CPC-GSCT: Visual quality assessment for coloured point cloud based on geometric segmentation and colour transformation

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Abstract
Coloured point cloud (CPC) is one of the important representations of three-dimensional objects, which has been used in many fields. CPC may encounter geometric and colour distortion during its compression, simplification or other processing. Thus, the objective visual quality assessment of CPC is one of the urgent issues to be resolved in the CPC’s applications. Aiming at this problem, this paper proposes a new full-reference visual quality assessment metric for CPC based on geometric segmentation and colour transformation (CPC-GSCT), which analyzes geometric distortion and colour distortion of CPC. First, considering the visual masking effect of CPC’s geometric information, CPC is segmented into different regions and distributed with different weights to describe the influence of visual masking effect in CPC quality assessment. At the same time, a geometric combination feature vector is defined and extracted for measuring the CPC’s geometric distortion. Then, considering the colour perception of human eyes, a colour combination feature vector is extracted to measure the CPC’s colour distortion in HSV colour space. Finally, all the extracted geometric and colour features are constituted as a feature vector to predict the quality of CPC. Experimental results on three databases (IRPC, SJTU-PCQA and CPCD2.0) show that the proposed CPC-GSCT metric can achieve better performance in predicting the visual quality of CPC than relevant existing methods.

1 | INTRODUCTION

Coloured point cloud (CPC) is one of the important representations of three-dimensional (3D) objects, it can provide more realistic visual information than ordinary images and give users better immersive experience [1]. CPC is a set of points in 3D space, which contain not only the geometry coordinate but also colour attribute. With the rapid development of sensor technologies (such as RGB-G sensor, LiDAR sensor, and so on), CPC data may be conveniently captured, and CPC processing has attracted widespread attention [2,3]. In CPC systems, CPC is subject to various distortions during its acquisition, compression, transmission, simplification and rendering, any of which may degrade the visual quality of CPC [4,5]. Thus, how to evaluate the visual quality of CPC accurately has become an important issue to be solved urgently.

In terms of visual content quality evaluation, the research on image quality assessment (IQA) has made considerable progress in recent decades. Many classical IQA metrics were presented, such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity (SSIM) [6], Multiscale Structural SIMilarity (MS-SSIM) [7] and Visual Information Fidelity in Pixel domain (VIFP) [8]. Recently, some new full-reference/non-reference IQA metrics had also been designed [9]. Obviously, these works are beneficial to the research of CPC quality evaluation. However, since CPC consists of geometric coordinate and colour attribute, the existing two-dimensional (2D) IQA metrics cannot be directly used to efficiently evaluate CPC’s quality.

For CPC quality assessment (CPCQA), its initial studies focused on subjective evaluation experiments [5,10–13], which can provide data to be used as benchmarks to compare the performance of objective point cloud quality metrics and study user behaviours, and so on. Alexiou and Ebrahimi established colourless point cloud subjective evaluation datasets with the distortions of octree-pruning, Gaussian noise and reconstruction, and they also analysed the impact of visualisation strategy.
For subjective evaluation [10]. In IRPC dataset [11], six original voxelised PCs from MPEG repository were compressed by using three codecs with different quality. Yang et al. [12] produced a CPC subjective evaluation dataset, denoted as SJTU-PCQA, with 10 original PCs and seven types of impairments. At the same time, He et al. [13] also established a CPC subjective evaluation dataset, called as CPCD2.0, using 10 original PCs with G-PCC/V-PCC coding and Gaussian noise. However, the subjective evaluation approach is time-consuming and difficult to be directly used to practical CPC systems. Thus, some objective metrics were presented for CPC processing.

For objective CPCQA, some studies have been carried out. From the perspective of point-to-point and point-to-plane, Tian et al. successively proposed the point-to-point metrics and point-to-plane metrics [14–16] as the basic CPCQA methods for CPC compression. Alexiou and Ebrahimi [17] analysed the point-to-point metrics and point-to-plane metrics, and proposed a colourless point cloud quality assessment metric with angular similarity of associated points belonging to the reference and distorted point clouds. Afterwards, they also proposed a point cloud structural similarity metric [18]. Alireza et al. [19] improved the classical Hausdorff distance and proposed a generalised Hausdorff distance-based quality metric for point cloud geometry. Considering that 3D mesh and colourless point cloud can be inter-converted, 3D mesh metrics can be also used to measure the distortion of colourless point cloud. Lavoue et al. [20] proposed a mesh structural distortion measure (MSDM) metric by extending SSIM to 3D meshes. Lin et al. [21] proposed a blind mesh quality assessment method based on graph spectral entropy and spatial features, in which the distortion of 3D mesh was described and the corresponding features were extracted in the graph spectral domain. Meynet et al. [22] extended MSDM to point cloud and presented a PC-MSDM metric, and their results showed that the local curvature statistics can better predict the geometric quality of point cloud, compared with the way of pure geometric distance. From the perspective of 3D point cloud matching, Bogoslavskyi and Stachniss [23] analysed the quality of the matched 3D point clouds of objects, and proposed a probabilistically motivated quality measure for the alignment of two point clouds corresponding to individual objects. This method considers the differences in the point locations and free-space information.

