Reduced Reference Perceptual Quality Model and Application to Rate Control for 3D Point Cloud Compression

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Abstract—In rate-distortion optimization, the encoder settings are determined by maximizing a reconstruction quality measure subject to a constraint on the bit rate. One of the main challenges of this approach is to define a quality measure that can be computed with low computational cost and which correlates well with perceptual quality. While several quality measures that fulfill these two criteria have been developed for images and video, no such one exists for 3D point clouds. We address this limitation for the video-based point cloud compression (V-PCC) standard by proposing a linear perceptual quality model whose variables are the V-PCC geometry and color quantization parameters and whose coefficients can easily be computed from two features extracted from the original 3D point cloud. Subjective quality tests with 400 compressed 3D point clouds show that the proposed model correlates well with the mean opinion score, outperforming state-of-the-art full reference objective measures in terms of Spearman rank-order and Pearson’s linear correlation coefficient. Moreover, we show that for the same target bit rate, rate-distortion optimization based on the proposed model offers higher perceptual quality than rate-distortion optimization based on exhaustive search with a point-to-point objective quality metric.

Index Terms—Point cloud, perceptual quality metric, subjective test, content features, rate-distortion optimization (RDO).

I. INTRODUCTION

With the rapid development of 3D data acquisition technologies, point clouds are now readily available and popular. A 3D point cloud (3DPC) comprises a set of points with geometric coordinates and associated attributes, such as color, reflectance, normal vectors, and so on. These points can be stored, transmitted, and rendered in a variety of ways. There are already many 3DPC applications in the fields of virtual reality, immersive communication, architecture, and automatic driving, etc. [1]. 3DPCs can be classified into objects and scenes. Each class can consist of static or dynamic 3DPCs. In this paper, we mainly focus on static 3DPC objects [2].

To represent the surface of an object with high fidelity, a 3DPC usually contains millions, even billions of points, which results in a large amount of data that needs to be efficiently stored and transmitted [3]. Recently, the Moving Picture Experts Group (MPEG) standardized two compression platforms for Point Cloud Compression (PCC): Geometry-based Point Cloud Compression (G-PCC) [4] and Video-based Point Cloud Compression (V-PCC) [5]. In these platforms, both geometry and color information are compressed [6]. Therefore, the distortion of geometry and color will inevitably influence the perceived quality of the reconstructed 3DPCs.

Similar to image/video quality assessment methods, point cloud quality assessment methods can be classified into three categories: Full Reference (FR), Reduced Reference (RR), and No Reference (NR). To evaluate the quality of a distorted point cloud, FR methods use the pristine uncompressed point cloud as a reference, while RR methods only require statistical features that are extracted from the reference point cloud. On the other hand, NR methods evaluate the quality of the distorted point cloud in the absence of the reference one.

FR 3DPC objective quality assessment techniques can be based on the point-to-point [7], point-to-plane [8] or point-to-mesh [9] distortion metric. The point-to-point metric uses geometric distances between points in the reference and distorted 3DPC, but it does not consider the fact that points in a 3DPC usually represent surfaces on the object. The point-to-plane metric is based on the projected error along the normal of a reference point. This method depends on the calculation of the normal and, essentially, larger costs are assigned to points deviated from the underlying surface. The point-to-mesh [9] metric requires construction of 3D meshes and is therefore hard to deploy in real time applications. Beyond that, there is an angular similarity-based FR metric [10] and a local curvature analysis-based FR metric [11] for 3DPC quality assessment. Both of them are limited by the high complexity of searching for the neighboring points to construct the normal or curvature. In addition, the above objective quality metrics cannot predict the visual quality of 3DPCs accurately, especially when the coding distortion is involved [12] [13].

In this paper, we propose a reduced reference model to...
accurately predict the mean opinion score (MOS) of V-PCC
compressed 3DPCs from the quantization parameters of the
gometry and color encoders. The proposed model is analyt-
ically simple and can be used for rate-distortion optimized
(RDO) rate control, as shown in Fig. 1. The main contributions
of this paper are as follows:
1) We conduct comprehensive subjective tests to obtain MOSs
of V-PCC compressed 3DPCs with different combinations
of geometry and color quantization steps.
2) We develop a simple yet effective analytical model to
predict the MOS from the geometry and color quantization
steps.
3) We study the dependent factors of the model parameters
and propose two features to estimate them.
4) We propose a perceptually optimal rate control method
based on the proposed analytical model.

The remainder of this paper is organized as follows. Section
II briefly reviews related work. The subjective test and the
test results are described in Section III. In Section IV, we
present the proposed perceptual quality model and validate its
accuracy by using the subjective test results. The dependent
factors of the model parameters are studied in Section V.
Based on the study, we propose an efficient model parameter
estimation method by extracting two features from the original
3DPCs. Subsequently, the subjective quality-based rate control
method is presented and evaluated in Section VI. Finally,
Section VII concludes the paper.

