B|$ stands for the surface area of region B. E is the set of edges that

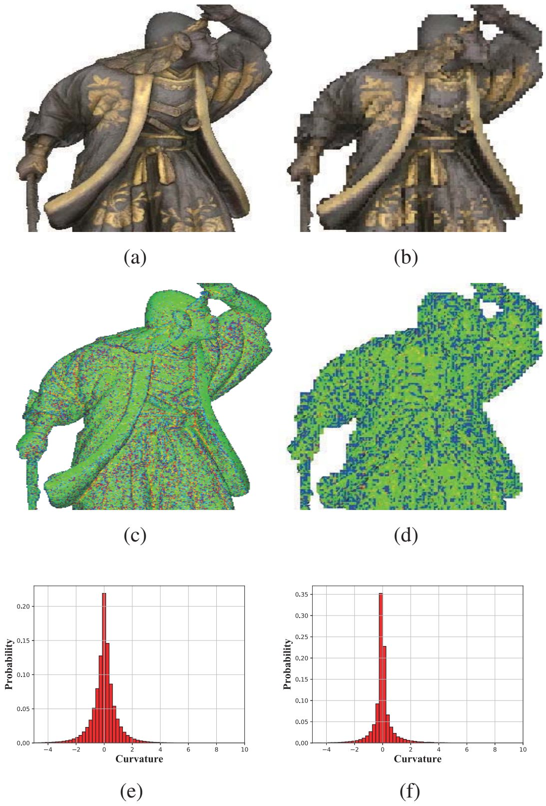

Fig. 3. Example of a reference 3D mesh and its corresponding geometry-distorted mesh from the CMDM database [11]. (a) and (b) are snapshots of the reference and its corresponding geometry-distorted mesh, (c) and (d) are the curvature maps of the reference and its corresponding geometry-distorted mesh, (e) and (f) are the normalized curvature probability distributions of the meshes respectively.

are linked to the vertex v, $C(e)$ indicates the curvature contribution of e (the signed angle between the normals of the two oriented triangles incident to edge e), $|e \cap B|$ denotes the weight which is defined as the length of $e \cap B$ (always between 0 and $|e|$) and $\bar{e}$ is a unit vector in the same direction as e. An example of the variables corresponding to the curvature calculation is shown in Fig. 2.

Fig. 3 illustrates an example of reference and distorted meshes along with their corresponding curvature probability distributions. Here we propose to adopt Gamma distribution to estimate curvature statistical parameters, which is proven effective in previous research [14]. Before estimating statistical parameters, the weighted averaged curvature should be normalized so that the features can be more comparable between different 3D meshes. Then the Gamma distribution parameters can be estimated as:

$$\widetilde{\mathbf{M}} \sim \Gamma(\alpha, \beta) \equiv \mathrm{Gamma}(\alpha, \beta), \tag{2}$$

where $\widetilde{\mathbf{M}}$ represents the normalized probability distribution of the weighted average curvature, α and β stands for the shape and rate parameters. The corresponding probability density function in the shape-rate Gamma model is $f(x; \alpha, \beta) = \frac{\beta^\alpha x^{\alpha-1} e^{-\beta x}}{\Gamma(\alpha)}$ for $x > 0, \alpha, \beta > 0$, where $\Gamma(\alpha)$ is the Gamma function. Finally, the parameters α and β can be taken as the curvature features.

2.1.2. Dihedral Angle

Normally speaking, dihedral angle is the angle between two planes. For a 3D mesh, the dihedral angle is the angle between the normals of two adjacent faces, which has been utilized in [15] as an effective indicator for measuring the loss of the mesh simplification. Furthermore, [8] exploits oriented dihedral angles instead of the simple dot product of normals to better distinguish the convex and concave angles, which achieves great performance. Encouraged by similar ideas, we adopt the dihedral angles set to describe the visual quality of 3D meshes. Assuming that the vertices for two adjacent faces f_1 and f_2 are $\{v1, v3, v4\}$ and $\{v2, v3, v4\}$, we have:

$$\mathbf{D}_{\mathbf{f_1},\mathbf{f_2}} = \arccos\left(n_1 \cdot n_2\right) * \mathrm{sgn}\left(n_1 \cdot (v_2 - v_1)\right), \tag{3}$$

where D_{f_1,f_2} is the oriented dihedral angle between two adjacent faces f_1 and f_2, n_1 and n_2 are the normals of f_1 and f_2, sgn denotes the signum function which is used to decide the orientation of the dihedral angle.