The above objective metrics had analysed the geometric distortion of point cloud, however, they did not sufficiently consider the colour distortion of CPC. So, Torlig et al. [24] designed rendering software to perform real-time voxelisation and projected 3D point clouds onto 2D planes, then they used 2D-IQA metrics to predict the quality of CPC. Su et al. [5] analysed the performance of the point-to-point metrics/point-to-plane metrics [14–17] and the projection-based metric [24]; their results show that the existing metrics are limited in providing accurate quality predictions of CPC. It implies that it is necessary to develop efficient quality assessment tools to predict the visual quality of CPC and optimise the CPC operations, such as acquisition, simplifying, compression, rendering, and so on.

To design effective CPCQA metrics, both the geometric and colour distortion of CPC have to be considered. Some studies have demonstrated that incorporating perceptual properties of Human Visual System (HVS) will benefit various 3D multimedia applications [25]. Since HVS is the visual evaluator of the majority of CPCs, the design of CPCQA metric should be closely related to human visual perception. As one of the important characteristics in HVS, visual masking effect is of significance in studying the mutual effects of human visual stimuli. It refers to the decrease of visibility of visual signals with the presence of background signals [26]. In the context of CPCQA, visual masking indicates that distortions are less visible on rough regions of CPC than on smooth regions. In addition, compared with the RGB colour space, the Hue-Saturation-Value (HSV) colour space is more consistent with the colour perceptual characteristics of HVS [27], which may be helpful for designing CPCQA metrics.

Based on the above analyses, this paper proposes a new full-reference CPCQA metric based on geometric segmentation and colour transformation, denoted as CPC-GSCT. Its main contributions are as follows:

1. According to the visual masking effect, the reference and distorted CPCs are segmented into different regions, which are distributed with different weights to describe the influence of visual masking effect in CPCQA.
2. For geometric distortion in CPC, a geometric combination feature vector is described and extracted to measure the geometric distortion of CPC with three aspects, including deviation distortion degree, angle distortion degree and density distortion degree.
3. For colour distortion in CPC, a colour combination feature vector is designed in the HSV colour space to describe the colour distortion of CPC. The colour combination feature vector is composed of hue distortion degree, saturation distortion degree and value distortion degree.

Finally, the extracted geometric and colour features are integrated to predict the quality of the distorted CPC.

The rest of this paper is arranged as follows. Section 2 describes the proposed metric in detail. Section 3 gives experimental results and discussions. Finally, Section 4 concludes the paper.

2 | THE PROPOSED CPC-GSCT Metric

According to the above analyses, a novel CPC quality assessment method is proposed based on CPC-GSCT. In Figure 1, the proposed CPC-GSCT metric calculates the distortion of CPC with two aspects: geometric distortion and colour distortion.

In geometric distortion evaluation, considering the visual masking effect when CPC is geometrically distorted, the CPC is segmented into regions. Gaussian function is used as weight strategy to depict the impact of visual masking effect in CPCQA. Then, the point clouds geometric combination feature vector \( \mathbf{F}_g \) is designed to describe the geometric distortion of CPC. Based on the geometric distortion types of CPC,
\( F_G \) uses three geometric attributes to extract three geometric features, that is, deviation distortion degree \( (P_{DV}) \), angle distortion degree \( (P_{AG}) \) and density distortion degree \( (P_{DE}) \), and \( F_G = (P_{DV}, P_{AG}, P_{DE}) \).

In the stage of colour distortion analysis, CPC’s colour representation is converted from RGB colour space into HSV colour space and the colour combination feature vector \( (F_T)\) is presented to describe CPC’s colour distortion with three aspects: hue distortion degree \( (H_{MR}) \), saturation distortion degree \( (S_{MR}) \) and value distortion degree \( (V_{MR}) \).

Finally, all the extracted geometric and colour features are formed as a final feature vector and pooled by random forest model to predict the quality of the distorted CPC.