II. RELATED WORK

To develop an accurate perceptual quality model for 3DPCs,
subjective experiments are necessary. In recent years, some
datasets were provided to study the impact of compression on
the subjective quality of the reconstructed point clouds. Alex-
iov et al. [14] provided a database which has eight reference
point clouds and the tested point clouds are compressed by G-
PCC and V-PCC. Zerman et al. [15] used V-PCC to generate
a dataset of 3DPCs showing two people playing football. The
remaining datasets [16] [17] study the impact of multiple
degradations types on point cloud subjective quality, without
focusing on the compression degradation type. Usually, the
number of raw 3DPCs limits the accuracy of the subjective
quality test. Therefore, we need to build a new subjective test
dataset that contains sufficient reference content and various
encoding degradation levels.

Generally, subjective quality assessment tests involve the
participation of subjects in experiments in which distorted ob-
jects are visualized and rated. In [13], [18], [19], the geometry
distortion was evaluated, while the effect of color distortion
was ignored. Torlig et al. [20] considered the geometry and
color distortion jointly when doing the subjective assessment.
However, only six 3DPCs and their related degradations were
assessed. Su et al. [21] proposed a complete point cloud data
sets with various quality levels and made preliminary veri-
fication on the performance of the existing objective quality
evaluation model. As reported in [21], the visual information
fidelity in pixel domain (VIFP) achieves the best performance
compared to other assessment models. However, the PLCC
and SRCC of VIFP is only 0.77 which means the accuracy of
3DPC quality assessment model still needs to be improved.
Inspired by the human visual system (HVS), eyes are not
directly sensing the individual point intensity, but rather the
connected local neighbor structures due to the low-pass spread
functionality of our eye optics [22]. Yang et al. [23] proposed
a graph-based objective metric instead of a point-based one.
Although the metric can predict the MOS more accurately than
point-wise metrics, the resampling and local graph construc-
tion operations greatly increase its complexity, which limits
its applications. Moreover, the existing FR objective 3DPC
quality model is hard to be satisfied in some applications. For
example, in 3DPC streaming, a 3DPC is often requested by
users with diverse sustainable channel bandwidth. To address
this diversity, it can be coded into a scalable stream with
several geometry and color quantization parameters (QP) com-
binations. Given a particular target bitrate, the encoder
needs to determine appropriate geometry and color QPs to
achieve the best perceptual quality. When there are only

FR metrics, time consuming exhaustive pre-coding must be conducted to evaluate the performance of different $QP$ combinations \cite{24,25,26}. In \cite{24}, a model-based technique was developed to efficiently determine the optimal maximum octree level (geometric distortion) and JPEG\_VALUE (color distortion) for point cloud library-based point cloud compression (PCL-PCC) platform. However, only the color difference between the original point cloud and the reconstructed point cloud was considered in the bit allocation problem. In \cite{25}, a linear combination of the geometry and color distortions was used to represent the point-to-point distortion of 3DPCs. In \cite{26}, a coarse to fine rate control algorithm was proposed, in which the point-to-point distortion metric was also adopted. In all those methods, the perceptual quality of the reconstructed 3DPCs was not considered, which may limit their performance to some extent.

III. SUBJECTIVE QUALITY ASSESSMENT

A. Subjective test dataset

It is hard for an observer to distinguish the quality degradation of 3DPC with intrinsic distortion \cite{18}. In the early stage of the MPEG standardization for point cloud compression (PCC), there are not enough high quality raw 3DPCs. Therefore, sixteen high quality point clouds, i.e., Bag (1267845 points), Banana (807184 points), Biscuits (952579 points), Cake (2486566 points), Cauliflower (1936627 points), Flowerpot (2407154 points), House (1568490 points), Litchi (1039942 points), Mushroom (1144603 points), Ping-pong\_bat (703879 points), Puer\_tea (412009 points), Pumpkin (1340343 points), Ship (684617 points), Statue (1637577 points), Stone (1086453 points), and Tool\_box (1054211 points) were chosen from the Waterloo Point Cloud (WPC) dataset \cite{21} in the subjective evaluation. These 3DPCs have various geometric and textural complexity. Since the MPEG V-PCC platform achieves almost the best performance \cite{6} in all the existing public encoders for both static and dynamic 3DPCs, all the 3DPCs were coded by the V-PCC test model v7 \cite{27}. For each 3DPC, there are 25 degraded versions with five geometry $QP$s (26, 32, 38, 44, and 50) and five color $QP$s (26, 32, 38, 44, and 50). The corresponding quantization steps range from 12.75 to 204. As a result, we have $16 \times 5 \times 5 = 400$ 3DPCs in the subjective evaluation. To show a 3DPC as fully as possible, we generated 180 pictures along the horizontal and vertical directions with a step of two degrees separately, for each 3DPC, as shown in Fig. 2. Afterwards, the degraded and the original pictures were concatenated to generate a 10-second video sequence with 360 frames.

