

Subjective Quality Study and Database of Compressed Point Clouds with 6DoF Head-mounted Display

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Abstract—In this paper, we focus on subjective and objective Point Cloud Quality Assessment (PCQA) in an immersive environment and study the effect of geometry and texture attributes in compression distortion. Using a Head-Mounted Display (HMD) with six degrees of freedom, we establish a subjective PCQA database, named SIAT Point Cloud Quality Database (SIAT-PCQD). Our database consists of 303 valid distorted point clouds compressed by the MPEG point cloud encoder with the combination of 20 sequences and 17 pairs of geometry and texture quantization parameters. The impacts of contents, geometry and texture attributes are further discussed in this paper. Then, we evaluate our subjective database with current objective PCQA methods and propose an objective weighted projection-based method to improve the consistency between observers' awareness and the importance of projected views. Our subjective database and findings can be used in perception-based point cloud processing, transmission, and coding, especially for Virtual Reality applications. The subjective dataset and quality scores will be available on the public repository.

Index Terms—Point clouds, subjective quality assessment, quality metrics, Virtual Reality, 6DoF.

I. INTRODUCTION

IN recent years, the major advance of Two-Dimension (2D) video is the improvement of resolution, which has evolved from Standard Definition (SD), High Definition (HD) to Ultra High Definition (UHD). Visual information perceived by humans at a moment has been enriched with the progress of resolution. Meanwhile, people gradually attach importance to the experience of watching videos, especially from the aspect of interaction. Extended reality (XR) technology, summarizing Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) technologies, has attracted much attention with the emergence of Head-Mounted Display (HMD). However, most of 360-degree videos only support Three Degrees of Freedom (3DoF), allowing users to track rotational motion but not translational. To keep pace with the consumption of visual media, some novel concepts of immersive media came

out, like 3DoF+, i.e., enabling additional limited translational movements, and Six Degrees of Freedom (6DoF), allowing rotational motion as well as translational motion. Many types of representation realizing 6DoF exist, such as simple proxy geometry, voxels, and point clouds [1].

A point cloud is a collection of Three-Dimension (3D) points in 3D space without space connections or ordering relations [2]. Each point in a point cloud consists of a geometry attribute, i.e., 3D position (x, y, z) , and other attributes denoted by vectors like color, reflectivity, opacity and so on. According to the Point Cloud Compression (PCC) group of MPEG, point clouds can be categorized as static, dynamic, and dynamically acquired point clouds [2]. Similar to the relationship between videos and images, a dynamic point cloud recognizes each static point cloud as a frame, showing the movement of a 3D object or a scene going after temporal variation. Targeting XR applications, static or dynamic point clouds can be captured in a studio full of high-speed cameras, especially for contents like people and objects. Targeting applications like autonomous driving, dynamically acquired point clouds are mainly obtained by LIDAR sensors on the top of a moving vehicle, enabling dynamic environment perception in robot navigation. Aimed at superior perceptual experience, point clouds are desired to be captured densely with high precision. Different from meshes, point clouds have no spatial connectivity nor ordering relations, excluding the concepts of edges, faces or polygon. The massive number of points and the inherent characteristics of disjunction and disorder pose challenges for point cloud processing [3] and compression [2], [4], [5].

For storage and transmission of point clouds, efficient compression frameworks were researched by scholars. In [4], a time-varying point cloud codec was first proposed in a 3D tele-immersive system and later regarded as the anchor of MPEG PCC standards. The emerging PCC is composed of two classes for compression for different categories of point clouds. One is Video-based PCC (V-PCC) targeting dynamic point clouds, the other is Geometry-based PCC (G-PCC). G-PCC is the combination of Surface PCC (S-PCC) for static point clouds and LIDAR PCC (L-PCC) for dynamically acquired point clouds. Nowadays PCC [2], [5] is a trending and intriguing research topic.

Both processing and compression may induce kinds of distortion for point clouds, including changes of numbers of points and the positions and attributes of points. The

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degradation of the contents might influence users' perception. Therefore, subjective and objective assessment is the pointed and valid method to reflect the quality of point clouds. Nowadays, point cloud evaluation is still a sophisticated and challenging problem involved with excessive factors such as degradation, rendering methods, display equipments, evaluation methodologies, quality of sources and so forth.

Now a normative and effective framework for Point Cloud Quality Assessment (PCQA) is necessitous but has not been explored fully yet. Learning from Image Quality Assessment (IQA) [6] and Video Quality Assessment (VQA) [7], many papers for PCQA came out since 2017. However, the early works [8]–[13] only focused on colorless point clouds and simple types of degradation, while point clouds with color and even reflectivity, as well as codec like V-PCC, are in the prevailing trend. Also, some works utilized a virtual camera around point clouds to render videos, and then those videos were displayed in a 2D screen for subjects to evaluate, which lacked human interaction.