### 2.1 Geometric feature extraction with segmentation

Visual masking effect plays an important role in visual content quality assessment. Figure 2 depicts the phenomenon of visual masking effect on the CPC of ‘Longdress’ in [13], where the head of ‘Longdress’ is displayed to illustrate the effect. Figures 2a and b are the parts of the original ‘Longdress’ and the distorted ‘Longdress’ with G-PCC [28], respectively. In Figures 2a and b, the hair in blue box refers to the rough regions of CPCs, while the forehead in red box refers to the smooth regions of the CPC. It can be found that the distortion on the smooth regions is more easily perceived by the human eyes than that on the rough regions.

The visual perception of CPC’s geometric distortion will be taken into account, and the visual masking effect will cause the same degree of geometric distortion to have different perception of distortion in the regions with different roughness. Here, CPC will be segmented into different regions by using K-means clustering [29,30] before its geometric distortion is estimated. The K-means clustering can cluster points with similarity geometric attribute to perform region segmentation [30], and it can keep the geometric continuity of sub-clouds in each cluster. The reference CPC is first segmented into regions, which are used as benchmarks to determine the corresponding regions of the distorted CPC by searching algorithm with the Kd-tree [22]. Then, the geometric combination feature vector is extracted in each
region corresponding to the reference CPC and the distorted CPC.

Figure 3 shows the process of the geometric feature extraction. After geometric region segmentation, the deviation distortion degree, angle distortion degree and density distortion degree are defined and computed in each segmented region. Then, each region is assigned a weight based on its roughness. Finally, the features of all segmentation regions are accumulated to obtain the final geometric combination feature vector.

The roughness of CPC can be described by its curvatures. To estimate the curvature at the point \( p \), local least squares fitting of a quadric surface is carried out. Principal component analysis is used to estimate an approximate tangent plane, which creates an approximate normal to the surface. Take the point \( p \) as the origin of the local coordinate system in the \( i \)-th region, the neighbour \( p_j \) of \( p \) has coordinate \((x_j,y_j)\). Thus, the minimum value of the quadric surface \( E(x,y) = ax^2 + by^2 + cxy + gx + gy \) can be calculated as follows:

\[
\min \sum_j \| z_j - E(x_j,y_j) \|^2. \tag{1}
\]

Let \( C_p \) denote the curvature at the point \( p \), it can be estimated from the derivatives of the quadric surface \( E(x,y) \), and expressed with the coefficients of \( a, b, c, g, a \) and \( e \) as follows:

\[
C_p = \frac{(1 + g^2)a + (1 + e^2)b - 4abc}{(1 + e^2 + g^2)^2}. \tag{2}
\]

Since the roughness of point cloud describes the spatial fluctuation degree of point cloud, that is, the relative change degree of the curvature, the standard deviation of curvatures of CPC is used to define CPC’s geometric roughness. The visual masking effect of CPC implies that the rougher the region, the lower its distorted visibility. Therefore, the regions of high roughness should be assigned small weight. Here, Gaussian function is used to assign different weights of different regions. After Gaussian weighting to different regions, the geometric combination feature vector \( F_{\text{CG}} \) will be produced with a total of 12 dimensional features, \( F_{\text{CG}} = (F_{i}, i = 1,2,\ldots,12) \), and expressed as follows:

\[
F_{\text{CG}} = (F_1, F_2, \ldots, F_{12}) = \frac{\sum_{i=1}^{N_S} w(i) f_{\text{LG}}(i)}{\sum_{i=1}^{N_S} w(i)}, \tag{3}
\]

where \( w(i) \) is the weight of the \( i \)-th region of CPC, \( Y_i \) is the normalised standard variation of the curvatures of the \( i \)-th region of the reference CPC, and \( N_S \) is the number of the segmented regions of the reference CPC, and \( \eta \) is the parameter of Gaussian function to describe the impact of visual masking effect, which can be selected in the range from 0.1 to 0.4 with \( N_S \). Here, \( \eta \) is empirically set to 0.3 when \( N_S \) is set to 500. \( f_{\text{LG}}(i) \) is the geometric feature vector of the \( i \)-th region of the distorted CPC related to the reference CPC, and defined by

\[
f_{\text{LG}}(i) = (P_{\text{DV}}(i), P_{\text{AG}}(i), P_{\text{DE}}(i)), \tag{5}
\]

where \( P_{\text{DV}}(i), P_{\text{AG}}(i) \) and \( P_{\text{DE}}(i) \) describe the deviation distortion degree, angle distortion degree and density distortion degree, respectively, in the \( i \)-th region of the distorted CPC related to the reference CPC.