A total of 30 subjects, consisting of 15 males and 15 females aged between 20 and 35, were recruited in the subjective evaluation. All subjects had normal or corrected-to-normal vision.

B. Subjective evaluation

The Double-Stimulus Impairment Scale (DSIS) methodology \cite{28} was adopted in the subjective evaluation. As normal operation, to expand the rating range and obtain finer distinctions, the DSIS method was adopted with 100 points continuous scale instead of 5 levels rating, as shown in Fig. 3. To display the stimuli, a DELL E2417H displayer with an In-Plane Switching Display of 23.8 inch (res. 1920 × 1080) was used. Both the original and the distorted videos generated from a 3DPC were simultaneously shown to the observer side-by-side, as shown in Fig. 4. The observer viewed these videos from a distance equal to twice the screen height and rated them through a customized interface after the playback finished by keyboard input to guarantee there is no time restriction.

At the beginning of each evaluation, a training session was conducted to make the observers familiar with the artifacts in the assessment. The 3DPCs used for training were different from those used for the evaluation. Therefore, the observers were familiar with the distortion types and the quality levels, but not familiar with the content. The duration of each test for a given subject was about two hours, divided into four sections, with three five-minute breaks in-between to minimize the effect of fatigue.

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Fig. 2. Illustration of the generation of pictures from 360 viewpoints of a 3DPC.

Fig. 3. Schematic diagram of the subjective experiment.

Fig. 4. Example of a subjective evaluation.
C. Data post-processing

Since the ratings range from 0 to 100, the scores given by different observers tend to fall in fairly small subranges. Therefore, we need to convert the subjective scores to Z-scores [29] based on the mean and standard deviation of all the scores of each observer. The Z-score of the \(m\)-th 3DPC at the \(j\)-th degraded level from the \(i\)-th viewer is

\[
Z_{mij} = \frac{X_{mij} - \mu X_i}{\delta X_i},
\]

where \(X_{mij}\) denotes the raw rating, and \(\mu X_i\) and \(\delta X_i\) represent the mean and the standard deviation of the ratings of the \(i\)-th viewer, respectively. Besides, we adopted the outlier removal technique suggested in [30] to remove outliers. No participants were removed but outlier ratings from each participant were discarded. The obtained Z-scores lie in the range [0, 100]. The average of the Z-scores from all valid subjects were calculated to be the MOS of each degraded 3DPC. By taking the MOS as the “ground truth”, the PLCC and SRCC between each viewer’s scores and MOSs were calculated to verify the performance of individual subjects [21]. Both the mean PLCC and SRCC between each observer scores and the calculated MOS were as high as 0.84, indicating substantial agreement between individual subjects.

IV. PROPOSED QUALITY METRIC MODEL

To determine the relationship between the perceived quality and the quantization steps of the geometry and color, the distorted 3DPCs with different geometry and color quantization steps were rated, as shown in Fig. 5. We can observe that there is a linear relationship between \(MOS^c = 100 - MOS\) and the color quantization step \(Q_c\) for a fixed geometry quantization step \(Q_g\), that is,

\[
MOS^c = c_{1,g} Q_c + c_{2,g},
\]

where \(c_{1,g}\) and \(c_{2,g}\) are the model parameters. Here, we use \(MOS^c\) to represent the perceptual distortion for the standard mathematical expression used in rate-distortion optimization. From Table I we can also see that the squared correlation coefficient (SCC) between \(MOS^c\) and \(Q_c\) with different \(Q_g\)s is larger than or equal to 0.995, while the root mean squared error (RMSE) is smaller than or equal to 1.785. Moreover, as shown in Fig. 6 the relationship between the slope \(c_{1,g}\) (respectively the intercept \(c_{2,g}\)) and \(Q_g\) can be represented by the linear models

\[
c_{1,g} = c_{11} Q_g + c_{12},
\]

\[
c_{2,g} = c_{21} Q_g + c_{22},
\]

where the SCCs of \(Q_g\) and \(c_{1,g}\), and \(Q_g\) and \(c_{2,g}\) are 0.988 and 0.990, respectively. Accordingly, the quality model can be rewritten as

\[
MOS^c = a Q_g Q_c + b Q_g + c Q_c + d,
\]

where \(a = c_{11}, b = c_{21}, c = c_{12}\), and \(d = c_{22}\) are model parameters. The accuracy of (5) for each 3DPC is given in Table II. By further considering the fact that the fitting parameter \(a\) is very small (Table I), (5) can be further simplified by removing the impact of \(Q_g\) on the perceptual quality. This makes the model convex, which is useful in many situations.

