Reduced-Reference Quality Assessment of Point Clouds via Content-Oriented Saliency Projection

Wei Zhou, Guanghui Yue, Ruizeng Zhang, Yipeng Qin, and Hantao Liu

***Abstract*—Many dense 3D point clouds have been exploited to represent visual objects instead of traditional images or videos. To evaluate the perceptual quality of various point clouds, in this letter, we propose a novel and efficient Reduced-Reference quality metric for point clouds, which is based on Content-oriented sAliency Projection (RR-CAP). Specifically, we make the first attempt to simplify reference and distorted point clouds into projected saliency maps with a downsampling operation. Through this process, we tackle the issue of transmitting large-volume original point clouds to end-users for quality assessment. Then, motivated by the characteristics of the human visual system (HVS), the objective quality scores of distorted point clouds are produced by combining content-oriented similarity and statistical correlation measurements. Finally, extensive experiments are conducted on SJTU-PCQA and WPC databases. The experiment results demonstrate that our proposed algorithm outperforms existing reduced-reference and no-reference quality metrics, and significantly reduces the performance gap between state-of-the-art full-reference quality assessment methods. In addition, we show the performance variation of each proposed technical component by ablation tests.**

***Index Terms*—Point clouds, reduced-reference quality metric, visual content, saliency projection, human visual system.**

I. Introduction

MASSIVE visual data are emerging in our daily lives. Especially in recent years, due to the vigorous development of 3D capture and rendering techniques, point cloud has become one of the most popular immersive media formats. It leads to lots of real-world applications, such as automatic diving, mixed reality, remote sensing, and so on [1], [2]. Usually, a dense point cloud is a 3D model and has a group of scattered points in space, which is employed to represent an object. Each point owns geometric coordinates and photometric attributes. Similar to conventional images/videos, point clouds have also undergone a variety of artifacts during the multimedia signal processing chain, from acquisition, compression, to transmission, reconstruction, and display [3]–[5]. In other words, these procedures will inevitably cause quality degradation at end-users. Therefore, the quality evaluation of point clouds is crucial to monitor and guarantee satisfactory quality-of-experience.

The subjective quality assessment is the most dependable method because humans are the final receivers of point clouds. By carrying out relevant subjective tests, several point cloud quality databases have been established [6]–[9]. However, such subjective tests are often time-consuming, expensive, and labor-intensive. Thus, how to design effectively objective quality assessment models according to the well-known human visual system (HVS) is a challenging yet promising research direction.

Generally, for the objective quality metrics of point clouds, there exist three categories including full-reference (FR), no-reference (NR), and reduced-reference (RR). When pristine information is entirely accessible, FR methods are proposed by computing the difference or similarity between the distorted and pristine point clouds. The earliest FR metrics are used for the standardization body of MPEG point cloud compression, which involve point-to-point [10], point-to-plane [11], point-to-mesh [12], and plane-to-plane [13], etc. These methods compute the distance deviation between reference and distorted point clouds. Afterward, Yang et al. [14] developed the graph similarity index (GraphSIM) method based on graph signal processing, and also extended it to a multiscale variant [15]. Inspired by the structural similarity index (SSIM) [16], Alexiou et al. [17] exploited geometry, normal vectors, curvature values, and color information to form PointSSIM. Moreover, in [18], Meynet et al. utilized local curvature statistics to construct PC-MSDM and also extended it to the point cloud quality metric (PCQM) [19] according to the optimal composition of color and curvature features. Lu et al. [20] compared the 3D edge similarity to quantify point cloud quality. Except for direct comparisons on 3D point cloud models, other FR methods project point cloud data onto many 2D images from different views. Then, the mainstream traditional quality evaluation algorithms can be employed, such as PSNR and SSIM.