When CPC is geometrically distorted by coding algorithm, Gaussian noise or other processing, CPC’s points will remove and change their geometric structural information. It is obvious that a single type of features cannot fully describe the geometric distortion of CPC. The distortion produced by noise attack will also make points removal, the distortion produced by coding algorithms can make CPC hollow and sparse. These distortions can attribute to three aspects: distance, angle and density. Therefore, three types of features are designed to describe the geometric distortion, that is, as deviation distortion degree, angle distortion degree and density distortion degree. They all have four-dimensional feature vectors. These features are described as follows.

The deviation distortion degree describes the removal distance variation of some points when CPC is geometrically distorted, and the angle distortion degree demonstrates the change of points’ normal angles, while the density distortion degree shows the sparsity of CPC.

When a CPC is geometrically damaged, the geometric distance between the CPC’s points will be changed. Before the deviation distortion degree in the \( i \)-th region is computed, the centre of the \( i \)-th region in CPC is defined. Let \( C_i(\hat{i}) \) and \( C_i(\bar{i}) \) denote the centres in the \( i \)-th region of the reference and distorted CPCs, respectively.

Let \( r_a \) denote the point \( a \) in the \( i \)-th region of the reference CPC and \( d_b \) denotes the point \( b \) in the \( i \)-th region of the distorted CPC. Let \( \varphi(\hat{i}) \) denote the distance from the point \( r_a \) to \( C_i(\hat{i}) \), and \( \psi(\bar{i}) \) denote the distance from the point \( d_b \) to \( C_i(\bar{i}) \). Then, \( \varphi(\hat{i}) \) and \( \psi(\bar{i}) \) are computed as follows:

\[
\varphi(\hat{i}) = ||r_a - C_i(\hat{i})||, \tag{6}
\]

\[
\psi(\bar{i}) = ||d_b - C_i(\bar{i})||. \tag{7}
\]

Similarly, when the CPC is geometrically distorted, the normal angles of the points will also be changed. The angle
distortion degree is computed. For the i-th region of the reference CPC, let $\theta(i)$ denote the angle between the normal vector $n_a$ of the point $a$ and the normal vector $n_b(i)$ of the centre $C_a(i)$. For the i-th region of the distorted CPC, let $\delta(i)$ denote the angle between the normal vector $m_b$ of the point $b$ and the normal vector $m_d(i)$ of the centre $C_d(i)$. Then, $\theta(i)$ and $\delta(i)$ can be defined by

$$
\theta(i) = \arccos\left(\frac{n_a \cdot n_b(i)}{||n_a|| \cdot ||n_b(i)||}\right),
$$

(8)

$$
\delta(i) = \arccos\left(\frac{m_b \cdot m_d(i)}{||m_b|| \cdot ||m_d(i)||}\right).
$$

(9)

For the distorted CPC, its density will be different from that of the corresponding original CPC. Here, the concept of density distortion degree is presented. The density of each point is defined according to the number of the adjacent points within a fixed neighbourhood of the point. The density $\beta(i)$ of the point $r_c$ in the i-th region of the reference CPC, the density $\rho(i)$ of the point $d$, in the i-th region of the distorted CPC can be calculated as follows:

$$
\beta(i) = \text{num}\{P_i, ||P - r_c|| \leq L_q\},
$$

(10)

$$
\rho(i) = \text{num}\{P_i, ||P - d|| \leq L_d\},
$$

(11)

where $L_q$ refers to 0.5% of the diagonal of the bounding box in the i-th region of the reference CPC, and $L_d$ refers to 0.5% of the diagonal of the bounding box in the i-th region of the distorted CPC.

In order to fully describe the variation of the distance, angle and density between the reference and distorted CPCs, four statistical features, that is, mean, standard deviation, skewness and kurtosis, are exploited to quantify the distance, angle and density aggregates. Let $E(i)$ be the mean operator, and let $\mu_{\phi}(i)$, $\sigma_{\phi}(i)$, $s_{\phi}(i)$ and $k_{\phi}(i)$ denote the mean, standard deviation, skewness and kurtosis of the distance $\phi(i)$ in the i-th region of the reference CPC, respectively, and they are expressed as follows:

$$
\mu_{\phi}(i) = E(\phi(i)),
$$

(12)

$$
\sigma_{\phi}(i) = \sqrt{E((\phi(i) - \mu_{\phi}(i))^2)},
$$

(13)

$$
s_{\phi}(i) = \frac{E((\phi(i) - \mu_{\phi}(i))^3)}{(\sigma_{\phi}(i))^3},
$$

(14)

$$
k_{\phi}(i) = \frac{E((\phi(i) - \mu_{\phi}(i))^4)}{(\sigma_{\phi}(i))^4}.
$$

(15)