Usually, quantization is exploited in many lossy 3D mesh compression and simplification operations, which may affect the visual quality of 3D meshes. To measure the information difference caused by the reasons mentioned above, we propose to use entropy, which has a good correlation with information loss and has been confirmed efficient for VQA of 3D meshes [16]. The dihedral angle feature can be computed as:

$$\mathbf{E}_{\widetilde{\mathbf{D}}} = entropy(\widetilde{\mathbf{D}}), \tag{4}$$

where $\widetilde{D}$ is the normalized result of dihedral angle probability distribution, $entropy(\cdot)$ indicates the entropy function, $E_{\widetilde{D}}$ is the entropy result of $\widetilde{D}$. We can then take $E_{\widetilde{D}}$ as the feature of dihedral angle.

2.1.3. Face Area and Angle

Area and angle are two simple attributes of 3D mesh faces which can be easily computed by making use of the coordinates of the face's vertices. In the mesh smoothing algorithm proposed in [17], attributes including face angle are used to predict the new location of the smoothed nodes. While in the 3D mesh encoding method introduced in [18], face angle is utilized to instruct the compression of 3D meshes, which indicates that face angle is related with the quality of 3D meshes. Meanwhile, the operation processes like compression or simplification usually change the location of the vertices and sometimes even remove part of the vertices to increase the compression rate, which inevitably influences the

(a) (b) (c) (d) (e)

Fig. 4. A comparison example for color distortion. (a) represents the snapshots of the reference 3D mesh while (b)-(e) stands for the snapshots of the meshes with 4 increasing levels of color distortion.

Table 1. The overview of features for proposed method

Feature Category	Feature Description	Symbol	Computation
Geometry	Gamma estimation parameters of normalized curvature distribution	α,β	Eq.2
	Entropy of normalized dihedral angle distribution	$E_{\widetilde{D}}$	Eq.4
	Entropy of normalized face area and angle distributions	$E_{\widetilde{Ar}}$,$E_{\widetilde{An}}$	Eq.5
Color	Entropy of normalized LAB color channels distrbutions	$E_{\widetilde{L}}$,$E_{\widetilde{A}}$,$E_{\widetilde{B}}$	Eq.6

distribution of the face area. Therefore, to further measure the visual quality degradation of 3D meshes introduced by the processes mentioned above, the face area is taken into consideration as well. The features for the face area and angle can then be derived as:

$$\mathbf{E}_{\widetilde{\mathbf{Ar}}} = entropy(\widetilde{\sigma}), \quad \widetilde{\sigma} \in \{\widetilde{An}, \widetilde{Ar}\}, \tag{5}$$

where $\widetilde{Ar}$ and $\widetilde{An}$ represents the normalized probability distributions of face area and angle, $entropy(\cdot)$ denotes the entropy fuction, $E_{\widetilde{Ar}}$ and $E_{\widetilde{Ar}}$ stands for the entropy results of $\widetilde{Ar}$ and $\widetilde{An}$.