In this work, we concentrate on subjective PCQA in an immersive 6DoF VR environment to study the effect of geometry and texture attributes in compression distortion. First, contents like human figures and inanimate objects are selected, showing the variety of test sequences. 20 sequences and 17 different combinations of geometry and texture Quantization Parameters (QP) are used to generate 340 distorted point clouds by the V-PCC codec. Second, subjective tests are conducted using an HMD to enable complete human interaction. The inherent 3D characteristics of point clouds suggest models are better to be perceived in Euclidean space, so we adopt the target equipment with 6DoF to make sure high prediction accuracy. In the VR environment, observers utilize eyes and head movement to explore scenes, which is completely different from traditional 2D viewing. In our experiment, 37 samples are removed and 303 samples remain as valid data after data processing and outlier detection. Our subjective database, named SIAT Point Cloud Quality Database (SIAT-PCQD), will be available on public repository. Finally, we evaluate the performance of current objective point cloud quality approaches, including point-based methods and projection-based methods, and propose an objective weighted projection-based method.

The remainder of the paper is organized as follows. Section II reviews the related work in subjective and objective point cloud evaluation. Section III details our subjective quality evaluation test, containing procedures like data creation, rendering techniques, equipment, test environment, and evaluation methodology. Section IV shows data processing and the discussions of subjective quality evaluation. Besides, the performance of objective metrics and a proposed weighted projection-based method are shown in Section V. Finally, the conclusion of our work and the challenges of PCQA are outlined in Section VI.

II. RELATED WORKS

In this section, related work in point cloud evaluation is described in the aspects of subjective and objective assessment.

A. Subjective Quality Assessment

Early works on point cloud subjective quality assessment came out in large numbers since 2014. In [16], distortions like down-sampling and noise generation were considered to study the relationship between 3D colored point cloud models and human visual perception. Later, some works [9]–[13] evaluated the quality of colorless point clouds and gradually built the workflow of subjective point cloud evaluation. In [8] [11], AR devices were first used in the modality of point clouds. However, only the subjective quality of geometry point clouds was evaluated in those work, namely, only position attributes were used. Also, point clouds were processed by Gaussian noise and octree-pruning degradation, and latter promising point cloud codecs were failed to be considered. In the early stage, limited types of degradation were focused and some prevailing codecs were absent in these works.

Alexiou *et al.* [10] compared Double Stimulus Impairment Scale (DSIS) and Absolute Category Rating (ACR) methodology while evaluating geometric point clouds of Gaussian noise and octree-pruning degradation. They compared the visualization of raw point clouds and point clouds after surface reconstruction [12], then they obtained similar results using 2D and 3D monitors to display the projected contents of geometry point clouds [13]. Javaheri *et al.* performed a subjective and objective evaluation of point cloud denoising algorithms in [9]. In this period, different methodologies and ways of displaying were further studied, but most of the subjective datasets still only used geometry point clouds as the evaluation contents.

Subsequently, the performance of colored point clouds was investigated. Javaheri *et al.* [17] performed subjective and objective PCQA by octree-based compression scheme, available in the Point Cloud Library (PCL), and graph-based compression scheme. They created a spiral virtual camera path moving around the point cloud sequences from a full view to a closer view, and the generated videos were evaluated by subjects. In [18], point cloud evaluation experiments were conducted in three different laboratories and it was found that removing points regularly was more acceptable for subjects. The quality scores, obtained by various point clouds with geometry and color information, showed a high correlation with objective metrics. Yang *et al.* [19] proposed the SJTU-PCQA database with point clouds augmented with octree-based compression, color noise, geometry noise, and scaling and they also developed an objective metric based on projection. In [20], Zerman *et al.* first considered V-PCC for colored point clouds and rendered point clouds by Unity in a way of no interaction. They recognized that texture distortion is more important than geometric distortion in the human figure database they created. They also found that the count of points severely affects geometric quality metrics rather than perceptual quality. Su *et al.* [21] built a point cloud database of diverse contents and applied down-sampling, Gaussian noise, and three state-of-the-art PCC algorithms to create distorted point clouds. They first specifically defined types of distortions for point clouds. Geometry distortions include hollow, geometry noise, hole, shape distortion, collapse, gap and burr. Texture distortions include texture noise, blockiness, blur, and color

TABLE I: Summary of subjective PCQA databases.

Method	Sequence set	Status of sequences	Colored	Degradation	#Distorted versions $seq \times dist \times rate$	Display	Inter-action	Methodology
Alexiou <i>et al.</i> [8]	objects		×	Gaussian noise, octree-pruning	$5 \times 2 \times 4 = 40$	AR		DSIS
Torlig <i>et al.</i> [14]	objects, humans	static	✓	octree-based compression & JPEG	$7 \times 9 = 63$	2D monitor	✓	DSIS
Alexiou <i>et al.</i> [15]	objects, humans		✓	V-PCC, G-PCC	$9 \times (5 + 6) = 99$	2D monitor		DSIS
Javaheri <i>et al.</i> [9]				2 outlier removal algorithms, 3 denoising algorithms	$4 \times 5 \times 3 = 60$	2D monitor		DSIS
Alexiou and Ebrahimi [10]	objects	static		Gaussian noise, octree-pruning	$5 \times 2 \times 4 = 40$	2D monitor		DSIS, ACR
Alexiou and Ebrahimi [11]			×		$5 \times 2 \times 4 = 40$	2D monitor	×	DSIS
Alexiou <i>et al.</i> [12]					$7 \times 1 \times 4 = 28$	2D monitor		DSIS
Alexiou <i>et al.</i> [13]				octree-pruning	$7 \times 1 \times 4 = 28$	2D/3D monitor		DSIS
Zhang <i>et al.</i> [16]	objects	static		down-sampling, geometry noise, color noise	$1 \times (6 + 7 + 12) = 25$			-
Javaheri <i>et al.</i> [17]	objects, humans	static		octree-pruning, graph-based compression	$6 \times 2 \times 3 = 36$	2D monitor	×	DSIS
da Silva Cruz <i>et al.</i> [18]	objects, humans, scenes	static	✓	octree-pruning, projection-based encoder	$8 \times 2 \times 3 = 48$			DSIS
SJTU-PCQA [19]	objects, humans	static		octree-based compression, color noise, geometry noise, scaling	$10 \times 7 \times 6 = 420$			SS
Zerman <i>et al.</i> [20]	humans	dynamic		down-sampling, V-PCC	$2 \times 2 \times 4 = 16$			DSIS, PWC
Su <i>et al.</i> [21]	objects	static		down-sampling, Gaussian noise, V-PCC, S-PCC, L-PCC	$20 \times (3 + 9 + 9 + 12 + 4) = 740$			DSIS
IRPC [22]	objects, humans	static		PCL, G-PCC, V-PCC	$6 \times 3 \times 3 = 54$			DSIS
Proposed SIAT-PCQD	objects, humans	static	✓	V-PCC	$20 \times 1 \times 17 - 37 = 303$	HMD	✓	DSIS