In real scenarios, the whole information of original reference point clouds may not be available. Several NR methods have been developed to estimate the visual quality from distorted point clouds, both from hand-crafted and learning-based aspects. For example, according to 3D natural scene statistics (NSS), Zhang et al. [21] presented the NR-3DQA for evaluating point cloud quality. In [22], the point cloud quality assessment network (PQA-Net) was designed on the basis of the multi-task learning. In addition, by view projection, 2D quality metrics in NR manner can be applied, e.g., the

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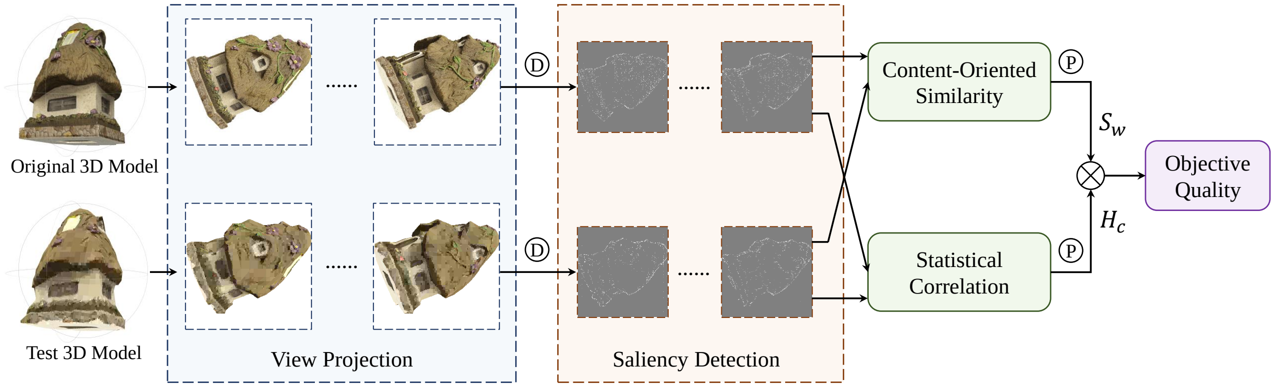


Fig. 1: Overall framework of the proposed RR-CAP, where Ⓓ and Ⓟ are the downsampling and pooling operations, respectively.

representative NSS methods called blind image spatial quality evaluator (BRISQUE) [23] and natural image quality evaluator (NIQE) [24]. Suppose when part of reference information can be obtained, RR metrics provide an intermediate solution. Nevertheless, in the literature, very few RR quality evaluation approaches for point clouds have been proposed. Liu et al. [25] exploited quantization parameters to estimate the perceptually visual quality of V-PCC compressed point clouds. To our best knowledge, there exists only one general-purpose RR metric named PCMRR [26] which relies on a small number of statistics from the original point clouds regarding geometry, normal vector, and color. The HVS characteristics are lacking in the design philosophy of the PCMRR method.

To fill the blank of the above-mentioned problem, we propose the RR metric based on Content-oriented sAliency Projection (RR-CAP). The primary contributions of the letter are summarized as:

1) Motivated by the HVS properties, we propose the first image-based RR point cloud quality assessment method via saliency projection.
2) The content-oriented similarity and statistical correlation measurements are developed in the proposed framework.
3) Our proposed quality metric can relieve the transmission burden for the large amount of point data, while still show competitive performance when tested on subject-rated databases.

The remaining parts of this paper are organized as follows. Section II first introduces RR-CAP metric in detail. In Section III, we then show experiment results and analyses on public point cloud quality databases. Finally, we conclude our work as well as give the link of the specific algorithm implementation in Section IV.

II. Proposed RR-CAP Metric

The general architecture of our RR-CAP metric is drawn in Fig. 1. To reduce the large-scale point cloud data from reference side, we first extract the downsampled saliency maps after view projection. The content-oriented similarity and statistical correlation are then integrated to estimate the perceptually visual quality score for test point cloud.

A. Saliency Extraction in Projected Planes

When subjects browse the targeted point clouds, they would synthesize the quality sensation from all views, resulting in the final experience. Therefore, we project both original and test 3D models into multiple 2D image planes. Here, we adopt the six perpendicular projections [6] which can uniformly cover most of the viewed content.