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**TABLE I**

| \(Q_g\) | \(c_{1,g}\) | \(c_{2,g}\) | SCC | RMSE |
|--------|---------|---------|-----|------|
| 12.75  | 0.249   | 0.986   | 0.994 | 1.731 |
| 25.5   | 0.238   | 12.782  | 0.993 | 1.785 |
| 51     | 0.218   | 19.765  | 0.993 | 1.634 |
| 102    | 0.159   | 38.187  | 0.994 | 1.070 |
| 204    | 0.093   | 60.571  | 0.996 | 0.525 |

**TABLE II**

| Point Cloud | \(a\) | \(b\) | \(c\) | \(d\) | SCC | RMSE |
|-------------|------|------|------|------|-----|------|
| Bag         | -0.0005 | 0.263 | 0.225 | 3.192 | 0.963 | 4.317 |
| Banana      | -0.0006 | 0.294 | 0.127 | 19.860 | 0.925 | 5.663 |
| Biscuits    | -0.0006 | 0.190 | 0.204 | 8.293 | 0.964 | 3.158 |
| Cake        | -0.0008 | 0.303 | 0.188 | 5.519 | 0.977 | 3.192 |
| Cauliflower | -0.0010 | 0.327 | 0.258 | 3.389 | 0.967 | 4.372 |
| Flowerpot   | -0.0005 | 0.332 | 0.115 | 13.016 | 0.889 | 8.097 |
| House       | -0.0012 | 0.311 | 0.361 | -3.666 | 0.981 | 3.814 |
| Litchi      | -0.0012 | 0.288 | 0.359 | -3.440 | 0.970 | 4.536 |
| Mushroom    | -0.0010 | 0.244 | 0.304 | 12.295 | 0.946 | 5.203 |
| Ping-pong_hat | -0.0014 | 0.351 | 0.332 | 5.463 | 0.951 | 5.875 |
| Puer_Lea    | -0.0009 | 0.192 | 0.366 | 6.488 | 0.982 | 3.379 |
| Pumpkin     | -0.0007 | 0.184 | 0.276 | 3.242 | 0.969 | 3.557 |
| Ship        | -0.0006 | 0.312 | 0.112 | 13.296 | 0.928 | 5.905 |
| Statue      | -0.0007 | 0.308 | 0.196 | 14.527 | 0.874 | 8.496 |
| Stone       | -0.0010 | 0.245 | 0.333 | -1.385 | 0.981 | 3.588 |
| Tool_box    | -0.0008 | 0.184 | 0.333 | 9.886 | 0.951 | 5.124 |

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Fig. 5. Relationships between \(MOS^c = 100 - MOS\) and \(Q_c\) for different \(Q_g\).

Fig. 6. Relationship between the slope \(c_{1,g}\) and intercept \(c_{2,g}\) in (2) and \(Q_g\). (a) \(c_{1,g}\) vs. \(Q_g\), (b) \(c_{2,g}\) vs. \(Q_g\).
applications such as rate-distortion optimization. Therefore, we also examined the statistical significance of the three parts in [5], i.e., $Q_g \cdot Q_c$, $Q_g$, and $Q_c$ using a two-way ANOVA test [31]. In the test, the $F$-values are based on the ratio of mean squares (MS) of the test factor group and the error group. The MS is the mean of the square of the standard deviation (SS) that accounts for the degrees of freedom (DF). Therefore the $F$-value can be calculated as

$$F = \frac{MS_t}{MS_e} = \left(\frac{SS_t}{DF_t}\right) / \left(\frac{SS_e}{DF_e}\right)$$

where $MS_t$ and $MS_e$ represent the mean sum of squares of deviations of the test factor group and the error group, respectively. They can be calculated as $\frac{SS_t}{DF_t}$ and $\frac{SS_e}{DF_e}$, respectively, where $SS_t$ and $SS_e$ represent the sum of squared deviations of the test factor group and the error group, respectively, while $DF_t$ and $DF_e$ represent the degrees of freedom of the test factor group and the error group, respectively. Specifically, $SS_t \in \{SS_{Qg}, SS_{Qc}, SS_{QgQc}\}$, where $SS_{Qg}$, $SS_{Qc}$, $SS_{QgQc}$ denote the SS of the test factors $Q_g$, $Q_c$, and $Q_g \cdot Q_c$, respectively. Here $SS_{Qg}$, $SS_{Qc}$, $SS_{QgQc}$, and $SS_e$ can be calculated as

Fig. 7. Accuracy of model [5]. (a)-(d): Bag, Banana, Biscuits, and Cake, (e)-(h): Cauliflower, Flowerpot, House, and Litchi, (i)-(l): Mushroom, Ping-pong bat, Puer tea, and Pumpkin, (m)-(p): Ship, Statue, Stone, and Tool box.
follows
\[
\begin{align*}
SS_{Q_g} &= JL \sum_{i=1}^{I} (MOS_{g,i} - \overline{MOS})^2 \\
SS_{Q_c} &= IL \sum_{j=1}^{J} (MOS_{c,j} - \overline{MOS})^2 \\
SS_{Q_g Q_c} &= LJ \sum_{i=1}^{I} \sum_{j=1}^{J} (MOS_{g,i} - \overline{MOS}) (MOS_{c,j} - \overline{MOS}) + (MOS_{g,i} + MOS_{c,j} - 2\overline{MOS})^2 \\
SS_e &= \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{l=1}^{L} (MOS_{ijl} - MOS_{ijl}^c)^2
\end{align*}
\]