Similarly, $\mu_{\psi}(i)$, $\sigma_{\psi}(i)$, $s_{\psi}(i)$ and $k_{\psi}(i)$ of the distance $\psi(i)$ in the i-th region of the distorted CPC can be obtained by analogy according to Equations (12)–(15), where $\varphi(i)$ is replaced by $\psi(i)$. Then, the deviation distortion degree $P_{DV}(i)$ in Equation (5) is defined as follows:

$$
P_{DV}(i) = (F_1(i), F_2(i), F_3(i), F_4(i)),
$$

(16)

$$
F_1(i) = \frac{||\mu_{\phi}(i) - \mu_{\psi}(i)||}{\max(\mu_{\phi}(i), \mu_{\psi}(i)) + K},
$$

(17)

$$
F_2(i) = \frac{||\sigma_{\phi}(i) - \sigma_{\psi}(i)||}{\max(\sigma_{\phi}(i), \sigma_{\psi}(i)) + K},
$$

(18)

$$
F_3(i) = \frac{||s_{\phi}(i) - s_{\psi}(i)||}{\max(s_{\phi}(i), s_{\psi}(i)) + K},
$$

(19)

$$
F_4(i) = \frac{||k_{\phi}(i) - k_{\psi}(i)||}{\max(k_{\phi}(i), k_{\psi}(i)) + K},
$$

(20)

where $K$ is a constant to prevent numerical instability when the denominators approach 0, and $K = 10^{-6}$.

For the angle distortion degree, $P_{AG}(i)$, of the i-th region, let $\mu_{\theta}(i)$, $\sigma_{\theta}(i)$, $s_{\theta}(i)$ and $k_{\theta}(i)$ denote the mean, standard deviation, skewness and kurtosis, respectively, of the angle $\theta(i)$ of the i-th region of the reference CPC; they can be computed by Equations (12)–(15), using $\theta(i)$ replacing $\phi(i)$. In the same way, $\mu_{\theta}(i)$, $\sigma_{\theta}(i)$, $s_{\theta}(i)$ and $k_{\theta}(i)$ of the angle $\delta(i)$ of the i-th region of the distorted CPC can be defined and computed. Then, $P_{AG}(i)$ in Equation (5) is expressed by

$$
P_{AG}(i) = (F_{12}(i), F_{13}(i), F_{14}(i), F_{15}(i)),
$$

(21)

where $F_{12}(i)$, $F_{13}(i)$, $F_{14}(i)$ and $F_{15}(i)$ can be obtained by analogy with Equations (17)–(20).

Similarly, for the density distortion degree, $P_{DE}(i)$, of the i-th region in Equation (5), it is defined by

$$
P_{DE}(i) = (F_6(i), F_{10}(i), F_{11}(i), F_{12}(i)),
$$

(22)

where $F_6(i)$, $F_{10}(i)$, $F_{11}(i)$ and $F_{12}(i)$ can be obtained by analogy with Equations (17)–(20).

### 2.2 Colour feature extraction with colour transformation

The HSV colour space starts from the human visual system and uses hue, saturation and value to represent colour attribute of CPC, and it is more consistent with human visual characteristics than the RGB colour space [27]. Here, colour attribute of CPC is first converted from the RGB colour space to the HSV colour space before CPC’s colour features are extracted. Figure 4 shows the visual difference between the HSV colour space and the RGB colour space from the same distorted ‘Longdress’. It can be found that the distortion visibility of CPC in the HSV colour space is better than that in the RGB colour space.
FIGURE 4  Example of colour space transformation. (a) Original ‘Longdress’ in RGB colour space. (b) Distorted ‘Longdress’ by Gaussian noise with standard deviation of 8 in RGB colour space. (c) Original ‘Longdress’ in HSV colour space. (d) Distorted ‘Longdress’ in HSV with the same Gaussian noise as Figure 3b

It implies that the HSV colour space has more advantages in describing colour distortion of CPC.

After colour transformation, the colour combination feature vector ($F_T$) is defined and extracted for three colour components of the HSV colour space. $F_T$ has total 12 dimensional features and can be expressed by

$$F_T = (H_{MR}, S_{MR}, V_{MR}), \quad (23)$$

where $H_{MR}$, $S_{MR}$ and $V_{MR}$ denote hue distortion degree, saturation distortion degree and value distortion degree in the HSV colour space, respectively. A better quality of CPC’s colour information should have lower distortion degree values.