Because introducing artifacts may change the saliency behaviors and the HVS is more sensitive to distortions in salient areas, visual saliency plays a vital role in quality evaluation [27], [28]. After view projection, we extract saliency maps by image signature [29]. Specifically, for each projected image I, we first downsample the projection to a coarser counterpart as follows:

$$\tilde{I}(i,j) = A * I(si, sj), \tag{1}$$

where s represents the downsampling scale. $i = 1, 2, \ldots, \frac{I}{s}$ and $j = 1, 2, \ldots, \frac{J}{s}$ are indexes for the row and column of downsampled image, respectively. A indicates a low-passing filter. Moreover, $*$ denotes the convolution operation.

Then, a sign function of discrete cosine transform (DCT) coefficients [30] is specified as image signature for downsampled projection, which can be calculated by:

$$\hat{I} = \text{sign}(\text{DCT}(\tilde{I})). \tag{2}$$

With the image signature in the transformed format, we can convert it back to the spatial domain by inverse DCT (IDCT) and compute the saliency map as:

$$m = \text{IDCT}(\hat{I}) \odot \text{IDCT}(\hat{I}), \tag{3}$$

where $\odot$ indicates the Hadamard product. As can be seen from Fig. 1, instead of using visual saliency as weighting maps in most existing works, the downsampled saliency maps serve as the reduced-reference information in our proposed framework, which can alleviate the large transmission data of original point clouds.

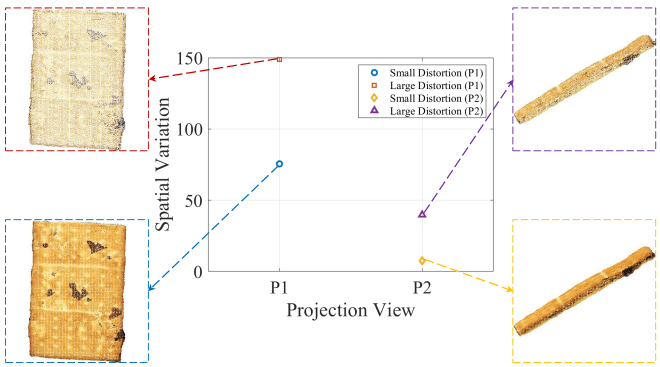


Fig. 2: An example to illustrate the relationship between visual content and quality degradation, where P1 and P2 are two projection views.

B. Content-Oriented Similarity Measurement

Intuitively, we can measure image structural similarity between original and test projected saliency maps. Given a distorted saliency map m_d along with the corresponding original reference saliency map m_r, we compute their structural similarity as follows:

$$S = \frac{(2\mu_r\mu_d + C_1)(2\sigma_{rd} + C_2)}{(\mu_r^2 + \mu_d^2 + C_1)(\sigma_r^2 + \sigma_d^2 + C_2)}, \tag{4}$$

where μ_r, μ_d, σ_r^2, σ_d^2, and σ_{rd} represent the corresponding local mean, variance, as well as covariance of pristine and distorted saliency maps. C_1 and C_2 are stabilizing constants.

Along with pooling the similarities for all views, we employ a content-oriented weighting strategy, which shows more consistency with the HVS perception. Considering that content is usually quantified by spatial information by using the Sobel filter [31], here the spatial variation is taken as the weight and calculated by:

$$w = \left|\mathrm{std}\left[\mathrm{Sobel}\left(I_d\right)\right] - \mathrm{std}\left[\mathrm{Sobel}\left(I_r\right)\right]\right|, \tag{5}$$

where $\mathrm{std}[\cdot]$ denotes the standard deviation that operates over the image pixels. I_r and I_d represent the reference and distorted projected images, respectively. Let n be the number of projection views. The content-oriented similarity measurement is obtained as follows:

$$S_w = \frac{1}{n}\sum S^w. \tag{6}$$

To show how the proposed content-oriented weighting strategy works, we provide two pairs of projection views with small and large distortion degrees, as illustrated in Fig. 2. We can discover that the visual contents from various views generally have different spatial variations. Additionally, the projection view with large distortion causes more spatial variation.