(7)

where \(I\) denotes the number of possible \(Q_g\) levels, \(J\) denotes the number of possible \(Q_c\) levels, \(L\) denotes the number of tested 3DPCs, \(MOS_{g,j}^{c}\) denotes the \(MOS^c\) value of the \(i\)-th \(Q_g\) level (\(i = 1, \ldots, I\)) and \(j\)-th \(Q_c\) level (\(j = 1, \ldots, J\)) for the \(i\)-th 3DPC (\(l = 1, \ldots, L\)). \(\overline{MOS}_{c,j}\) denotes the \(MOS^c\) value of the \(i\)-th \(Q_g\) level with all the possible \(Q_c\) levels for all the 3DPCs, \(MOS_{g,j}^{c}\) denotes the \(MOS^c\) value of the \(j\)-th \(Q_c\) level with all the possible \(Q_g\) levels for all the 3DPCs, \(MOS_{ij}^{c}\) denotes the \(MOS^c\) value of the \(i\)-th \(Q_g\) and the \(j\)-th \(Q_c\) level for all the 3DPCs, and \(\overline{MOS}^c\) is the mean of different combinations of \(Q_g\) level, \(Q_c\) level, and the tested 3DPCs.

The degree of freedom of the test factor group \(DF_i \in \{DF_{Q_g}, DF_{Q_c}, DF_{Q_g Q_c}\}\) and the values of \(DF_{Q_g}, DF_{Q_c},\) and \(DF_{Q_g Q_c}\) are \(I-1\), \(J-1\), and \((I-1)(J-1)\), respectively. Finally, \(DF_e = JL(L-1)\). Through (6), we can calculate the corresponding \(F\) values, i.e., the \(MOS^c\) variations over \(Q_g\), \(Q_c\), and \(Q_{g c}\), as shown in Table III. The larger the \(F\)-value is, the more significant the corresponding parameter is. From Table III, we can see that the statistical significance of \(Q_g\) and \(Q_c\) is much smaller than that of \(Q_g Q_c\). Therefore, (5) is further simplified to

\[MOS^c = p_1 Q_g + p_2 Q_c + p_3,\]

(8)

where \(p_1\), \(p_2\), and \(p_3\) are model parameters. By using (8), the SCC between the fitted \(MOS^c\) and the actual one is up to 0.949. The model parameters \(p_1\), \(p_2\), and \(p_3\) in (8), the SCCs, and the RMSEs between the actual \(MOS^c\)'s and the fitted values of all the evaluated 3DPCs are given in Table IV. We can see that the average SCC is 0.914, indicating that the derived simplified perceptual quality model is accurate. Fig. 7 illustrates the accuracy of (8).

V. MODEL PARAMETER PREDICTION USING CONTENT FEATURES

As shown in Fig. 8, 3DPCs with rich texture characteristics (e.g., Cake) usually have lower \(MOS^c\) (corresponding to higher \(MOS\)) for the same quantization steps. In contrast, 3DPCs with simple texture characteristics (e.g., Ping-pong bat) have higher \(MOS^c\) (corresponding to lower \(MOS\)) for the same quantization steps. This is because the content has a concealed effect on the coding distortion, which is consistent with the characteristics of the human visual system [32]. That is to say, the model parameters are highly content dependent. In this section, we propose two features to predict the model parameters efficiently. The perceptual quality of a 3DPC depends on both the geometry and color distortion. But the influence of geometry and color distortion are different [33]. By analyzing the local topological and color consistencies, Alexiou and Ebrahimi [34] and Meynet et al. [35] reported that color-based features achieve the best performance in predicting the perceptual quality. Accordingly, we extracted two novel texture features (local feature and a global feature) to predict the model parameters effectively. The local feature represents the color fluctuation over a geometric distance (CFGD), while the global feature is the color block mean variance (CBMV).

### Table III
**Two-way ANOVA on MOS^c**

| Factors | \(Q_g\) | \(Q_c\) | \(Q_g Q_c\) |
|---------|--------|--------|-------------|
| \(F\)-value | 226.802 | 197.838 | 4.660 |

