Perceptual Quality Assessment of Colored 3D Point Clouds

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Abstract—3D point clouds have found a wide variety of applications in multimedia processing, remote sensing, and scientific computing. Although most point cloud processing systems are developed to improve viewer experiences, little work has been dedicated to perceptual quality assessment of 3D point clouds. In this work, we build a new 3D point cloud database, namely the Waterloo Point Cloud (WPC) database. In contrast to existing datasets consisting of small-scale and low-quality source content of constrained viewing angles, the WPC database contains 20 high quality, realistic, and omni-directional source point clouds and 740 diversely distorted point clouds. We carry out a subjective quality assessment experiment over the database in a controlled lab environment. Our statistical analysis suggests that existing objective point cloud quality assessment (PCQA) models only achieve limited success in predicting subjective quality ratings. We propose a novel objective PCQA model based on an attention mechanism and a variant of information content-weighted structural similarity, which significantly outperforms existing PCQA models. The database has been made publicly available at https://github.com/qdushl/Waterloo-Point-Cloud-Database.

Index Terms—Point cloud, subjective quality assessment, attention model, objective quality assessment.

1 INTRODUCTION

A 3D point cloud is a collection of points representing a 3D shape, object or environment. Each point can be described by its geometric coordinates and optional associated attributes. 3D point clouds [1]–[4] have found broad applications in manufacturing, construction, environmental monitoring, navigation, and animation. Many of these applications require high quality point clouds that faithfully reflect the geometry and perceptual attributes of the physical world. However, various distortions may be introduced during the acquisition, compression [5], transmission, storage, and rendering processes, leading to degraded perceptual quality by end users. Over the past decade, point cloud quality assessment (PCQA) has become an active field of research [6]–[62].

Since the human visual system (HVS) is the ultimate receiver of 3D point clouds in most applications, subjective quality assessment is the most straightforward and reliable approach to evaluate the quality of point clouds. A comprehensive subjective user study on a large-scale point cloud database brings several benefits. First, it advances our understanding about the HVS in evaluating the perceived quality of point clouds. Second, a diverse set of high quality source stimuli supply a fertile playground for point cloud processing algorithms, such as denoising [63], super-resolution [64], and compression [65]. Third, a subject-rated dataset provides a valuable source to train, validate, and test existing objective PCQA models.

Despite its importance, subjective quality evaluation is inconvenient, time-consuming, and expensive. To enable quality-centric point cloud systems in practice, objective PCQA models that can accurately predict subjective quality are highly desired. Although substantial effort has been made to develop objective PCQA models [12], [16], [21], [23], [25], [28]–[30], [32], [33], [35], [37]–[40], [44]–[47], [49]–[55], [55]–[62], they often fail to draw a connection to the HVS [66], [67] and/or struggle in handling the irregular representation of point clouds [21], [23]. Most importantly, none of these models is validated on large-scale subject-rated PCQA databases with diverse and high quality original point clouds, making their generalizability questionable.

In this work, we first introduce so-far the largest high quality point cloud dataset. By degrading the reference point clouds with diverse distortion types and levels, we create 740 distorted point clouds. A subjective experiment is then carried out in a controlled environment to evaluate the perceptual quality of these point clouds. The new database, named the Waterloo Point Cloud database (WPC), together with subjective labels are made publicly available to facilitate reproducible research. Using the WPC database, we conduct a comprehensive evaluation of existing objective PCQA models, which suggests that state-of-the-art models only achieve a moderate correlation with human visual perception. To overcome the problem, we develop an attention guided objective PCQA model, inspired by the information content weighted structural similarity measure (IW-SSIM) [69]. Experimental results demonstrate that the proposed model well correlates with subjective quality evaluations and significantly outperforms all existing PCQA models.
2 RELATED WORK

2.1 Existing PCQA Databases

The history of point cloud generation dated back at least to 1990’s, when Turk and Levoy investigated computational methods for 3D surface reconstruction [71]. The resulting Stanford 3D scanning dataset is still in use in recent PCQA research [9], [14], [15]. The MPEG point cloud database [72] and the JPEG Pleno database [73] introduced more content types, such as cultural heritages, computer-generated objects, and human figures. These early databases provide a solid foundation for a series of subjective PCQA studies. Most later subject-rate point cloud databases were derived from these datasets [9], [13]–[15], [23], [24], [34], [36], [45], [48], [49], [52], [55], [68], as summarized in Table 1. Due to the simplified data collection process, these PCQA databases inherently suffer from several limitations. First, most point clouds in the Stanford 3D scanning repository [71] are colorless. Second, the scanning process fails to capture the aesthetic aspect of the objects, especially for those of cultural heritages. Typical examples include the “RomanOilLight” [73] as shown in Fig. 1 (a) and the “Head” [72] as shown in Fig. 1 (b). Third, some point clouds are of inferior perceptual quality, containing scanning noise (“Statue_Klimt” [72] in Fig. 1 (c)) or irregular edges (“Phil” [74] in Fig. 1 (d)). Fourth, many point clouds were scanned from a limited number of directions, as exemplified in Fig. 1 (e). However, real-world applications often require point clouds that allow for omni-directional presentation [9], [13]–[15], [23], [24], [52]. Fifth, existing PCQA databases are often of low content diversity. We wish to address these limitations in this study.