bleeding. Javaheri *et al.* [22] created a subjective database named as IRPC and studied the impacts of different coding and rendering solutions on the perceived quality. Thus, researchers considered prevailing point cloud codecs like V-PCC and G-PCC on diverse colored point clouds. However, point clouds were displayed in a limited way, lacking interaction.

From the perspective of interaction, a quality evaluation methodology for colored and voxelized point clouds was proposed in [14]. In their experiment, subjects visualized the contents through renderer and interacted with point clouds by zooming, rotation and translation using the mouse. Alexiou *et al.* [15] focused on the evaluation of test conditions defined by MPEG for core experiments and conducted two additional rate allocation experiments for geometry and color encoding modules. A new software, which supports interaction and would be used in the web applications for point cloud rendering, was developed. In a word, these works enabled interaction by allowing subjects to operate on point clouds displayed in a 2D monitor, namely the desktop condition. Nevertheless, it has not been thoroughly explored how would people observe point clouds in a fully interactive VR environment, supporting 6DoF.

A summary of the available PCQA databases is shown in Table I. First, displaying point clouds on 2D monitors limits the visualization of point clouds to some extent. some works [9]–[12], [16]–[22] displayed point clouds on the 2D monitors which deliver information in 2D plane without the awareness of binocular parallax cues, making the 3D characteristics of point clouds less effective. Alexiou *et al.* [13] visualized point clouds on the 3D monitor, which adds the binocular perception of depth by giving each eye with a different view image. But the 3D monitors create a convincing illusion of 3D and are unable to completely convey information of the Euclidean space. Secondly, the traditional screens lack any peripheral vision with a Field Of View (FOV) commonly less than 60° , while humans have a maximum horizontal FOV of approximately 190° with two eyes. Thirdly, Torlig *et al.* and Alexiou *et al.* [14], [15] derived a rendering software to allow subjects to operate point clouds by interactively using the mouse. This approach is much better than designing a

specific track around point clouds to make videos, which is still different from human perception that observers naturally use eyes and head movement to explore objects and scenes. At last, the current subjective PCQA databases usually design about five rates for a specific type of distortion and seldom further study the impacts of different levels of quantization.

B. Objective Quality Assessment

Objective quality assessment of point clouds aims to create an accurate mathematical model to predict the quality of point clouds. Desirable objective assessment metrics should correspond to the visual perception of humans. According to the research [14], the state-of-the-art objective evaluation metrics of point clouds can be classified into two categories: point-based metrics and projection-based metrics. Moreover, Javaheri *et al.* [17] recommended that some simple metrics, like the number of points, can also be taken into consideration.

Point-based metrics are mainly composed of the point-to-point error (D1), the point-to-plane error (D2) [23] and the plane-to-plane error [24] for geometric errors. D1 measures the Euclidean distances between corresponding point pairs, indicating how far the points in the distorted point cloud moved away from their original positions. Considering local plane properties, D2 [23] computes the projected errors along the normal direction on the associated point, imposing a larger penalty on points far from the perceived local plane surface. In addition, they proposed the intrinsic resolution of point clouds as a normalizer to convert Mean Squared Error (MSE) into Peak Signal-to-Noise Ratio (PSNR) numbers, rather than using the diagonal distance of the bounding box around a point cloud as the peak value. The plane-to-plane metric [24] focuses on the angular similarity between tangent planes of associated points, and tangent planes indicate the linear approximation of the surface. All of them are full-reference metrics for geometric degradations, and the former two metrics are recommended for assessment by the MPEG group in the Common Test Conditions (CTC) for PCC [25].