### Table IV
**Parameters and accuracy of the perceptual quality model**

| Point Cloud | \(p_1\) | \(p_2\) | \(p_3\) | SCC | RMSE |
|-------------|--------|--------|--------|-----|------|
| Bag         | 0.223  | 0.183  | 6.432  | 0.949 | 4.954 |
| Banana      | 0.247  | 0.080  | 23.601 | 0.902 | 6.336 |
| Biscuits    | 0.143  | 0.156  | 12.072 | 0.927 | 4.387 |
| Cake        | 0.241  | 0.125  | 10.489 | 0.938 | 5.153 |
| Cauliflower | 0.246  | 0.177  | 9.773  | 0.916 | 6.782 |
| Flowerpot   | 0.291  | 0.075  | 16.212 | 0.877 | 8.339 |
| House       | 0.210  | 0.269  | 3.597  | 0.930 | 7.059 |
| Litchi      | 0.195  | 0.266  | 3.874  | 0.914 | 7.488 |
| Mushroom    | 0.164  | 0.225  | 18.579 | 0.890 | 7.262 |
| Ping-pong bat | 0.240 | 0.221  | 14.240 | 0.872 | 9.243 |
| Puer tea    | 0.124  | 0.297  | 11.921 | 0.948 | 5.568 |
| Pumpkin     | 0.131  | 0.223  | 7.424  | 0.939 | 4.898 |
| Ship        | 0.268  | 0.068  | 16.756 | 0.910 | 6.438 |
| Statue      | 0.254  | 0.142  | 18.777 | 0.852 | 9.011 |
| Stone       | 0.170  | 0.291  | 4.555  | 0.945 | 6.026 |
| Tool box    | 0.117  | 0.266  | 15.152 | 0.914 | 6.630 |

**Average** | - | - | - | **0.914** | **6.598**
A. Color fluctuation over geometric distance (CFGD)

Color gradient appropriately describes local texture variation, therefore, we define the CFGD to describe the local content characteristic for a 3DPC. As shown in Fig. 9, the mean value of the neighboring color intensity differences of the current point is calculated to be the CFGD feature of the point:

$$CFGD_i = \frac{1}{N_i} \sum_{p_j \in S_i} \frac{|C(p_i) - C(p_j)|}{d_{i,j}},$$

(9)

where $CFGD_i$ denotes the value of CFGD for point $p_i$, $C(\cdot)$ denotes the color attribute of a point, $d_{i,j}$ denotes the distance between points $p_i$ and $p_j$, $S_i$ is the set of the $K$ nearest neighbors of point $p_i$, and $N_i$ is the number of points in $S_i$. For simplicity, we only consider the $Y$ (luminance) component [36] in this paper. Then, the CFGD of all the points is defined as

$$CFGD = \frac{1}{T} \sum_{i \in P} CFGD_i,$$

(10)

where $T$ is the number of points in the 3DPC $P$.

B. Color block mean variance (CBMV)

The standard deviation is commonly used as a global feature for image/video quality assessment [37] [38] [39]. Similarly, we use it to build a global feature for 3DPCs. Assuming that the 3DPCs are voxelized [40] (Fig. 10), the CBMV is computed as

$$CBMV = \frac{1}{B} \sum_{i=1}^{B} \sqrt{\frac{1}{D} \sum_{j=1}^{D} (C(p_{ij}) - \mu_i)^2},$$

(11)

where $B$ denotes the number of non-empty voxels, $D$ denotes the number of points in the $i$-th non-empty voxel, $C(p_{ij})$ is the color of the $j$-th point in the $i$-th non-empty voxel, and $\mu_i$ is the color mean value of the $i$-th non-empty voxel.

C. Model parameter estimation

We used a generalized linear model (GLM) [41] to predict the model parameters from the extracted two features. Let $p_{m,j}$ denote the $j$-th parameter in (8) of the $m$-th 3DPC, $m = 1, 2, ..., M$, where $M$ is the number of 3DPCs. Let $f_{m,k}$ denote the value of the $k$-th feature for the $m$-th 3DPC, $k = 1, 2, ..., K$, and $K$ is the number of extracted features (in this paper, $K = 2$). Then, the parameter $p_{m,j}$ is estimated by a generalized linear predictor

$$p_{m,j} = h_{j,0} + \sum_{k=1}^{K} f_{m,k} h_{j,k},$$

(12)

where $h_{j,k}$ is the weight of the $j$-th parameter in (8) of the $k$-th feature, $j = 1, 2$, and 3. The $h_{j,0}$ is the constant weight of the $j$-th parameter. The generalized linear predictor can be described using the vector form $\hat{P}_m = F_m H$, where $\hat{P}_m$ is a three-dimensional vector, representing the model parameters $[p_{1,1}, p_{2,1}, p_{3,1}]$ in (8) of the $m$-th 3DPC, and $F_m = [1, f_{m,1}, f_{m,2}]$, where $f_{m,1}$ and $f_{m,2}$ represent the two feature values of the $m$-th 3DPC. $H$ is a $3 \times (K + 1)$ coefficients matrix with elements $h_{j,k}$. The aim is to find a matrix $H$ that minimizes the prediction error $\varepsilon$.