In order to fully describe the variation of the hue $H$, saturation $S$ and value $V$ colour components of CPC, this paper also uses first-order mean value, the second-order standard deviation, the third-order skewness value and the fourth-order kurtosis to quantify the hue, saturation and value aggregates. Let $\mu_{Hr}$, $\sigma_{Hr}$, $\gamma_{Hr}$ and $k_{Hr}$ denote the mean, standard deviation, skewness and kurtosis of the hue $H$ of the reference CPC, respectively. Similarly, $\mu_{Hd}$, $\sigma_{Hd}$, $\gamma_{Hd}$ and $k_{Hd}$ can be denoted for the distorted CPC. Then, the hue distortion degree $H_{MR}$ is defined as

$$H_{MR} = (F_{13}, F_{14}, F_{15}, F_{16}), \quad (24)$$

$$F_{13} = \frac{|\mu_{Hr} - \mu_{Hd}|}{\max(\mu_{Hr}, \mu_{Hd})} + K, \quad (25)$$

$$F_{14} = \frac{|\sigma_{Hr} - \sigma_{Hd}|}{\max(\sigma_{Hr}, \sigma_{Hd})} + K, \quad (26)$$

$$F_{15} = \frac{|\gamma_{Hr} - \gamma_{Hd}|}{\max(\gamma_{Hr}, \gamma_{Hd})} + K, \quad (27)$$

$$F_{16} = \frac{|k_{Hr} - k_{Hd}|}{\max(k_{Hr}, k_{Hd})} + K. \quad (28)$$

The saturation distortion degree $S_{MR}$ is defined by

$$S_{MR} = (F_{17}, F_{18}, F_{19}, F_{20}), \quad (29)$$

where $F_{17}$, $F_{18}$, $F_{19}$ and $F_{20}$ can be obtained by analogy with Equations (25)–(28).

Finally, the value distortion degree $V_{MR}$ is defined by

$$V_{MR} = (F_{21}, F_{22}, F_{23}, F_{24}), \quad (30)$$

where $F_{21}$, $F_{22}$, $F_{23}$ and $F_{24}$ can be also computed by analogy with Equations (25)–(28).

2.3  |  Quality prediction

In order to solve the problem of pooling geometric and colour features of CPC, Random Forest (RF) [31] is adopted for nonlinear fusion of the extracted geometric and colour features. RF is an integrated classifier, which defines decision trees as a weak classifier and it is widely used in quality evaluation. As an efficient machine learning method, RF has the unique characteristics of multidimensional features processing, superior operation efficiency and high prediction accuracy. It has a good prospect in the field of CPC quality assessment.

This paper used RF as a tool to integrate features. From the reference and distorted CPCs, the extracted geometric combination feature vector, $F_G$, and colour combination feature vector, $F_T$, are formed into the final feature vector with 24 dimensional features, and denoted as $(F_G, F_T)$. The final feature vector and the corresponding mean opinion scores (MOS) are used to construct training and testing sets. In the training phase, the feature vectors of the training set are taken into RF to build a CPC quality prediction model; in the testing phase, the feature vectors extracted from the testing set are taken into the quality model.
In the experiments, three open point cloud subjective evaluation databases are used, that is, CPCD2.0 from Ningbo University [13], ISPC from Instituto Superior Técnico and Instituto de Telecomunicações [11] and SJTU-PCQA from Shanghai Jiao-tong University [12]. Table 2 lists the main information about three databases.

### 3.1 Databases and evaluation criteria

In the CPCD2.0 database, it has a total of 10 original CPCs, selected from the MPEG content repository [32] and JPEG pleno database [33], and the corresponding 360 distorted CPCs. The 360 distorted CPCs are produced with three ways of distortion, Gaussian noise adding to geometry and/or colour, geometry and/or colour compressed by V-PCC or G-PCC (including G-PCC1 and G-PCC2). Thus, three cases exist in the CPCD2.0 database, that is, the only geometric distortion, only colour distortion and both of geometric and colour distortion. As examples, Figure 5 shows five of the 10 original CPCs in the CPCD2.0 database.

To analyze the performance of different quality assessment metrics, four criteria in [34] are used, that is, Pearson linear correlation coefficient (PLCC) to measure the prediction accuracy, Spearman rank-order correlation coefficient (SRCC) to measure the prediction monotonicity, Kendall rank-order correlation coefficient (RCC) to reflect the order of prediction and root mean square error (RMSE).

Taking the human visual perception into consideration, before calculating the values of the criteria, a five-parameter logistic regression function was used by [35]

\[ f(Q) = r_1 \left( 1 - \frac{1}{1 + \exp\left(\frac{-r_2 (Q - r_3) - r_4}{r_5}\right)} \right) + r_6 Q + r_5, \]

where \( r_1, r_2, r_3, r_4 \) and \( r_5 \) are five parameters to be fitted by minimising the sum of squared differences between the mapped quality score and the MOS.