C. Statistical Correlation Measurement

Apart from the content-oriented similarity measurement, statistical information from the saliency maps is also important for point cloud quality. Therefore, for each test point cloud, we formulate the statistical correlation measurement by:

$$H_c = \frac{1}{n}\sum \frac{\mathrm{E}\left[h_r h_d\right] - \mathrm{E}\left[h_r\right]\mathrm{E}\left[h_d\right]}{\sqrt{\mathrm{E}\left[h_r^2\right] - \left(\mathrm{E}\left[h_r\right]\right)^2}\sqrt{\mathrm{E}\left[h_d{}^2\right] - \left(\mathrm{E}\left[h_d\right]\right)^2}}, \tag{7}$$

where $\mathrm{E}[\cdot]$ represents the expectation operator. h_r and h_d are the statistical histograms of original reference and distorted saliency maps, respectively.

Through the aforementioned procedures, we have two quality measurements, i.e., S_w and H_c, for content-oriented similarity and statistical correlation, respectively. Finally, the objective quality scores for distorted point clouds can be calculated as:

$$Q = S_w \cdot H_c. \tag{8}$$

III. Results and Analyses

In this section, we here compare our RR-CAP with many existing quality metrics on publicly subject-rated quality databases for point clouds. Besides, the ablation test is also conducted to verify the performance of each proposed technical component.

A. Experimental Protocols

We carry out extensive experiments on SJTU-PCQA [6] and WPC [7] databases. Both databases provide mean opinion score (MOS) as ground-truth subjective label for each distorted point cloud sample.

- SJTU-PCQA database: is composed of 9 reference point cloud samples. Several distortion types including geometry Gaussian noise, color noise, downscaling, octree-based compression, and their mixture are applied to generate 378 distorted point clouds. Each distortion type involves six levels.
- WPC database: has 20 original point clouds with four distortion types, resulting in 740 distorted point clouds. To be specific, there exist 60 samples with downsampling distortion, 180 point clouds with Gaussian noise, 320 and 180 samples compressed by the G-PCC and V-PCC codecs, respectively.

Four widely used evaluation criteria are adopted for performance comparisons, including Spearman rank-order correlations coefficient (SROCC), Kendall rank-order correlation coefficient (KROCC), Pearson linear correlation coefficient (PLCC), and root mean square error (RMSE). Among them, SROCC and PLCC/RMSE are employed to measure the monotonicity and accuracy of predictions, respectively. The KROCC is used for the ordinal association between two measured quantities. An excellent quality metric should have SROCC, KROCC, and PLCC near one, and RMSE closes to zero. Note that a nonlinear fitting process [32] is utilized to map the predicted qualities into the common scale space of subjective quality labels before computing the PLCC and RMSE for different quality metrics.

TABLE I: The performance comparisons of objective quality metrics on SJTU-PCQA and WPC databases. Note that the best performance values for FR, NR, and RR are in bold.

Ref	Type	Method	SJTU-PCQA Database				WPC Database			
			SROCC	KROCC	PLCC	RMSE	SROCC	KROCC	PLCC	RMSE
FR	Model-based	GraphSIM [14]	0.8483	0.6448	0.8449	1.5721	0.5831	0.4194	0.6163	17.1939
		PointSSIM [17]	0.6867	0.4964	0.7136	1.7001	0.4542	0.3278	0.4667	20.2733
		PCQM [19]	**0.8544**	**0.6586**	**0.8653**	**1.2162**	**0.7434**	**0.5601**	**0.7499**	**15.1639**
	Image-based	PSNR	0.2422	0.1077	0.2317	2.3124	0.4235	0.3080	0.4872	15.8133
		SSIM [16]	0.2987	0.1919	0.3476	2.1770	0.3878	0.3234	0.4944	15.7749
NR	Model-based	NR-3DQA [21]	**0.7144**	**0.5174**	**0.7382**	**1.7686**	**0.6479**	**0.4417**	**0.6514**	**16.5716**
	Image-based	BRISQUE [23]	0.2051	0.1121	0.2241	2.2428	0.3781	0.2444	0.4176	22.5414
		NIQE [24]	0.2214	0.1512	0.3764	2.2671	0.3887	0.2551	0.3957	22.5502
RR	Model-based	PCMRR [26]	0.4816	0.3362	0.6191	1.9342	0.3097	0.2082	0.3433	21.5302
	Image-based	**Proposed RR-CAP**	**0.7577**	**0.5508**	**0.7691**	**1.5512**	**0.7162**	**0.5260**	**0.7307**	**15.6485**