Fig. 1. Sample point clouds from existing datasets. (a) RomanOilLight. (b) Head. (c) Statue_Klimt. (d) Phil. (e) Phil2. (f) Longdress.

| Database                | Attribute | Source contents | Distortion type       | Subject-rated point clouds |
|-------------------------|-----------|-----------------|-----------------------|---------------------------|
| IRC-2 [24]              | None, Color | 6              | FCL, G-PCC, V-PCC    | 54                        |
| vsenseVDBB [13]         | Color     | 2              | G-PCC                | 52                        |
| vsenseVDB2R [34]        | Color     | 8              | Draco+JPEG, G-PCC, V-PCC | 164                      |
| G-PCCD [14], [15]       | None      | 5              | Octree-purning, Gassian noise | 40                        |
| RG-PCCD [9]             | None      | 6              | Octree-purning, Gassian noise | 24                        |
| M-PCCD [23]             | Color     | 8              | G-PCC, V-PCC         | 244                       |
| PointXIX [56]           | Color     | 5              | G-PCC                | 100                       |
| NBU-PCCD 1.0 [55]       | Color     | 5              | Octree               | 160                       |
| CPCD 2.0 [49]           | Color     | 10             | Octree               | 160                       |
| SJTU-PCQA [45]          | Color     | 10             | G-PCC, V-PCC         | 360                       |
| CPCD2020 [48]           | Color     | 10             | G-PCC, V-PCC         | 420                       |
| 3DMDC [68]              | Color     | 5              | G-PCC, V-PCC         | 90                        |
| SIAT-PCQA [52]          | Color     | 10             | QGeo, QCol, SGeo, SCol | 80                       |
| WPC (ours)              | Color     | 20             | V-PCC                | 340                       |
|                        |           |                | Gassian noise, dowmsampling, G-PCC, V-PCC | 740                      |

2.2 Objective Quality Assessment of 3D Point Clouds

Depending on the application scope, objective PCQA models may be categorized into geometry-only models [16], [25], [26], [28]–[30], [33], [39], [40], [78] and general-purpose models [12], [21], [23], [28], [29], [32], [35], [37], [38], [44]–[47], [49]–[62]. Geometry-only PCQA models are dedicated to assess the perceptual quality of point clouds with only ge-
ometric information, while general-purpose PCQA models take all quality-related attributes including color and surface normal into consideration. From the perspective of feature extraction, objective PCQA models may also be classified into point-based [16], [25], [28]–[30], [33], [35], [37]–[40], [44], [46], [47], [49]–[51], [54]–[57], [59], [60], [62] and projection-based models [12], [21], [23], [32], [45], [52], [53], [58], [61].

Both point-to-point and point-to-plane models employ variants of the Euclidean distance to quantify geometric distortions [25], [28], [29]. In [16], the cosine similarity measure is applied to the local surface normal. Similarly, the PC-MSDM model [30] computes the similarity between the curvature of the original and distorted signals. However, surface normal-based approaches are often susceptible to random noise in the acquisition process [16], [25], [28]–[30]. By incorporating machine learning techniques, [33] developed a generalized Hausdorff distance measure with enhanced robustness. In [39], a PSNR-based metric [25], [28], [29] is proposed by including a normalization factor that accounts for changes in the intrinsic point cloud resolution after rendering. In [29], PSNR-based methods are modified by a density coefficient determined by the peak of coordinate and the rendering resolution. In [40], a point-to-distribution quality assessment model is proposed by exploiting the correspondence between a point and a distribution of points in a small point cloud region. As such, the point cloud surface is characterized through the covariance of points within the local region, which is not overly influenced by the number of reconstructed points after decoding, but rather by a statistical characterization of the point locations.

Compared with geometry-only point clouds, colored point clouds have a broad range of applications. Many quality or distortion metrics for colored PCs have emerged recently [6], [28], [29], [35], [37], [38], [42], [44], [46], [47], [49]–[51], [54], [55], [57], [59], [60]. In [28], [29], point-to-point PSNR on the Y component (MPEG PSNR_Y) is used to estimate texture distortion of colored PCs, though such a direct extension of PSNR inevitably inherits the widely-known disadvantages of PSNR [66], [67]. Similarity based measures [66] are extended to PCQA [35], [37], [55]. In these methods, geometry-based, color-based, normal-based and curvature-based features are extracted from both the reference and distorted PCs, then geometry and color feature similarities are evaluated and combined to produce the overall objective scores. In [38], color histograms and correlograms are used to estimate the impairment of a distorted point cloud with respect to its reference. Geometry-only and color-only approaches are then combined to a rendering-independent objective PCQA metric. More recently, statistics of a variant of the Local Binary Pattern (LBP) [46], [47], Perceptual Color Distance Pattern (PCDP) [50] and Local Luminance Pattern (LLP) [51] descriptors are introduced to the area. In [54], the BitDance metric uses color and geometry texture descriptors. The statistics of color and geometry information of the reference and test PCs are compared and combined to estimate the perceived quality of the test point cloud. The GraphSIM approach [44], [60] uses graph signal gradient as a quality index to evaluate point cloud distortions. Considering the visual masking effect of point cloud’s geometric information and the color perception of human eyes, the CPC-GSCT metric [49] uses geometric segmentation and color transformation respectively to construct geometric and color features and then to estimate the point cloud quality. Inspired by the point cloud generation process, the elastic potential energy similarity (EPES) model [59] introduces elastic forces to record the shaping of the point set, and uses the elastic potential energy difference to quantify point cloud distortion.

In addition to the aforementioned point-based models, there are also many projection-based models [12], [21], [23], [32], [45], [52], [53], such as projection-based PSNR (PSNRp) [12], [32], projection-based structural similarity (SSIMp) [12], [32], [66], projection-based multi-scale struc-
tural similarity (MS-SSIMp) [12], [32], [79] and projection-based pixel-domain visual information fidelity (ViFPP) [12], [32], [80]. Yang et al. [45] choose to project the 3D point cloud onto six perpendicular image planes of a cube for the color texture image and corresponding depth image, and aggregate image-based global and local features from all projected planes to a final objective index. Wu et al. [52] propose two projection-based objective quality evaluation methods: a weighted view projection based model and a patch projection based model. He et al. [53] project the colored texture information and curvature of point cloud onto 2D planes and extract texture and geometric statistical features, respectively, so as to characterize the texture and geometric distortion. However, these methods treat background padding pixels on projected image planes the same way as the foreground ones, leading to inferior quality prediction accuracy [69]. Alexiou et al. [21], [23] develop a post-processing algorithm to remove the influence of background pixels, but model complexity increases and robustness declines.