Projection-based metrics project both reference and test point clouds into six planes of their bounding boxes [14] or

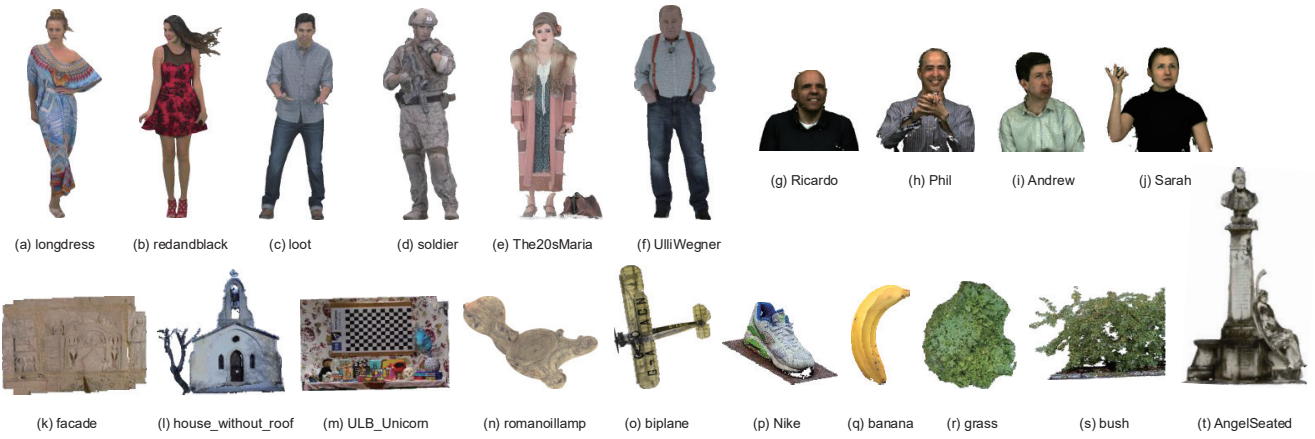


Fig. 1: The thumbnail images of the sequences used in our experiment.

TABLE II: Summary of Pre-processed Test Sequences.

Sequence	Category	Source	Pre-processing	#Points	Geometry Precision	Bounding Box	Pairs of geometry and texture QP
redandblack_vox10_1450	Full body figures	MPEG ¹ /JPEG ²	No	729, 133	10 bits	(393, 977, 232)	
longdress_vox10_1051	Full body figures	MPEG ¹ /JPEG ²	No	765, 821	10 bits	(356, 1003, 296)	
loot_vox10_1000	Full body figures	MPEG ¹ /JPEG ²	No	784, 142	10 bits	(352, 992, 354)	
soldier_vox10_0536	Full body figures	MPEG ¹ /JPEG ²	No	1, 059, 810	10 bits	(360, 1016, 405)	
The20sMaria	Full body figures	MPEG ¹	Yes	950, 423	10 bits	(405, 908, 324)	
UlliWegner	Full body figures	MPEG ¹	Yes	598, 448	10 bits	(376, 997, 258)	(20,27), (20,37),
Ricardo_frame0000	Upper body figures	JPEG ²	No	960, 703	10 bits	(743, 296, 605)	(20,47), (28,27),
Phil_frame0000	Upper body figures	JPEG ²	No	1, 660, 959	10 bits	(735, 655, 772)	(28,37), (28,47),
Andrew_frame0000	Upper body figures	JPEG ²	No	1, 276, 312	10 bits	(653, 494, 739)	(36,27), (36,37),
Sarah_frame0000	Upper body figures	JPEG ²	No	1, 355, 867	10 bits	(813, 578, 777)	(36,47), (24,32),
Facade_00064	Inanimate objects	MPEG ¹	Yes	292, 169	10 bits	(555, 375, 75)	(32,42), (0,0) ,
House_without_roof	Inanimate objects	MPEG ¹	Yes	581, 213	10 bits	(488, 481, 455)	(20,0), (28,0),
ULB_Unicorn_2M_PC	Inanimate objects	MPEG ¹	Yes	1, 086, 944	10 bits	(571, 361, 303)	(36,0), (0,27),
Romanoillamp	Inanimate objects	JPEG ²	Yes	343, 186	10 bits	(517, 355, 352)	(0,37), (0,47)
1x1_Biplane_Combined	Inanimate objects	JPEG ²	Yes	400, 972	10 bits	(439, 569, 410)	
Nike180	Inanimate objects	Sketchfab ³	Yes	186, 960	10 bits	(303, 213, 303)	
Bananamesh	Inanimate objects	Sketchfab ³	Yes	145, 243	10 bits	(201, 337, 102)	
Grass	Inanimate objects	Sketchfab ³	Yes	724, 725	10 bits	(494, 159, 434)	
Bush	Inanimate objects	Sketchfab ³	Yes	1, 211, 816	10 bits	(587, 400, 435)	
AngelSeated01a_PC	Inanimate objects	Sketchfab ³	Yes	770, 184	10 bits	(543, 942, 305)	

Bold number denotes lossless compression.

more planes, then compute the average scores of projected images evaluated by the state-of-the-art image quality metrics. In [26], projection-based objective quality assessment was extended by assigning weights to perspectives based on user interactivity data. The authors identified additional views does not severely improve the prediction of subjective visual quality.

The subjective PCQA databases are the basis of the development of objective PCQA methods. But traditional PCQA databases fail to consider the immersive VR environment, and datasets of large scales and various contents in the immersive 6DoF VR environment are expected to be established under a normative framework of PCQA.

III. SUBJECTIVE EXPERIMENT FOR PCQA

In this section, we describe the details of our point clouds subjective quality assessment experiment with contents prepa-

ration, rendering techniques, equipment, test environment, and evaluation methodology.