In this paper, $H$ is obtained by training, and we set the voxel size equal to $64^3$ as an example for the CBMV. Eight 3DPCs: Cauliflower, Stone, House, Ship, Tool box, Pumpkin, Biscuits and Ping-pong bat that cover a wide range of content characteristics were used for training. The remaining 3DPCs, i.e., Litchi, Puer tea, Flowerpot, Bag, Cake, Statue, Banana and Mushroom were used for testing. We determined the optimal $H$ by minimizing the fitting error $\varepsilon$ for the training 3DPCs set, defined as

$$\varepsilon = \sum_{m=1}^{8} \|\hat{P}_m - P_m\|^2,$$

(13)

where $\hat{P}_m$ and $P_m$ are the predicted model parameter vector and the model parameter vector of the $m$-th 3DPC, respectively. The optimal $H$ is then calculated to be

$$H^{\text{opt}} = \begin{bmatrix}
0.1817 & 0.2058 & 18.4528 \\
0.0034 & -0.0070 & -0.0199 \\
-0.0116 & 0.0292 & -1.5427
\end{bmatrix}.$$  

(14)

By using $H^{\text{opt}}$ and the extracted feature vector $F_m$, the model parameter vector $\hat{P}_m$ can be calculated directly. Furthermore, based on the estimated model parameters, we can obtain the MOS through (8). We use PLCC, SRCC [42], and RMSE between the actual MOS's and the predicted ones to evaluate the accuracy of the proposed model with the estimated parameters. Table VII shows that the PLCC and
SRCC of the proposed perceptual quality model of the test set are as high as 0.9133 and 0.9095, respectively, and RMSE is as small as 8.9090 (noting that the maximum MOS is 100). The accuracy of the model is also illustrated in Fig. 11 which shows the relationship between the actual MOSs and the estimated ones. To further validate the accuracy of the proposed RR quality metric model, we compared it to three representative FR objective metric models: a point-based model [9], a projection-based model [20] [43] [44] [45], and a graph-based model [23]. The point-based method captures the difference between the points in the reference and the tested 3DPC, and we name it as PSNR\(_g\). Currently, the point-based method is adopted by MPEG. For the projection-based approaches, a 3DPC is mapped onto six conventional two-dimensional image planes by orthographic projection. After obtaining the projected image planes, the 2D image quality metrics structural similarity (SSIM) [44], multi-scale structural similarity (MS-SSIM) [45], and visual information fidelity in pixel domain (VIFP) [43] are used to evaluate the six projection image quality, finally, the average image quality of these six projection is mapped to MOS by the best fitting logistic function, the mapped MOS is taken as the quality of the 3DPC. We call these projection-based methods SSIM\(_{projection}\), MS-SSIM\(_{projection}\), and VIFP\(_{projection}\), respectively. For the graph-based method [23], local graphs centered at the key points were used to calculate the similarity between the original and the distorted 3DPC. We call this method GraphSIM. Table VI shows the comparison results with the point-based and projection-based methods. We can see that the point-based PSNR\(_g\) model does not seem to provide enough accuracy due to a lack of overall perception. GraphSIM improves the prediction accuracy to some extent; however, it is more complex and requires many parameters to be determined. In contrast, the projection-based models perform better among which VIFP achieves the best performance compared to PSNR, SSIM and MS-SSIM. Nevertheless, the quality prediction accuracy is only moderate when compared with their performance on 2D images [21]. Table VI shows that the PLCC of FR quality metrics is in the range 0.4027 to 0.8199. In contrast, the PLCC of the proposed RR quality metric is as high as 0.9133. In addition to the PLCC, the SRCC of the worst and best FR quality metrics are 0.3926 and 0.8187 respectively, whereas the SRCC of the proposed RR quality metric is 0.9095. Beyond that, the RMSE of the proposed quality metric is also much smaller than those compared metrics. Fig. 12 shows scatter plots of MOS vs. objective scores for all models. The plots illustrate the superiority of the proposed RR quality metric over the other models.

### VI. APPLICATION

The developed perceptual quality model would be of great benefit to applications involving coding and rate control in 3DPC broadcasting systems. In this paper, we solve the rate control problem for a static 3DPC. Our method can also be extended to dynamic 3DPCs as they can be seen as a sequence of successive static 3DPCs. For a given target bitrate, we aim to find the combination of the geometry \(Q_g\) and color \(Q_c\) (corresponding to \(Q_g\)) that provide the best perceptual quality. We formulate this rate control problem as a constrained optimization problem where the objective function is the derived perceptual quality model,

\[
\min_{(Q_g, Q_c)} MOS^{c}(Q_g, Q_c) \quad (15)
\]

subject to

\[
R_g(Q_g) + R_c(Q_g, Q_c) \leq R_T,
\]

where \(R_g\) and \(R_c\) are the geometry and color bitrate, respectively, and \(R_T\) is the overall target bitrate. Based on \[9\], \[15\] and the Cauchy-based rate model [25], the rate control problem can be rewritten as

\[
\min_{(Q_g, Q_c)} p_1Q_g + p_2Q_c + p_3 \quad (16)
\]

subject to

\[
\gamma_g Q_g^{\theta_g} + \gamma_c Q_c^{\theta_c} \leq R_T,
\]