Reduced reference and no reference PCQA models have also been developed. Reduced reference PCQA models [6], [42] only require partial information about the reference PCs. In [42], geometry-based, normal-based and luminance-based features are extracted from the reference point cloud, transmitted alongside the content, and employed at the receiver side to help assess the quality of the distorted point cloud. In [6], two color features are proposed to estimate three content dependent parameters for reduced reference PCQA. No reference PCQA models require no information about the reference PCs [43], [57], [58], [61], [62]. Cao et al. [43] define point cloud quality as a function of the bitrate and observation distance. Nevertheless, bitrate alone cannot accurately estimate the point cloud quality, and the observation distance, a parameter often used in the rendering algorithm, is often not available in practical systems. The BQE-CVP metric [57] uses geometric feature, color feature and joint feature to develop a blind quality evaluator. Zhang et al. [62] project the 3D models from 3D space into quality related geometry and color feature domains, extract natural scene statistics (NSS) and entropy for quality aware features, and employ a Support Vector Regressor (SVR) to regress the quality-aware features into quality scores. Liu et al. [61] propose a deep learning-based PQA-Net model, which consists of a multi-view-based joint feature extraction and fusion (MVFEF) module, a distortion type identification (DTI) module, and a quality vector prediction (QVP) module. By using the distortion type labels, the DTI and the MVFEF modules are pre-trained to initialize the network parameters, and the full network is then jointly trained for quality prediction. Tao et al. [58] propose a point cloud projection and multi-scale feature fusion network that includes a joint color-geometric feature extractor, a two-stage multi-scale feature fusion, and a spatial pooling module.

3 Point Cloud Database Construction

3.1 Point Cloud Construction

Motivated by the lack of source 3D point clouds, we gather a collection of objects with diverse geometric and textural complexity, including snacks, fruits, vegetables, office supplies, and containers, etc. The selected contents are moderate in size and are omnidirectional in viewing angle. Fig. 2 shows a snapshot for the reference point clouds constructed. The construction process is as follows.

- **Image acquisition**: The image acquisition is performed in a laboratory environment of a normal lighting condition without reflecting ceiling, walls and floors. A single-lens-reflex camera and a turntable are employed to take photos of an object from a variety of perspectives. A graph illustration of the acquisition process is shown in Fig. 3, where each photo is placed at its capture position relative to the object in the center.
- **3D reconstruction**: A sequence of operations including image alignment, sparse point cloud reconstruction, dense point cloud reconstruction, and point cloud merging are applied to each sequence of images using Agisoft Photoscan [81]. The resulting point clouds are further refined by Screened Poisson Surface Reconstruction [82] and re-sampled using CloudCompare [83].
- **Normalization**: Each point cloud is normalized to be fully contained in a unit-cube with a step size of 0.001, where duplicated points are removed [83]. A total of 20 voxelized point clouds are generated. The number of points in each point cloud ranges between 400K and 3M, with an average of 1.35M and a standard deviation of 656K. The specifications are given in Table 3.

3.2 Distortion Generation

We distort the source PCs with the following processes to simulate real-world application scenarios.

- **Downsampling**: Octree-based downsampling [83] is applied to the source point clouds. Each dimension is uniformly divided into \(2^N\) intervals, where \(N\) represents the octree level. Points located in the same cube are then merged into one. In this study, \(N\) is set to be 7, 8, and 9, to cover diverse spatial resolutions.
- **Gaussian noise contamination**: White Gaussian noise is added independently to both geometry and texture elements with standard deviations of \(\{0, 2, 4\}\) and \(\{8, 16, 32\}\), respectively. Then both geometry and texture elements are rounded to the nearest integer, followed by points removal by Meshlab [84].
- **MPEG-PCC**: Two technologies were chosen as test models following MPEG’s call for proposals for International Organization for Standardization [65]: G-PCC for static content and dynamically capturing, and V-PCC for dynamic content. In this work, G-PCC (Trisoup) reference codec [85] is employed to encode the original point clouds with ‘max_NodeSizeLog\(_2\)’ of \(\{10\}\), ‘NodeSizeLog\(_2\)’ of \(\{2, 4, 6\}\) and ‘rahQuantizationStep’ of \(\{64, 128, 256, 512\}\), respectively. G-PCC (Octree) [86] employs a downsampling method to encode the geometry information, and is thus not performed redundantly. We set the ‘quantizationSteps’ of texture encoding as \(\{16, 32, 48, 64\}\). V-PCC reference codec [87] is employed to encode the original point clouds at three ‘geometryQP’ values and three ‘textureQP’ values, ranging from 35-50 and 35-50, respectively, followed by duplicated points removal [84].
Table 3