B. Performance Comparisons

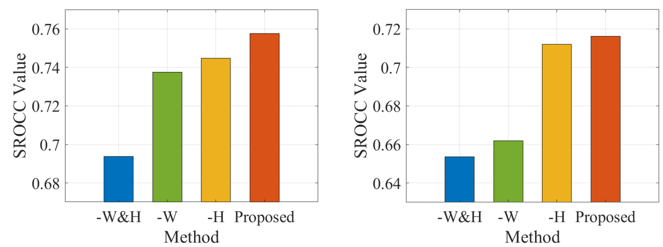
In order to validate the proposed RR-CAP method, we compare it with existing objective quality evaluation approaches including FR, NR, and RR metrics. As shown in TABLE I, we provide the performance results regarding SROCC, KROCC, PLCC, and RMSE. Generally, the compared metrics are classified into 2 types: model-based and image-based methods. The model-based metrics directly operate from 3D models, which consist of GraphSIM [14], PointSSIM [17], PCQM [19], NR-3DQA [21], and PCMRR [26]. The image-based metrics project the 3D models into 2D image planes, and then perform quality assessment on the corresponding projections. The compared image-based metrics involve PNSR, SSIM [16], BRISQUE [23], and NIQE [24]. Note that PCMRR is the only RR method and belongs to model-based metrics. That is, there has been no investigation on image-based RR metrics specifically designed for point clouds yet. Therefore, we try to fill this gap and propose an image-based RR point cloud quality evaluation method according to the HVS characteristics.

From the quantitative table, we make the following analyses. First, conventional image-based metrics show fewer effects in estimating perceptual quality since they do not take the properties of point clouds into account. Second, our proposed RR-CAP are superior to other RR and NR methods including both model-based and image-based ones. This demonstrates the superiority of the proposed method although it is an image-based metric. Note that our proposed metric significantly performs better than PCMRR. This is mainly due to the consideration of the HVS perception and viewing process in our framework. Third, we find that the proposed RR metric can greatly reduce the performance gap compared to the FR model-based quality assessment methods.

C. Ablation Tests

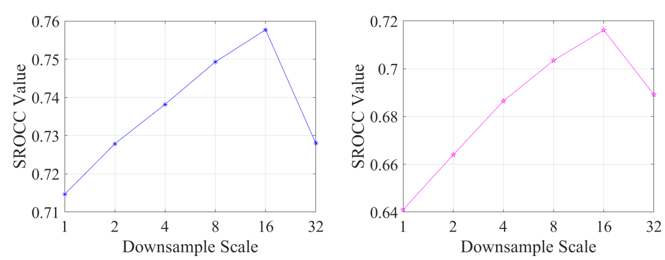
It is interesting to test the performance of each proposed component and parameter of our method. In Figs. 3 and 4, we show the results regarding content-oriented weighting strategy, statistical histogram feature, and downsampling scales.

From the figures, we can see that our method improves gradually by adding the weighting strategy and statistical information. This validates the effectiveness of the proposed technical components. Besides, larger downsampling scales can save more transmitted resources. To obtain the best



(a) (b)

Fig. 3: Performance variation regarding each component, where "-" indicates removing the item. W and H are the weighting strategy and statistical histogram feature. (a) Run on SJTU-PCQA database; (b) Run on WPC database.



(a) (b)

Fig. 4: Performance change with various downsampling scales. (a) Run on SJTU-PCQA database; (b) Run on WPC database.

performance and also relieve transmission burden, we choose 16 for the downsampling scale in our proposed framework. With the saliency projection and downsampling operations, we only need 2,166 pixels for the reference information.

IV. Conclusion

In this letter, we have proposed an effective RR metric for the objective quality evaluation of point clouds. Inspired by the characteristics of the HVS, our method is based on downsampled saliency projection, followed by content-oriented similarity and statistical correlation measurements. Experiments show that our RR-CAP obtains promising consistency with subjective ratings, compared to state-of-the-art quality assessment methods. The source codes of our metric are available at: https://github.com/weizhou-geek/RR-CAP.

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