where \(p_1\), \(p_2\), and \(p_3\) are the parameters of the perceptual quality model, and \(\gamma_g\), \(\theta_g\), \(\gamma_c\), \(\theta_c\) are the parameters of the geometry and color rate models.
Together with the proposed model parameter estimation method in Section V, the proposed model can be embedded in the V-PCC (TMC2) encoder to determine the optimal $Q_g$ and $Q_c$. First, the CFGD and CBMV features of the input 3DPC are extracted, as described in Section V. Then by using the pre-trained matrix $H$ in (14), the parameter vector $\hat{P}_m$ can be calculated. For the rate model, the parameters $\gamma_g$, $\theta_g$, $\gamma_c$, and $\theta_c$ can be obtained by precoding with two geometry and color quantization step pairs. Finally, with the target bitrate $R_T$, the optimal $Q_{g,\text{opt}}$ and $Q_{c,\text{opt}}$ can be obtained by solving (16) using an interior point method or another convex optimization method [46].

To assess the proposed perceptual quality model-based rate control algorithm, we compared its performance to that of point-to-point based exhaustive search algorithm (P2P$_{ES}$). For P2P$_{ES}$, a 3DPC was first encoded by all the tested geometry and color QP pairs ranging from 26 to 50. Then the subset of admissible pairs (pairs whose bitrates are smaller than or equal to the target bitrate) was determined. Finally, the pair that gave the highest PSNR for
Fig. 14. Perceptual quality comparison between our rate control algorithm and $P^2P_{ES}$. Left: original, Centre: proposed, Right: $P^2P_{ES}$. (a) subjective quality of Bag with a target bitrate of 510 kbpmp, (b) subjective quality of Banana with a target bitrate of 85 kbpmp, (c) subjective quality of Flowerpot with a target bitrate of 405 kbpmp, (d) subjective quality of Cake with a target bitrate of 170 kbpmp, (e) subjective quality of Mushroom with a target bitrate of 275 kbpmp, (f) subjective quality of Puer tea with a target bitrate of 190 kbpmp, (g) subjective quality of Statue with a target bitrate of 165 kbpmp, (h) subjective quality of Litchi with a target bitrate of 110 kbpmp.

| Point Cloud | $R_{T,1}$ | $R_{T,2}$ | $R_{T,3}$ | $R_{T,4}$ |
|-------------|-----------|-----------|-----------|-----------|
| Bag         | 170       | 510       | 1495      | 2130      |
| Banana      | 40        | 120       | 310       | 850       |
| Cake        | 110       | 170       | 265       | 460       |
| Flowerpot   | 75        | 135       | 265       | 405       |
| Litchi      | 110       | 250       | 565       | 1200      |
| Mushroom    | 50        | 150       | 220       | 375       |
| Puer tea    | 75        | 190       | 640       | 1525      |
| Statue      | 55        | 105       | 155       | 200       |

VII. CONCLUSION

We proposed an RR linear quality model that accurately predicts the perceptual quality of V-PCC compressed 3DPCs from the V-PCC geometry and color quantization parameters. The three coefficients of our linear model are estimated using a training set of reference 3DPCs and two features (CPGD and CBMV) that are computed from the test reference 3DPC. Because the number of high quality original 3DPCs used by the Y component ($PSNR_Y$) was selected from this subset. We focused on the Y component because it plays an important role in visualization and in our perception of objective structure and surface shape [47]. Since the texture complexity of the tested 3DPCs are different, we set different target bitrates for each 3DPC, as shown in Table VII. The rate-MOS curves of the proposed algorithm and $P^2P_{ES}$ are compared in Fig. 13. The results demonstrate that the proposed rate control algorithm can achieve better rate-MOS performance than $P^2P_{ES}$ with much lower complexity. Since the value of $PSNR_Y$ in $P^2P_{ES}$ is not consistent with the MOS, the MOSs of the reconstructed 3DPCs by the $P^2P_{ES}$ fluctuate with different target bitrates. The proposed algorithm used the proposed RR model to better predict the MOSs, and better subjective quality can be achieved with given target bitrates. Finally, Fig. 14 compares the subjective quality between the proposed rate control algorithm and $P^2P_{ES}$. We can see that a significant subjective quality improvement can be achieved by the proposed RR model-based rate control algorithm.
the MPEG PCC group is rather limited, we selected high quality 3DPCs from the WPC dataset to conduct the subjective experiments for static 3DPCs. The results show that the PLCC and the SRCC between the predicted MOSs and the actual MOSs are both as high as 0.91, indicating high accuracy of the proposed model.

Moreover, to illustrate the applications of the proposed model, we also proposed an optimized rate control algorithm for 3DPC compression. Benefitting from the accuracy of the proposed RR quality model, the subjective quality of the proposed algorithm is much better than that of $P2F_{ES}$. In future work, we will assess the performance of the proposed model on the high quality 3DPCs recently provided by the MPEG PCC group. We will also apply the proposed quality metric to rate-distortion optimized coding and quality enhancement for 3DPCs.

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