| Index | Name            | Points | Xmin, Ymin, Zmin | Xmax, Ymax, Zmax | Min DNN | Max DNN | Description                        |
|-------|-----------------|--------|------------------|------------------|---------|---------|------------------------------------|
| a     | Bag             | 120744 | 0 0 0            | 999 999 999     | 1       | 18.47  | Daily supply, high TC              |
| b     | Banana          | 807184 | 0 0 0            | 999 999 999     | 1       | 10.05  | Snack, thin, medium TC             |
| c     | Biscuits        | 952759 | 0 0 0            | 999 999 999     | 1       | 10.05  | Snack, topological hole, medium TC |
| d     | Cake            | 248466 | 0 0 0            | 999 999 999     | 1       | 7.14   | Vegetable, low TC                  |
| e     | Cauliflower     | 193662 | 0 0 0            | 999 999 999     | 1       | 10.20  | Container, thin wall, low TC       |
| f     | Flowerpot       | 240715 | 0 0 0            | 999 999 999     | 1       | 15.65  | Daily supply, high TC              |
| g     | Glasses_case    | 716659 | 0 0 0            | 999 999 999     | 1       | 23.75  | Container, medium TC               |
| h     | Heirloom melon  | 143107 | 0 0 0            | 999 999 999     | 1       | 29.97  | Container, high GC, high TC        |
| i     | House           | 156494 | 0 0 0            | 999 999 999     | 1       | 8.77   | Fruit, medium TC                   |
| j     | Litchi          | 103994 | 0 0 0            | 999 999 999     | 1       | 2.45   | Vegetable, thin, different GC and TC on both sides |
| k     | Mushroom        | 114403 | 0 0 0            | 999 999 999     | 1       | 18.60  | Office supply, thin, high GC and different TC on both sides |
| l     | Pen_container   | 287381 | 0 0 0            | 999 999 999     | 1       | 23.58  | Fruit, high TC                     |
| m     | Pineapple       | 162891 | 0 0 0            | 999 999 999     | 1       | 12.95  | Sports equipment, thin, different GC and TC on both sides |
| n     | Ping-pong bat   | 703079 | 0 0 0            | 999 999 999     | 1       | 2.10   | Container, medium TC               |
| o     | Puer tea        | 412780 | 0 0 0            | 999 999 999     | 1       | 6.71   | Vegetable, high TC                 |
| p     | Pumpkin         | 134034 | 0 0 0            | 999 999 999     | 1       | 3.74   | Container, medium GC, low TC       |
| q     | Ship            | 687412 | 0 0 0            | 999 999 999     | 1       | 2.85   | Container, high GC, low TC         |
| r     | Statue          | 163775 | 0 0 0            | 999 999 999     | 1       | 52.20  | Container, high GC, different TC on both sides |
| s     | Stone           | 108453 | 0 0 0            | 999 999 999     | 1       | 75.77  | Container, low TC                  |
| t     | Tool_box        | 107421 | 0 0 0            | 999 999 999     | 1       | 3.32   | Container, low TC                  |

In total, 760 point clouds with a wide range of visual quality levels are included in the WPC database.

Sampled distortion point clouds are shown in Fig. 4. It is interesting to observe that distorted point clouds not only exhibit loss of texture information similar to 2D images such as blockiness and blur, but also novel geometric distortion types. For example, hollow is caused by downsampling, where the point density may not be sufficient to cover the object surface. Holes and collapses arise from unsuccessful triangulations and inappropriate downsampling in G-PCC (Trisoup), respectively. Even when the triangulation is successful, geometric distortions may still appear as a consequence of ill-conditioned triangles. A sample case is given in the bottom right part of Fig. 4 (d). Moreover, a large ‘geometryQP’ in V-PCC may potentially introduce gaps and burrs. All these distortions are point cloud-specific, which create new challenges to objective PCQA models.

4 Subjective Experiments

4.1 Subjective User Study

We employ Technicolor Renderer [88] to render each point cloud to a video sequence. The rendering window, point size and point type parameters are set to 960×960, 1, and ‘point’, respectively. A horizontal and a vertical circles both with a radius of 5,000 are selected successively as the virtual camera path with the center of circles at the geometry center of an object. The remaining parameters are set as default. These settings preserve detail information as much as possible while maintaining the original point clouds to be watertight. One viewpoint is generated every two degrees on these circles, resulting in 360 image frames for each point cloud. Each distorted clip is then concatenated with its pristine counterpart into a 10-second video sequence for presentation. A screenshot is shown in Fig. 5.

Our subjective testing environment is the same as that for image acquisition. All video sequences are displayed on a 23.6” LCD monitor at a resolution of 1920×1080 with
Fig. 4. Point cloud distortions. Geometry distortions: (a) Hollow. (b) Geometry noise. (c) Hole. (d) Shape distortion. (e) Collapse. (f) Gap and burr. Texture distortions: (g) Texture noise. (h) Blockiness. (i) Blur. (j) Color bleeding.

Fig. 5. Source and distorted point clouds of “PenContainer”.

Truecolor (32bit) at 60 Hz. The monitor is calibrated in accordance with ITU-R Recommendation BT.500-13 [75]. DSIS methodology is applied in our subjective test [75]. Videos are displayed in random order using a customized graphical user interface, where subjective scores of individual viewers are recorded.

A total of 60 naive subjects, including 32 males and 28 females aged between 21 and 40, participated in the subjective test. All subjects have normal or corrected-to-normal vision, and viewed videos from a distance of twice the screen height. Before the testing session, a training session is performed during which 18 videos different from those in the testing session are shown. The same methods are applied to generate videos used in both the training and testing sessions. Therefore, subjects knew what distortion types and levels to expect before the testing session, and thus the learning effects are kept minimal. Considering the limited testing capacity, each subject is assigned 10 objects in a circular fashion. Specifically, if subject $i$ is assigned objects 1 to 10, then subject $i + 1$ watches objects 2 to 11. Each video is scored for 30 times, resulting in totally 22,800 subjective ratings, including 600 for source point clouds. For each subject, the whole study takes about 2 hours, which is divided into 4 sections with three 5-minute breaks in between to minimize the impact of fatigue effect. For finer distinctions between ratings, 100-point continuous scale is utilized instead of a 5-point rating as in ITU-R ACR.

Fig. 6. MOS statistics of WPC database.
4.2 Subjective Data Analysis

After converting the raw subjective scores into Z-scores, an outlier removal scheme is applied [75]. No outlier detection is conducted participant-wise. Then the Z-scores are linearly rescaled to lie in the range of [0, 100]. The mean opinion score (MOS) for each distorted point cloud is calculated by averaging the re-scaled Z-scores from all valid subjects. The histograms for the MOS and the associated standard deviation are shown in Fig. 6, which demonstrates that the distorted point clouds span most of the quality range. Considering the MOS as the “ground truth”, the performance of individual subjects can be evaluated by calculating the correlation coefficient between individual subject ratings and MOS values for each source point cloud, and then averaged over all source point clouds. Pearson linear correlation coefficient (PLCC) and Spearman rank-order correlation coefficient (SRCC) are employed as the evaluation criteria. Fig. 7 depicts the mean and standard deviation of each individual subject’s performance, where most individual subjects perform quite consistently with relatively low variations across source point clouds. The average performance across all individual subjects is also given in the rightmost columns of Fig. 7.