A. Dataset Creation

To better explore how people perceive point clouds, we chose contents like human figures and inanimate objects. As Fig. 1 and Table II show, 20 static sequences were selected in our test. In particular, the human category consists of 6 full body figures (*Longdress* [27], *Redandblack* [27], *Loot* [27], *Soldier* [27], *The20sMaria* [28], *UlliWegner* [29]) and 4 upper body figures [30] (*Ricardo*, *Phil*, *Andrew*, *Sarah*), while the other category includes 10 different inanimate objects (*Biplane* [31], *Romanoillamp* [32], *Facade*, *House*, *ULBUnicorn*, *Nike*, *Grass*, *Bush*, *Banana*, *AngelSeated*).

To show the diverse point cloud contents from the edge and color perspective, we considered the characteristics, i.e., Spatial Information (SI) [33] and ColorFulness (CF) [34], which are commonly used to evaluate the properties of images

¹<https://mpeg.chiariglione.org/tags/point-cloud>

²<https://jpeg.org/plenodb/>

³<https://sketchfab.com/>

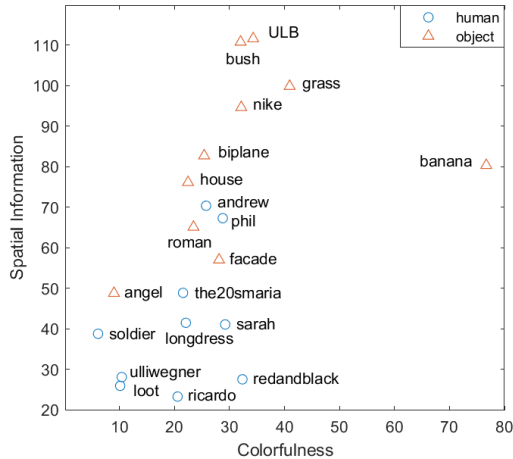


Fig. 2: Distribution of spatial information and colorfulness of the 20 source sequences in the dataset.

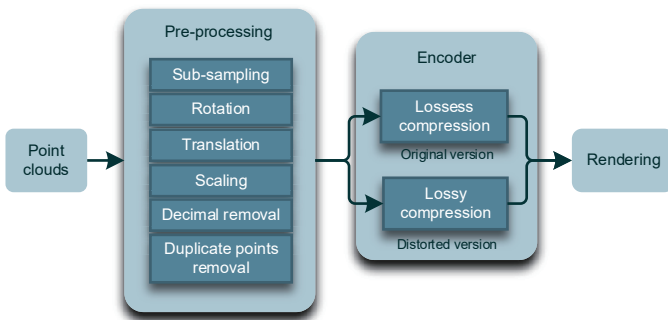


Fig. 3: The procedure of processing.

or videos. We projected the source point cloud into the six views of its bounding box so as to apply SI and CF. Similar to video contents in [33], we obtained the maximum value among six views as the final SI for a sequence. Fig. 2 shows the distribution of 20 sequences along the horizontal (CF) and vertical (SI) axes. The disperse state in CF/SI shows the diversity of our contents in the space/color domain. In particular, the luminance of the sequence *Banana* is generally higher than others, making a difference in CF measurement.

B. Processing

Before compression, it requires making preparations for the contents to minimize the impact of unconcerned influencing factors in our test. Fig. 3 shows the workflow of our test before displaying point clouds, and the details of processing are mentioned as follows.

- **Pre-processing:** The sequences, as mentioned above, are selected from different repositories, which means their sizes, positions and orientations vary. However, we desire sequences are exhibited in life-size rendering to achieve realistic tele-immersive scenarios. To deal with this situation, the pre-processing stage normalizes sequences to remain point clouds within a similar bounding box (600, 1000, 400). All of the source models

had been through sub-sampling, rotation, translation, and scaling, except 4 figures *Longdress*, *Redandblack*, *Loot*, and *Soldier* from 8i Voxelized Full Bodies Database. Additionally, the point cloud encoder fails to deal with decimals, so that we converted the geometric attributes of each sequence from decimals to integers, then removed duplicate points. Pre-processed versions will be released online within our database. In particular, it is unnecessary to have integer conversion for 4 upper body figures from the Microsoft database, so we just adjusted their position and orientation in rendering software.

- **Encoding:** Distorted versions were generated using the state-of-the-art MPEG PCC reference software Test Model Category 2 version 7.0 (TMC2v7.0). The V-PCC method takes advantage of a progressive 2D video codec after projecting point clouds into frames. First, a point cloud is split into patches by clustering normal vectors. The obtained patches would be packed into images and the gaps between patches would be padded to reduce pixel residuals. Then projected images of sequences are compressed utilizing the HEVC reference software HM16.18. More information about the framework of V-PCC can be referred to [2].

A pair of parameters, namely geometry QP (gQP) and texture QP (tQP), were exploited to achieve different levels of geometry and color quality. Similar to the CTC document from the MPEG group, the gaps of gQP and tQP were set as 4 and 5, ranging from 20 to 32 and from 27 to 42 respectively. Considering the display devices, we removed the least degraded pair (16, 22). Furthermore, more combinations were performed by fixing one parameter and changing the other one to explore the impact of geometry and color quantization levels on quality of point clouds, as shown in Table II. For this purpose, we chose a losslessly compressed version as our reference contents.