2.2. Color-based Features

Color is a significant aspect of VQA for 3D color meshes. Fig. 4 shows four levels of color distortion and we can see clearly that with the increase of color distortion level, the visual quality is damaged more severely. To better understand the perceived quality of 3D meshes with diffuse colors, we first transform the RGB color channels to LAB color channels, which are more in line with the human vision system (HVS) [19]. The color information loss usually occurs during quantification, where the bits are simply compressed to represent the color, and also in simplification algorithms, where some color information is directly removed along with the vertices. To measure the color information loss, we exploit the entropy of LAB color channels, which can be given as:

$$\mathbf{E}_{\widetilde{\phi}} = entropy(\widetilde{\phi}), \quad \widetilde{\phi} \in \{\widetilde{L}, \widetilde{A}, \widetilde{B}\}, \tag{6}$$

where $\widetilde{L}$, $\widetilde{A}$, and $\widetilde{B}$ represent the normalized probability distributions of the LAB color channels, $E_{\widetilde{\phi}}$ stands for the entropy result of the LAB color channels.

2.3. Regression

After the feature extraction processes described above, a total of 8 features are computed to represent the visual quality of 3D color meshes. The feature categories, descriptions, symbols, and computation equations are listed in the Tab. 1. In this section, we utilize the SVR model to integrate the extracted features into a quality score. The distorted 3D meshes' features along with the corresponding subjective scores are used to train the SVR model, then the trained SVR model can predict the quality score based on the same feature extraction processes.

3. EXPERIMENT

3.1. Database

The method proposed in this paper is validated on the color mesh distortion measure (CMDM) database [11]. The database is generated from 5 source models subjected to geometry and color distortions. Then the source models are corrupted with 4 types of distortions based on color and geometry and each type of distortion is adjusted with 4 different strengths. The selected distortions are able to represent the common visual quality loss, which can usually be perceived during typical 3D model processing. In all, there are 80 distorted models in this database and each distorted model is provided with 5 subjective scores according to its viewpoints and animation types. For simplification, we use the average of the 5 subjective scores as the final quality score for the distorted model.

3.2. Evaluation Criterion

Three mainstream consistency evaluation criteria are utilized to compare the performance, which include Spearman Rank

Table 2. Performance comparison with competitors

Type	Metric	SRCC	PLCC	KRCC
2D IQA	CPBD	0.5559	0.4676	0.4076
	ILNIQE	0.5412	0.5726	0.4167
	NIQE	0.4059	0.4768	0.3000
	BRISQUE	0.4882	0.5786	0.3598
3D VQA	NR-SVR	0.4489	0.6082	0.3420
	NR-GRNN	0.6948	0.6599	0.5130
	NR-CNN	0.5022	0.5204	0.3420
Proposed	NCMQE	**0.8794**	**0.8896**	**0.7000**

Table 3. Performance results of ablation experiment

Groups	All	G1	G2	G3	G4
SRCC	0.8794	0.8412	0.8618	0.7647	0.6089
PLCC	0.8896	0.8197	0.8400	0.7775	0.7300
KRCC	0.7000	0.6500	0.6667	0.5941	0.4788

Correlation Coefficient (SRCC), Kendall's Rank Correlation Coefficient (KRCC), and Pearson Linear Correlation Coefficient (PLCC). The three indexes mentioned above can effectively reflect the correlation between predicted scores and subjective scores. Additionally, a good model should obtain values of SRCC, KRCC, and PLCC close to 1. Since there are 5 groups of models, we select 4 groups of models (4 source models $\times$ 16 distortions) as the training set and leave 1 group of models (1 source model $\times$ 16 distortions) for testing. Repeating the process 5 times with different selections, each group of models would have been used as a testing set. The median performance result would be reported as the final result.

3.3. Evaluation Competitors

In the literature, few metrics are proposed to deal with the VQA of 3D color meshes. In order to evaluate the performance of the proposed method, some quality assessment metrics that might be able to predict the visual quality of 3D meshes are utilized as competitors. Unfortunately, few no-reference quality assessment metrics for 3D meshes are open-sourced, thus we try to reproduce some of the metrics. Specifically, the metrics used for comparison can be divided into two types:

• **2D IQA metrics**: No-reference image quality assessment metrics which may be effective by evaluating the quality of 2D images rendered from the 3D color meshes: CPBD [20], NIQE [21], ILNIQE [22], BRISQUE [23].