4.3 Performance of Existing Objective PCQA Models

Using the aforementioned database, we test the performance of 13 PCQA models, which are selected to cover a wide range of design methodologies. Geometry distortion metrics except the MPEG metrics and algorithms unavailable to public are not included. The models include point-wise models: 1) point-to-point mean squared error-based PSNR (PSNRp2p,M) [26], [27], 2) point-to-point Hausdorff distance-based PSNR (PSNRp2p,H,M) [26], [27], 3) point-to-plane mean squared error-based PSNR (PSNRp2p,M) [26], [27], 4) point-to-plane Hausdorff distance-based PSNR (PSNRp2p,H,M) [26], [27], 5) point-to-point PSNR on color component (PSNRY) [28],[29], 6) PCMRR [42], 7) PointSIM [35], 8) PCQM [37], 9) GraphSIM [44], and projection-based models: 10) projection-based PSNR (PSNRp) [12], 11) projection-based structural similarity (SSIMp) [12],[66], 12) projection-based multi-scale structural similarity (MS-SSIMp) [12],[79], and 13) projection-based pixel-domain visual information fidelity (VIFPp) [12],[80]. The implementation of all models are obtained from the original authors or their public websites.

We use PLCC, SRCC and RMSE between MOSs and model predictions as the evaluation criteria, and the results are shown in Table 4, 5 and 6. First, it comes as no surprise that all geometry distortion models performs unfavorably to the geometry-plus-color PCQA models. Second, projection-based models, such as VIFPp, provide the most promising results, but often fall short in making a distinction of the perceptual importance between the background and the regions corresponding to points in a 2D projection of a 3D point cloud. Third, even the best PCQA model only moderately correlates with human perception, leaving large space for improvement.

5 Objective Quality Assessment

5.1 Proposed PCQA Model

A point cloud can be omni-directionally inspected from a view-sphere at a given distance, while it is both cumbersome and unnecessary to use a large number of viewpoints when acquiring its 2D snapshots. Icosphere, a unit geodesic sphere created by subdividing a regular icosahedron with normalized vertices, are employed to generate viewpoints by uniformly distributed vertices [21],[89]. The number of vertices that may be generated is

\[ N_v = 12 + 10 \left( 4^l - 1 \right), \]

where \( l \) represents the subdivision level. For any point in a 3D point cloud, let \( p = (g c) \) be a 6 dimensional row vector where \( g \) and \( c \) contain its 3D coordinates \((g_x, g_y, g_z)\) and attributed color information \((c_r, c_g, c_b)\), respectively. We use a series of transformations to obtain the projected images.

Firstly, we translate a point cloud to align its geometric center to the origin \((0,0,0)\). Specifically, for each \( p \)

\[ g_t = g - t_c, \]

where \( g_t \) represents the 3D coordinates after translation, and \( t_c \) represents the translation vector equaling the geometric center coordinates of its corresponding reference point.
TABLE 4
PLCC PERFORMANCE EVALUATION OF THE PROPOSED MODEL AGAINST EXISTING MODELS. ABSOLUTE PLCC ARE TAKEN FOR DISTORTION MEASURES FOR BETTER VISIBILITY.

| Subset     | Geometry distortion metric | Geometry-plus-color distortion metric | IW-SSIM_p |
|------------|-----------------------------|--------------------------------------|-----------|
|            | PSNR_p,SSIM Q,PSNR_p,SSIM Q | PSNR_p,SSIM Q,PSNR_p,SSIM Q         |            |
| Bag        | 0.7018                      | 0.5136                               | 0.4870    |
| Banana     | 0.7236                      | 0.4866                               | 0.4967    |
| Biscuits   | 0.5288                      | 0.5197                               | 0.5203    |
| Cake       | 0.4203                      | 0.1227                               | 0.3577    |
| Cauliflower| 0.4555                      | 0.2914                               | 0.2914    |
| Flowerpot  | 0.7076                      | 0.5271                               | 0.6381    |
| GlassCase  | 0.6209                      | 0.5132                               | 0.4370    |
| HoneydewMelon| 0.4617                     | 0.4337                               | 0.4337    |
| House      | 0.6931                      | 0.3956                               | 0.4132    |
| Litchi     | 0.4219                      | 0.3749                               | 0.3472    |
| Mushroom   | 0.6406                      | 0.4866                               | 0.5460    |
| PetContainer| 0.7782                     | 0.5065                               | 0.6805    |
| Pineapple  | 0.4678                      | 0.2923                               | 0.3719    |
| PruneFot   | 0.7234                      | 0.4191                               | 0.6662    |
| Pumpkin    | 0.5163                      | 0.4919                               | 0.4379    |
| Ship       | 0.7676                      | 0.3848                               | 0.6305    |
| Statue     | 0.8288                      | 0.4298                               | 0.7011    |
| Stone      | 0.6140                      | 0.5508                               | 0.5161    |
| TVBox      | 0.4485                      | 0.2923                               | 0.3736    |
| Downscaling| 0.4242                      | 0.5088                               | 0.3212    |
| Gaussian noise | 0.8667                    | 0.6992                               | 0.6867    |
| G-PCC (T)  | 0.4019                      | 0.3029                               | 0.4050    |
| V-PCC      | 0.1704                      | 0.2156                               | 0.2121    |
| G-PCC (O)  | 0.6508                      | 0.3029                               | 0.3482    |
| All        | 0.8333                      | 0.3255                               | 0.3952    |