- **Rendering:** Point clouds are appropriate to freely represent objects and scenes in immersive applications, providing a novel experience of 6FoF. Different from traditional 2D media, rendering and display devices are critical issues for visualization of point clouds.

Contrary to 2D views generated from virtual cameras around point clouds in limited tracks, we developed an actively interactive VR experiment software for subjects to observe point cloud models in an unrestricted way, avoiding any occlusion. Our experiment software was created in Unity (version 5.6.5f1), exploiting the SteamVR plugin (version 1.2.3) to connect VR headsets. Point Cloud Viewer and Tools (version 2.20) helped us import and view data of point clouds inside Unity. Particularly, a large size of point cloud files might take up too much memory and cause a system hang. We first packed all the resources related to rendering point clouds like prefabs and meshes, and dynamically loaded the asset bundles in an asynchronous way to improve software stability. Particularly, the default factor in Point Cloud Viewer and Tools was set as 0.0165 to make the size of point clouds in the software suitable to the realistic environment in our experiment.

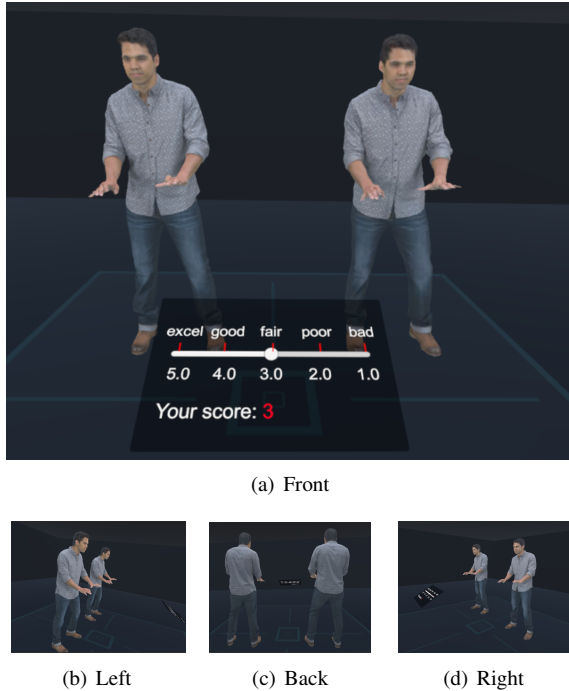


Fig. 4: Different views of the experiment system in HMD.

C. Equipment and Environment

HTC Vive devices with an HMD and two hand controllers were used for every subject to interact in our test. The headset features resolution of 1080×1200 pixels per eye, namely 2160×1200 pixels, and a 110-degree field of view. Following the recommendations from Recommendation ITU-R BT.500-13 [35], a room with gray walls was created as the virtual environment to conduct the experiment. Meanwhile, a virtual lamp of 6500 K color temperature was placed near the ceiling within the room.

Fig. 4 shows different views of our experiment system using the HMD. To simulate the real environment for VR applications, subjects were asked to initially stand at a distance of 2 meters away from models and allowed to walk around the scene with no time limitation. In our test, subjects could walk freely in the room to watch the point clouds, which is different from a traditional approach to watching images or videos that subjects only stand or sit in a fixed position to watch the monitor. Distance influences how people can perceive small changes in the scene, as they are more sensitive to errors from a close distance and focus more on the whole from a long distance. However, if we fix the viewing distance, the experiment would be in 3DoF rather than 6DoF, which is inverse to our intention to explore the characteristics of point clouds in VR applications. Therefore, to reduce the effect of distance as far as possible, subjects in our experiment were required to finally come back to the initial position to observe and give scores.

D. Subjective Evaluation Methodology

Double Stimulus Impairment Scale (DSIS) evaluation methodology variant II with the continuous 5-scale rating

was applied in our test to explore degradation characteristics. Scores were normalized to integer values between 0 and 100. Subjects were asked to vote on the right one, comparing with the left one. As Fig. 4 shows, pairwise visualization was performed to compare the perceptual quality of different point clouds. With a reference model, i.e., lossless, on the left and a distorted model, i.e., lossy, on the right, subjects are able to fully observe the quality in an omnidirectional view and then rate by moving a controller related to a bar in the application.

A total of 47 subjects involved in our subjective tests aged from 22-35. Seven are experts in video compression or quality assessment. According to the contents, our experiment was separated into two sessions of human figures and inanimate objects. 22 males and 16 females participated in the first session, while 27 males and 11 females participated in the second session. Furthermore, 29 subjects engaged in both sessions. All subjects received the same information during the test guidance, and a training phase was conducted respectively before the test to make sure each subject has fully understood the test. Every session takes about 1 hour with a break of 5 to 10 minutes, presenting distorted versions in random order.

IV. DATA PROCESSING AND ANALYSES

In this section, Differential Mean Opinion Scores (DMOS) are calculated as final scores after outlier detection of subjects and samples. The correlation between human figure session and inanimate object session is analyzed. Then, the impacts of different sequences and QP are discussed.