### 3.2 Influence of different training set sizes and learning algorithms for pooling

To enhance the test of generalisation performance, the distorted CPCs are classified into 10 categories according to 10 original CPCs. This paper randomly selects several categories as the training set and other categories as the testing set to ensure that there is no intersection between the training set and the testing set. The tree quantity of RF is set to the default value of 1000 and the random feature quantity is defined as 2. To ensure that the final result is stable and reliable, here, the training and testing steps are repeated 1000 times. The final evaluation performance result is obtained by the mean value computation.
To investigate whether the prediction performance is highly dependent on the training data, the impact of prediction performance is analysed, in which the percentage of the training set related to the overall CPCD2.0 database is varied from 10% to 90%. The experimental results are shown in Table 3. The first three criteria of the proposed CPC-GSCT metric decrease as the percentage of the training set decreases. Furthermore, the experimental results also confirm a general tendency that the performance of the model is improved as the percentage of the training set increases. Finally, the percentages of the training set and the testing set are set to 80% and 20%, respectively.

In the proposed CPC-GSCT metric, RF is adopted to learn the regression mapping from feature space to quality space. For analysis of quality regression, RF is compared with two representative regression algorithms used in predicting quality, that is, General Regression Neural network (GRN) [36] and Support Vector Regression (SVR) [37]. Table 4 compares the performance of three learning algorithms in the proposed CPC-GSCT metric on the CPCD2.0 database, and the following observations can be derived. First, the results with RF-based algorithm are better than those of the NN-based and SVR-based algorithms. Second, single type of feature vector cannot efficiently describe the distortion of CPC because the geometric distortion is complex. The geometric combination feature vector, \( F_G \), outperforms single type of feature vector, that is, \( P_{DV}, P_{AG} \) or \( P_{DE} \). Third, the colour combination feature vector, \( F_T \) includes the
Influence of geometric segmentation

Overall performance comparison

| Feature types | Features | Criteria | PLCC | SROCC | KROCC | RMSE |
|---------------|----------|----------|------|-------|-------|------|
| Geometric features \(F_G\) | \(P_{DY}\) | 0.6590 | 0.6469 | 0.4882 | 0.8773 |
| \(P_{MG}\) | 0.6750 | 0.6784 | 0.4970 | 0.8562 |
| \(P_{DR}\) | 0.7016 | 0.6987 | 0.5124 | 0.8146 |
| \(\langle P_{DY}, P_{MG}, P_{DR} \rangle\) | 0.7567 | 0.7405 | 0.5669 | 0.7705 |
| Colour features \(F_T\) | \(S_{MR}\) | 0.5435 | 0.5296 | 0.3655 | 0.9731 |
| \(V_{MR}\) | 0.7049 | 0.6988 | 0.5107 | 0.7117 |
| \(\langle H_{MR}, S_{MR}, V_{MR} \rangle\) | 0.7935 | 0.7969 | 0.6120 | 0.7117 |
| All features: \(\langle F_G, F_T \rangle\) | 0.9049 | 0.9063 | 0.7451 | 0.5027 |

Table 5: Performance of different features and their combinations of the CPC-GSCT metric in CPCD2.0

| Feature types | Geometric segment | \(N_s\) | Criteria |
|---------------|-------------------|--------|----------|
| \(F_G\) | - | 1 | 0.7063 | 0.6694 | 0.4933 | 0.8296 |
| \(\sqrt{F_G}\) | 125 | 0.7402 | 0.7279 | 0.5498 | 0.7902 |
| \(\sqrt{F_G}\) | 250 | 0.7485 | 0.7321 | 0.5504 | 0.7815 |
| \(\sqrt{F_G}\) | 500 | 0.7567 | 0.7405 | 0.5669 | 0.7705 |
| \(\sqrt{F_G}\) | 1000 | 0.7517 | 0.7333 | 0.5584 | 0.7767 |
| \(\langle F_G, F_T \rangle\) | - | 1 | 0.8855 | 0.8797 | 0.7023 | 0.5486 |
| \(\sqrt{F_G, F_T}\) | 125 | 0.9005 | 0.9001 | 0.7367 | 0.5160 |
| \(\sqrt{F_G, F_T}\) | 250 | 0.8999 | 0.9003 | 0.7383 | 0.5150 |
| \(\sqrt{F_G, F_T}\) | 500 | 0.9049 | 0.9063 | 0.7451 | 0.5027 |
| \(\sqrt{F_G, F_T}\) | 1000 | 0.9000 | 0.9030 | 0.7389 | 0.5149 |

Table 6: Performance of the proposed metric with or without geometric segmentation/colour transformation in CPCD2.0 database

Note \(F_G\) denotes geometric combination feature vector, and \(F_T\) denotes colour combination feature vector.