TABLE 5
SACCE PERFORMANCE EVALUATION OF THE PROPOSED MODEL AGAINST EXISTING MODELS. ABSOLUTE SACCE ARE TAKEN FOR DISTORTION MEASURES FOR BETTER VISIBILITY.

| Subset     | Geometry distortion metric | Geometry-plus-color distortion metric | IW-SSIM_p |
|------------|-----------------------------|--------------------------------------|-----------|
|            | PSNR_p,SSIM Q,PSNR_p,SSIM Q | PSNR_p,SSIM Q,PSNR_p,SSIM Q         |            |
| Bag        | 0.6785                      | 0.5041                               | 0.5188    |
| Banana     | 0.6471                      | 0.1903                               | 0.5911    |
| Biscuits   | 0.5963                      | 0.3406                               | 0.5069    |
| Cauliflower| 0.3074                      | 0.1724                               | 0.1798    |
| Flowerpot  | 0.3001                      | 0.0918                               | 0.2085    |
| GlassCase  | 0.3074                      | 0.4342                               | 0.2463    |
| HoneydewMelon| 0.5845                     | 0.2020                               | 0.3238    |
| House      | 0.5109                      | 0.3478                               | 0.4291    |
| Mushroom   | 0.6386                      | 0.3567                               | 0.3156    |
| PetContainer| 0.5288                     | 0.3129                               | 0.3249    |
| Pineapple  | 0.4580                      | 0.2768                               | 0.2390    |
| Litchi     | 0.5109                      | 0.3478                               | 0.4291    |
| Mushroom   | 0.6386                      | 0.3567                               | 0.3156    |
| PetContainer| 0.5288                     | 0.3129                               | 0.3249    |
| Pineapple  | 0.3777                      | 0.1376                               | 0.2785    |
| PruneFot   | 0.5924                      | 0.4958                               | 0.4309    |
| Pumpkin    | 0.6069                      | 0.1173                               | 0.4746    |
| Statue     | 0.4947                      | 0.3029                               | 0.3242    |
| Stone      | 0.6219                      | 0.3551                               | 0.3242    |
| TVBox      | 0.5907                      | 0.1329                               | 0.2483    |
| Downscaling| 0.4814                      | 0.3586                               | 0.2321    |
| Gaussian noise | 0.6351                    | 0.6419                               | 0.6150    |
| G-PCC (T)  | 0.3435                      | 0.2601                               | 0.3685    |
| V-PCC      | 0.1602                      | 0.2051                               | 0.2370    |
| G-PCC (O)  | 0.6101                      | 0.3406                               | 0.3008    |

The reason \( t \) is used instead of the geometric center of a distorted point cloud is that geometric distortions may change the upper and lower bounds of the 3D coordinates, leading to misalignment of the projected images.

Secondly, we rotate the point cloud to obtain a number of viewpoints. More specifically, let \( n_v \), a 3 dimensional row vector, be the unit normal \( n_v \) be \((0\,0\,1)\), then the rotation vector \( \theta \) can be calculated as

\[
\theta = \arccos(\langle n_v, n_r \rangle)
\]

and

\[
r = \left\| n_r \times n_v \right\|
\]

where \( \cdot \) denotes the \( l_2 \) norm of a vector, \( r \) is the rotation axis, and \( \theta \) is the angular radius. The rotation matrix \( R \) is obtained using \( (\theta) \). Then we use \( R \) to calculate \( g_p \), the 3D coordinates after rotation, for each \( p \).

\[
g_p = g \cdot R.
\]

Thirdly, a scaling transformation is applied to make 2D snapshots of all reference point clouds approximately watertight while keeping the details as much as possible. For each \( p \), this operation can be expressed as

\[
g_p = s \cdot g_p,
\]

where \( g_p \) represents 3D coordinates after scaling and \( s \) is a scaling factor. Since the values of the coordinates are rounded to integer numbers, for which the maximum rounding error is bounded by half of the pixel spacing, the default value of \( s \) is set to 1/2. Empirically, we also find this leads to the best performance.

Fourthly, we use orthogonal projection [12] and rasterization to obtain a projected image. For each \( p \), the projected image...
The table below shows the performance evaluation of the proposed model against existing models.