A. Outlier Detection & DMOS

As shown in Fig. 1, the original quality of sequences varies and hollows in the original point clouds may give rise to the lower rating. Giving fair positions for the different quality of point clouds, the differential score of reference and the distorted point cloud is calculated as,

$$d_{i,j} = s_{ref,i,j} - s_{i,j}, \quad (1)$$

where $s_{ref,i,j}$ and $s_{i,j}$ respectively stand for the subjective rating of the original and distorted point clouds from subject i over samples of the point cloud j , where $i = 1, \dots, N$ and $j = 1, \dots, M$ with N and M being the numbers of subjects and samples, respectively, and $d_{i,j}$ is the DMOS of subject i rating on sample j . The score from a subject over all samples is represented as $\mathbf{s}_i = (s_{i,1}, \dots, s_{i,M})$.

Another issue is that it is too hard to make sure all subjects are involved in the test properly and carefully in the subjective experiment. Therefore, outlier detection for subjects and samples would be performed. The Z-scores over all samples $Z(j, i)$ are computed by

$$Z(y, x) = \frac{d_{x,y} - \bar{d}_y}{\sigma_y}, \quad (2a)$$

$$\begin{cases} \bar{d}_y = \frac{\sum_{x=1}^K d_{x,y}}{K} \\ \sigma_y = \sqrt{\frac{1}{K-1} \sum_{x=1}^K (d_{x,y} - \bar{d}_y)^2} \end{cases}, \quad (2b)$$

where \bar{d}_y and σ_y show the mean value and standard deviation of variable y over all values of variable x , and K is the number

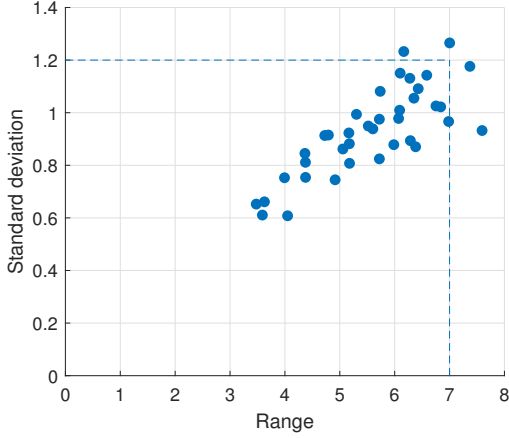


Fig. 5: The range and standard deviation of all subjects.

of variable x . $Z(j, i)$ indicates the rating deviation of subject i from other subjects for sample j .

The distribution of range and standard deviation of all subjects are shown in Fig. 5. Four subjects, whose score range and standard deviation are over 7 and 1.2, respectively, were considered as outliers. Subjective scores from the remaining 35 subjects were calculated as valid data.

Furthermore, abnormal samples are removed by the Grubbs' test [36], i.e.,

$$G_j = \frac{\max_{i=1, \dots, N} |d_{i,j} - \bar{d}_j|}{\sigma_j}, \quad (3)$$

where G_j denotes the score of sample j in the Grubbs' test, and N is the number of all samples. $d_{i,j}$ is the DMOS of subject i rating on sample j , and \bar{d}_j and σ_j show the mean value and standard deviation of sample j over all subjects. We compare G_j with marginal values $G(\alpha, N)$, provided in the table [36]. The significance level α is set as 0.025 and it means the confidence coefficient is 0.95. If $G_j > G(\alpha, N)$, the sample j is defined as an outlier. Finally, we eliminated 37 samples, implying the rating statistics of those samples are different from others. Excluded samples accounted for 10.9% of all samples, and other 303 samples were used to compute the DMOS as follows.

To reduce the deviation from subjects whose rating range and mean score vary, the Z-scores over all subjects $Z(i, j)$ are computed by Equation 2. $Z(i, j)$ focuses on the deviation of one sample from other samples rated by a certain subject, while $Z(j, i)$ focuses on the rating deviation of one subject from other subjects for a certain sample.

Then Z-scores $Z(i, j)$ are rescaled to $[0, 1]$ by the sigmoid function. Finally, the subjective scores are computed by

$$DMOS_{i,j} = \frac{1}{1 + e^{-z_{i,j}}}. \quad (4)$$

B. Correlation between Two Sessions

Our tests were separated into two parts by considering the different categories of contents, i.e., human figures and inanimate objects. To better analyze the data, we examine the

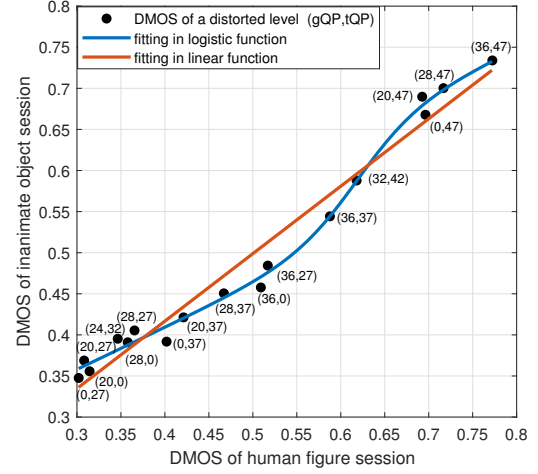


Fig. 6: Correlation between the human figure session and inanimate object session.

correlation between the DMOS of these two sessions, and a linear function and a logistics function are used to fit the data. As shown in Fig. 6, a point denotes a kind of distorted setup and the corresponding scores are obtained by averaging scores of all sequences corresponding to the setup in two sessions separately. The R-square value of linear fitting and logistic fitting are 0.5423 and 0.9223, and two lines are close together as shown in Fig. 6. So we will discuss these two sessions as a whole in later parts.