• **3D VQA metrics**: No-reference quality assessment metrics designed especially for 3D meshes usually without color: NR-SVR [8], NR-GRNN [9], NR-CNN [10].

3.4. Performance Discussion

Tab. 2 presents the final results of experiment performance. We refer to our method as NCMQE (no-reference color mesh quality evaluation). In general, our method achieves the highest correlation with the subject scores among the tested metrics. The 2D IQA metrics have a certain ability to predict the quality of color 3D meshes, however, restricted to the limited viewpoints, the performance of 2D IQA metrics is not satisfactory and convincing. Besides, the current 3D VQA metrics also do not perform well, of which the NR-GRNN obtains the highest SRCC score but still inferior to NCMQE. It can be easily explained that the mainstream 3D VQA metrics rarely take the color information into consideration and only the geometry features can't enable such metrics to evaluate the visual quality of color meshes properly.

3.5. Ablation Experiment

To analyze the contributions of different groups of features, several ablation experiments are conducted in this section. During each experiment, only one group of features is eliminated and the other groups of features are reserved. The results can are reported in Tab. 3. Specifically, the following feature combinations are tested:

• ALL: All groups of features are included.

• $G1$: Only curvature features are removed.

• $G2$: Only dihedral angle features are removed.

• $G3$: Only face area and angle features are removed.

• $G4$: Only color features are removed.

It can be seen from the results that $G1 - G4$ performs worse than all groups of features, which indicates that the four groups of features all make contributions to the final result. Among $G1 - G4$, $G4$ achieves the lowest performance result, which means that the color features are crucial for evaluating the quality of color meshes. What's more, there's little difference between the performance results of $G1$ and $G2$, while $G3$ performs worst among the geometry features, indicating that face area and angle features may make more contributions when it comes to the geometry features.

4. CONCLUSION

This paper proposes a no-reference model-based metric to evaluate the visual quality of 3D color meshes. The feature extraction of the proposed metric is mainly dependent on the statistical parameters and entropy estimated from the probability distributions of curvature, dihedral angles, face area, face angle, and diffuse color information. Then the extracted features are integrated into a single quality score by the support vector regression model. The performance comparison experiment results show that NCMQE achieves the highest correlation with the subjective scores among the selected comparison metrics, and the ablation experiment shows that all groups of features make their own contributions to the final results.

5. REFERENCES

[1] H. Graf, S. P. Serna, and A. Stork, "Adaptive quality meshing for "on-the-fly" volumetric mesh manipulations within virtual environments," in *IEEE Symposium on Virtual Environments, Human-Computer Interfaces and Measurement Systems*, 2006, pp. 178–183.

[2] J. Vollmer, R. Mencl, and H. Müller, "Improved laplacian smoothing of noisy surface meshes," *Computer Graphics Forum*, vol. 18, no. 3, pp. 131–138, 1999.

[3] L. Dong, Y. Fang, W. Lin, and H. S. Seah, "Perceptual quality assessment for 3d triangle mesh based on curvature," *IEEE Transactions on Multimedia*, vol. 17, no. 12, pp. 2174–2184, 2015.

[4] Kai Wang, Fakhri Torkhani, and Annick Montanvert, "A fast roughness-based approach to the assessment of 3d mesh visual quality," *Computers Graphics*, vol. 36, no. 7, pp. 808–818, 2012.

[5] Guillaume Lavoué, "A multiscale metric for 3d mesh visual quality assessment," *Computer Graphics Forum*, vol. 30, no. 5, pp. 1427–1437, 2011.

[6] Sheng Yang, Chao-Hua Lee, and C.-C. Jay Kuo, "Optimized mesh and texture multiplexing for progressive textured model transmission," in *Proceedings of the 12th Annual ACM International Conference on Multimedia*, 2004, p. 676–683.

[7] F. Caillaud, V. Vidal, F. Dupont, and G. Lavoué, "Progressive compression of arbitrary textured meshes," *Computer Graphics Forum*, vol. 35, no. 7, pp. 475–484, 2016.