| Subet | Geometry distortion metric  | Geometry-plus-color distortion metric | IW-SSIM |
|-------|-----------------------------|--------------------------------------|---------|
|       | PSNR_{K_a,M} | PSNR_{K_a,T} | PSNR_{K_T,M} | PSNR_{K_T,T} | PointSSIM | FCM | GraghSIM | PSNR | SIME | SIME | VIFP |
| Bag   | 16.74 | 20.17 | 18.73 | 19.63 | 13.69 | 23.47 | 19.20 | 11.74 | 15.26 | 14.74 | 12.46 | 11.81 | 11.27 | 12.44 |
| Banana | 14.98 | 19.97 | 17.56 | 19.81 | 14.20 | 22.75 | 19.90 | 14.25 | 15.09 | 19.27 | 16.35 | 14.88 | 14.43 | 10.35 |
| Biscuits | 19.68 | 19.44 | 18.80 | 19.43 | 14.20 | 22.75 | 19.90 | 14.25 | 15.09 | 19.27 | 16.35 | 14.88 | 14.43 | 10.35 |
| Cake | 20.55 | 23.32 | 21.37 | 21.02 | 19.10 | 23.51 | 22.36 | 18.29 | 20.47 | 19.69 | 17.92 | 17.84 | 17.74 | 16.62 |
| Cauliflower | 19.95 | 21.44 | 21.01 | 21.44 | 17.35 | 24.21 | 22.08 | 15.95 | 17.94 | 17.80 | 17.80 | 17.80 | 17.80 | 15.52 |
| Flowerpot | 16.81 | 20.24 | 18.33 | 21.98 | 17.94 | 23.78 | 22.67 | 16.92 | 17.26 | 17.48 | 13.49 | 13.39 | 13.34 | 8.322 |
| GlassCase | 18.06 | 19.68 | 19.41 | 20.36 | 13.99 | 21.62 | 19.72 | 12.91 | 15.52 | 13.69 | 12.50 | 13.31 | 13.34 | 13.24 |
| HoneydewMelon | 20.99 | 21.36 | 21.34 | 21.33 | 16.62 | 26.66 | 20.05 | 17.90 | 15.85 | 20.08 | 15.42 | 14.41 | 13.43 | 10.37 |
| House | 17.88 | 21.36 | 20.98 | 21.76 | 14.04 | 23.25 | 21.15 | 15.29 | 15.61 | 17.33 | 12.93 | 13.17 | 12.81 | 9.395 |
| Litchi | 20.98 | 21.53 | 21.78 | 21.54 | 16.11 | 23.22 | 18.32 | 14.17 | 15.96 | 16.97 | 14.86 | 13.11 | 12.06 | 9.395 |
| Mushroom | 17.02 | 19.37 | 18.58 | 19.71 | 13.23 | 22.17 | 19.89 | 13.20 | 15.56 | 18.21 | 13.32 | 12.88 | 11.85 | 10.94 |
| PetContainer | 14.76 | 20.26 | 17.47 | 20.26 | 13.68 | 23.50 | 20.46 | 13.53 | 21.46 | 13.17 | 9.306 | 9.563 | 9.465 | 7.897 |
| Pineapple | 18.04 | 19.52 | 18.95 | 19.32 | 13.58 | 20.71 | 18.17 | 13.32 | 20.20 | 17.34 | 14.14 | 14.34 | 13.60 | 12.73 |
| ProngingBat | 15.69 | 20.64 | 16.94 | 17.61 | 13.46 | 22.73 | 19.11 | 11.60 | 22.73 | 18.84 | 17.07 | 15.80 | 13.37 | 9.442 |
| PuErTeaPot | 21.75 | 22.15 | 22.05 | 22.11 | 11.43 | 23.71 | 21.04 | 12.86 | 23.71 | 19.36 | 17.12 | 11.86 | 10.82 | 9.288 |
| Pumpkin | 18.63 | 19.84 | 19.56 | 18.98 | 15.41 | 21.75 | 19.96 | 14.84 | 20.93 | 14.84 | 11.05 | 11.08 | 10.18 | 9.591 |
| Ship | 15.44 | 22.23 | 18.30 | 20.06 | 14.71 | 24.09 | 21.94 | 15.72 | 24.09 | 15.44 | 13.78 | 12.55 | 11.48 | 9.780 |
| Statue | 13.24 | 20.93 | 16.53 | 20.53 | 15.12 | 22.16 | 21.84 | 14.33 | 22.19 | 12.71 | 8.932 | 9.170 | 8.841 | 6.309 |
| Stone | 16.85 | 18.48 | 18.28 | 17.76 | 13.14 | 21.35 | 18.36 | 11.29 | 23.12 | 16.00 | 11.96 | 11.08 | 10.20 | 9.551 |
| ToolBox | 18.65 | 19.95 | 20.01 | 20.00 | 8.923 | 20.86 | 18.33 | 13.41 | 12.27 | 18.33 | 17.47 | 17.11 | 14.61 | 10.88 |

5.2 Validation and Discussion

We validate the proposed IW-SSIM<sub>p</sub> model using the WPC database presented in Section 4 and compare its performance against existing objective PCQA models. Note that IW-SSIM<sub>p</sub> does not involve a training process and is independent of any existing PCQA databases including the WPC database. Tables 4, 5 and 6 summarize the PLCC, SRCC and RMSE evaluation results. We find that the performance of IW-SSIM<sub>p</sub> when N<sub>v</sub> = 12, 42, 162 are very close to each other, while the computational complexity is proportional to N<sub>v</sub>. Therefore we use N<sub>v</sub> = 12 in all results reported here.

It can be seen that the proposed model delivers the best performance in predicting subjective quality of 3D point cloud not only on the whole database but also on almost every subset. In addition, its PLCC and SRCC performance is at the same level as compared to an average human subject as given in Fig.7.

To ascertain that the improvement of the proposed model is statistically significant, we carry out a statistical significance analysis following by the approach introduced in [90]. First, a nonlinear regression function is applied to map the objective quality scores to predict the subjective scores. We observe that the prediction residuals all have zero-mean, and thus the model with lower variance is generally considered better. We conduct a hypothesis testing using F-statistics. Since the number of samples exceeds 50, the Gaussian assumption of the residuals approximately hold based on the central limit theorem [91]. The test statistic is the ratio of variances. The null hypothesis is that the prediction residuals from one quality model come from the same distribution and are statistically indistinguishable (with 95% confidence) from the residuals from another model. We compare every possible pair of objective models. The results are summarized in Table 7, where a symbol “1” means that the row model performs significantly better than the column model, a symbol “0” means the opposite, and a symbol “-” indicates that the row and column models are statistically indistinguishable.