4. Influence of geometric segmentation and weights

This work uses the geometric segmentation and colour transformation procedures as pre-processing. To illustrate their effectiveness, an example of geometric region segmentation and the performance comparison on influence of geometric segmentation and colour transformation are given.

To explain the segmentation of CPC’s geometric regions, the CPC ‘Longdress’ in [13] is segmented by the \(k\)-means clustering. Figure 6 depicts the geometric region segmentation of the head of ‘Longdress’. The different colours in Figure 6b represent the different geometrically segmented regions. It implies that different segmented regions of CPC have different roughness and produce different visual perception.

Table 6 shows the performance comparison of the proposed CPC-GSCT metric with or without geometric segmentation/colour transformation, where \(F_G\) implies that only geometric feature vector is used to characterize the CPC’s distortion, and \(\langle F_G, F_T \rangle\) represents that both of the geometric and colour features are used in the proposed CPC-GSCT metric. In Table 6, \(\eta\) is set to 0.3, \(N_s\) denotes the number of the segmented regions, and \(N_s = 1\) means that the CPC is not segmented. The results show that colour transformation and reasonable geometric segmentation can improve the performance of the CPC quality metric.

5. Overall performance comparison

To illustrate effectiveness of the proposed CPCP-GSCT metric, it is compared with other existing quality metrics in Table 1, in which some existing quality metrics evaluate only CPC’s geometric distortion, not colour distortion. The CPCD2.0 database consists of the CPCs with only geometric distortion, only colour distortion, and both of the geometric distortion and the colour distortion, so we select a subset of the CPCD2.0 database, which is composed of the CPCs with only geometric distortion, to fairly compare the performance of the point-based metrics. The subset has 120 CPCs with only geometric distortion, 30 of which are with Gaussian noise and 90 are produced by coding, and it is called as Only Geometric Distortion Subset (OGDS). First, for the sake of fairness, the proposed CPC-GSCT metric will only use the geometric combination feature vector (\(F_G\)),
To better illustrate the effectiveness and robustness of the proposed CPC-GSCT metric, in addition to the CPCD2.0 database, we also conducted performance comparison experiments on other two public databases, IRPC database [11] and SJTU-PCQA database [12]. Tables 9 and 10 depict the performance comparison of all metrics in the IRPC and SJTU-PCQA databases, where a total of 54 distorted CPCs in the IRPC database and a total of 378 distorted CPCs in the SJTU-PCQA database, respectively, are used to test the metrics. From these tables, the experimental results also show that the proposed CPC-GSCT metric can also get more accurate evaluation results in these databases, compared with the other metrics.

4 | CONCLUSIONS

This paper has presented a full-reference CPC quality assessment metric with GSCT. The main idea is to exploit some known facts of the human visual system to build a model that...
is useful for CPC quality assessment. For this purpose, the proposed CPC-GSCT metric dedicated to characterise the distortion of the distorted CPC from both geometric and colour perspectives. For analysis of geometric distortion, the $K$-means clustering algorithm is used to segment CPC into regions with different roughness, and Gaussian weights are used to depict the influence of visual masking effect in CPC quality assessment. The geometric combination feature vector is designed to describe CPC's geometric distortion. To analyse the CPC's colour distortion, colour transformation is performed, and the colour combination feature vector is designed to describe colour distortion in the HSV colour space. Finally, the extracted geometric and colour features are pooled to predict the quality of the distorted CPC. Experimental results on three subjective evaluation databases, CPCD2.0, IPRC and SJTU-PCQA, demonstrate the superiority of the proposed CPC-GSCT metric to other existing metrics. It should be noted that the proposed CPC-GSCT metric is a full-reference metric and this paper only considers the visual masking effect in geometric information. Authors will focus on blind CPC quality metrics and explore the joint visual masking effect of CPC with region segmentation in the future work.

ACKNOWLEDGEMENTS
The authors thank the scholars for providing the point cloud data, which was used to construct the coloured point cloud.
subjective evaluation database, CPCD2.0. The authors also thank the scholars with their subjective quality assessment databases. This work was supported by the National Natural Science Foundation of China under Grant Numbers 61671258 and 61931022. It was also sponsored by the K.C. Wong Magna Fund of Ningbo University.

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How to cite this article: Hua, L., et al.: CPC-GSCT: Visual quality assessment for coloured point cloud based on geometric segmentation and colour transformation. IET Image Process. 1–13 (2021) https://doi.org/10.1049/ipr2.12211