[8] Ilyass Abouelaziz, Mohammed El Hassouni, and Hocine Cherifi, "No-reference 3d mesh quality assessment based on dihedral angles model and support vector regression," in *Image and Signal Processing*, 2016, pp. 369–377.

[9] I. Abouelaziz, M. El Hassouni, and H. Cherifi, "A curvature based method for blind mesh visual quality assessment using a general regression neural network," in *12th International Conference on Signal-Image Technology Internet-Based Systems (SITIS)*, 2016, pp. 793–797.

[10] I. Abouelaziz, M. E. Hassouni, and H. Cherifi, "A convolutional neural network framework for blind mesh visual quality assessment," in *IEEE International Conference on Image Processing (ICIP)*, 2017, pp. 755–759.

[11] Y. Nehmé, F. Dupont, J. P. Farrugia, P. Le Callet, and G. Lavoué, "Visual quality of 3d meshes with diffuse colors in virtual reality: Subjective and objective evaluation," *IEEE Transactions on Visualization and Computer Graphics*, vol. 27, no. 3, pp. 2202–2219, 2021.

[12] T. Surazhsky, E. Magid, O. Soldea, G. Elber, and E. Rivlin, "A comparison of gaussian and mean curvatures estimation methods on triangular meshes," in *IEEE International Conference on Robotics and Automation*, 2003, vol. 1, pp. 1021–1026 vol.1.

[13] Pierre Alliez, David Cohen-Steiner, Olivier Devillers, Bruno Lévy, and Mathieu Desbrun, "Anisotropic polygonal remeshing," New York, NY, USA, 2003, Association for Computing Machinery.

[14] Ilyass Abouelaziz, Mohammed El Hassouni, and Hocine Cherifi, "No-reference 3d mesh quality assessment based on dihedral angles model and support vector regression," in *Image and Signal Processing*, Cham, 2016, pp. 369–377.

[15] M. Corsini, E. D. Gelasca, T. Ebrahimi, and M. Barni, "Watermarked 3-d mesh quality assessment," *IEEE Transactions on Multimedia*, vol. 9, no. 2, pp. 247–256, 2007.

[16] Yaoyao Lin, Mei Yu, Ken Chen, Gangyi Jiang, Fen Chen, and Zongju Peng, "Blind mesh assessment based on graph spectral entropy and spatial features," *Entropy*, vol. 22, no. 2, 2020.

[17] N. Mukherjee, "A hybrid, variational 3d smoother for orphaned shell meshes," in *IMR*, 2002.

[18] Haeyoung Lee, Pierre Alliez, and Mathieu Desbrun, "Angle-analyzer: A triangle-quad mesh codec," *Computer Graphics Forum*, vol. 21, no. 3, pp. 383–392, 2002.

[19] W. Sun, X. Min, G. Zhai, K. Gu, S. Ma, and X. Yang, "Dynamic backlight scaling considering ambient luminance for mobile videos on lcd displays," *IEEE Transactions on Mobile Computing*, 2020.

[20] N. D. Narvekar and L. J. Karam, "A no-reference image blur metric based on the cumulative probability of blur detection (cpbd)," *IEEE Transactions on Image Processing*, vol. 20, no. 9, pp. 2678–2683, 2011.

[21] A. Mittal, R. Soundararajan, and A. C. Bovik, "Making a "completely blind" image quality analyzer," *IEEE Signal Processing Letters*, vol. 20, no. 3, pp. 209–212, 2013.

[22] L. Zhang, L. Zhang, and A. C. Bovik, "A feature-enriched completely blind image quality evaluator," *IEEE Transactions on Image Processing*, vol. 24, no. 8, pp. 2579–2591, 2015.

[23] A. Mittal, A. K. Moorthy, and A. C. Bovik, "No-reference image quality assessment in the spatial domain," *IEEE Transactions on Image Processing*, vol. 21, no. 12, pp. 4695–4708, 2012.