There are several useful findings from the statistical sig-
Table 7

| PSNR_{p2p,M} | PSNR_{p2p,H} | PSNR_{p2p,M} | PSNR_{p2p,H} | PSNR_{Y} | SSIM | MS-SSIM | VIFP | IW-SSIM | PCQM | PCGR | GRaphSIM | PSNR_{p2p,M} | PSNR_{p2p,H} | PSNR_{p2p,M} | PSNR_{p2p,H} | PSNR_{Y} | SSIM | MS-SSIM | VIFP | IW-SSIM |
|--------------|--------------|--------------|--------------|-----------|------|---------|------|---------|-----|------|------------|----------------|----------------|----------------|----------------|-----------|------|---------|------|---------|
| -            | -            | -            | -            | 0         | -    | -       | -    | -       | -   | -    | -          | -               | -               | -               | -               | 0         | 0    | 0       | 0    | 0       |
| -            | -            | -            | -            | 0         | -    | -       | -    | -       | -   | -    | -          | -               | -               | -               | -               | 0         | 0    | 0       | 0    | 0       |
| -            | -            | -            | -            | 0         | -    | -       | -    | -       | -   | -    | -          | -               | -               | -               | -               | 0         | 0    | 0       | 0    | 0       |
| 1            | 1            | 1            | 1            | 1         | 1    | 1       | 1    | 1       | 1   | -    | -          | -               | -               | -               | -               | 0         | 0    | 0       | 0    | 0       |
| 1            | 1            | 1            | 1            | 1         | 1    | 1       | 1    | 1       | 1   | -    | -          | -               | -               | -               | -               | 0         | -    | 0       | 0    | 0       |
| 1            | 1            | 1            | 1            | 1         | 1    | 1       | 1    | 1       | 1   | -    | -          | -               | -               | -               | -               | 0         | 0    | 0       | 0    | 0       |
| IW-SSIM_{p}  | 1            | 1            | 1            | 1         | 1    | 1       | 1    | 1       | 1   | 1    | 1          | -               | -               | -               | 1               | 0         | 0    | 0       | 0    | 0       |

Table 8

| SJTU-PCQA [45] | GraphSIM | PointSSIM | PCQM | PCGR | GRaphSIM | PSNR_{p2p,M} | PSNR_{p2p,H} | PSNR_{p2p,M} | PSNR_{p2p,H} | PSNR_{Y} | SSIM | MS-SSIM | VIFP | IW-SSIM |
|----------------|----------|-----------|------|------|-----------|--------------|--------------|--------------|--------------|-----------|------|---------|------|---------|
| 0.5910         | 0.7913   | 0.6578    | 0.7233 | 0.4848 | 0.8907    | 0.8599       | 0.6480       | 0.6670       | 0.5535       | 0.5362    | 0.7712 | 0.8504   | 0.8504 | 0.8504 |
| IRPC [24]      | 0.8603   | 0.7839    | 0.5366 | 0.4030 | 0.9511    | 0.8519       | 0.7487       | 0.7487       | 0.7487       | 0.7487    | 0.8504 | 0.8504   | 0.8504 | 0.8504 |
| ICIP2020 [48]  | 0.9024   | 0.8519    | 0.6670 | 0.7487 | 0.9428    | 0.8328       | 0.8504       | 0.8504       | 0.8504       | 0.8504    | 0.8504 | 0.8504   | 0.8504 | 0.8504 |
| M-PCCD [23]    | 0.9428   | 0.8519    | 0.6670 | 0.7487 | 0.9428    | 0.8328       | 0.8504       | 0.8504       | 0.8504       | 0.8504    | 0.8504 | 0.8504   | 0.8504 | 0.8504 |
| WPC            | 0.4420   | 0.3436    | 0.7487 | 0.3639 | 0.5362    | 0.6538       | 0.3639       | 0.3639       | 0.3639       | 0.3639    | 0.8504 | 0.8504   | 0.8504 | 0.8504 |

Table 9

| SJTU-PCQA [45] | GraphSIM | PointSSIM | PCQM | PCGR | GRaphSIM | PSNR_{p2p,M} | PSNR_{p2p,H} | PSNR_{p2p,M} | PSNR_{p2p,H} | PSNR_{Y} | SSIM | MS-SSIM | VIFP | IW-SSIM |
|----------------|----------|-----------|------|------|-----------|--------------|--------------|--------------|--------------|-----------|------|---------|------|---------|
| 0.5910         | 0.7913   | 0.6578    | 0.7233 | 0.4848 | 0.8907    | 0.8599       | 0.6480       | 0.6670       | 0.5535       | 0.5362    | 0.7712 | 0.8504   | 0.8504 | 0.8504 |
| IRPC [24]      | 0.8603   | 0.7839    | 0.5366 | 0.4030 | 0.9511    | 0.8519       | 0.7487       | 0.7487       | 0.7487       | 0.7487    | 0.8504 | 0.8504   | 0.8504 | 0.8504 |
| ICIP2020 [48]  | 0.9024   | 0.8519    | 0.6670 | 0.7487 | 0.9428    | 0.8328       | 0.8504       | 0.8504       | 0.8504       | 0.8504    | 0.8504 | 0.8504   | 0.8504 | 0.8504 |
| M-PCCD [23]    | 0.9428   | 0.8519    | 0.6670 | 0.7487 | 0.9428    | 0.8328       | 0.8504       | 0.8504       | 0.8504       | 0.8504    | 0.8504 | 0.8504   | 0.8504 | 0.8504 |
| WPC            | 0.4420   | 0.3436    | 0.7487 | 0.3639 | 0.5362    | 0.6538       | 0.3639       | 0.3639       | 0.3639       | 0.3639    | 0.8504 | 0.8504   | 0.8504 | 0.8504 |

6 Conclusion

In this work, we tackle the problem of 3D point cloud quality assessment. Our major contributions are fourfold. First, we construct 20 high quality, realistic and omni-directional dense point clouds with a wide range of geometric and textural complexity, which are voxelized with an average number of 1.35M points and a standard deviation of 656K, respectively. These point clouds provide fertile ground for PC processing and PCQA research. Second, PCQM and NR-3DQA are the best performers on the IRPC and M-PCCD database. Third, GraphSIM has the best performance on the IRPC and M-PCCD database. Fourth, we propose a projection-based IW-SSIM\textsubscript{p} model that significantly outperforms existing objective PCQA methods.

There are several research directions that are worth future investigation. It should be noted that the all projection-
based PCQA models so far including the proposed one is limited to outside views of the point clouds. One possible solution for PCQA of indoor scenes may be obtained by projecting the point cloud onto a panoramic image and then applying traditional image quality assessment models. Another promising direction is to leverage deep learning methods for PCQA research. State-of-the-art data-driven methods have demonstrated strong promises in full-reference [92] and no-reference image quality assessment [93], [94]. How to extend these works to PCQA is an interesting direction yet to be explored.

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