C. Impacts of Sequences

Other geometry and texture QP pairs are the same as CTC from MPEG V-PCC group. As shown in Fig. 7, the visual quality remains good with small slopes from (20, 27) to (24, 32), indicating redundancy for compression. And the slopes arise from (28, 37) to (36, 47), showing that people are sensitive to the change of QP in these intervals. Furthermore, the DMOS of upper body figures vary smaller numbers of values compared to full body figures as shown by dotted lines in Fig. 7(a), indicating it is harder for subjects to perceive the distortions in the former set. In particular, the perceptual quality of sequence *Ulliwegner* has a gap between (28, 37) and (32, 42) QP pairs.

In the second session of object sequences, subjects are easier to detect quality degradations in the area smooth texture. Related to Fig. 7(b), those sequences that have large flat regions like *Romanoillamp*, *Banana* and *Facade* own a slower slope, especially compared to sequences with intricate texture like *Bush* and *Grass*. Comparing slopes in the Fig. 7(a) and Fig. 7(b), subjects are more sensitive to sequences in the human figure session than sequences in the inanimate object session.

In conclusion, people are more sensitive to the degradation in the QP interval from (28, 37) to (32, 42) and regions of smooth texture.

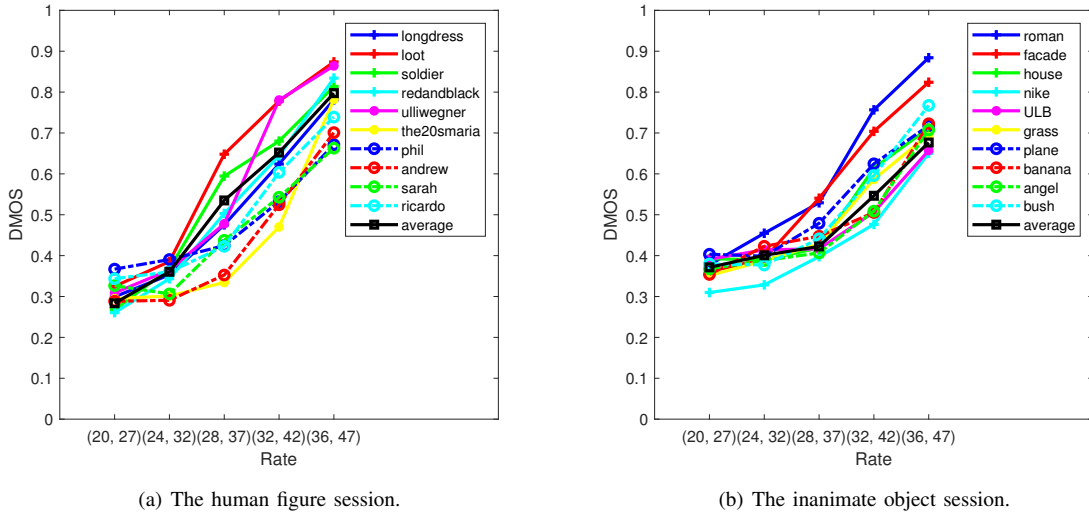


Fig. 7: The DMOS of different pairs defined in CTC from MPEG PCC.

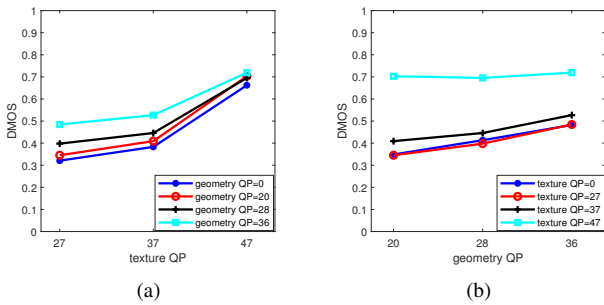


Fig. 8: The DMOS of variable texture/geometry QP.

D. Impacts of Geometry and Texture

The impact of geometry and texture attributes on visual quality is illustrated in Fig. 8 and the DMOS in the figure computes the average values of different distorted levels over all sequences and subjects. From the gap or slope in Fig. 8(a), the perceptual quality of point clouds declines evidently when gQP changing from 28 to 36 or tQP changing from 37 to 47. In Fig. 8(a), the abruptly declining slope demonstrates that texture attribute has a great impact on visual quality. In addition, the cyan line in Fig. 8(b) also represents that subjects are insensitive to geometry attributes when facing intolerable texture quality. And visual quality remains good when gQP within [0, 20] and tQP within [0, 27] shown by blue and red lines in both figures. It is evident that poor texture is unacceptable for consumers in a VR scenario, especially with tQP changing from 37 to 47.

Furthermore, a multi-way ANalysis Of VAriance (ANOVA) was performed to analyze the significant difference of geometry and texture. The ANOVA method explores two situations where one is fixed gQP and another one is fixed tQP. The results of ANOVA are shown in Table III with Sum-of-Squares (SS), DoF, Mean Squares (MS), F ratio, P values, and critical

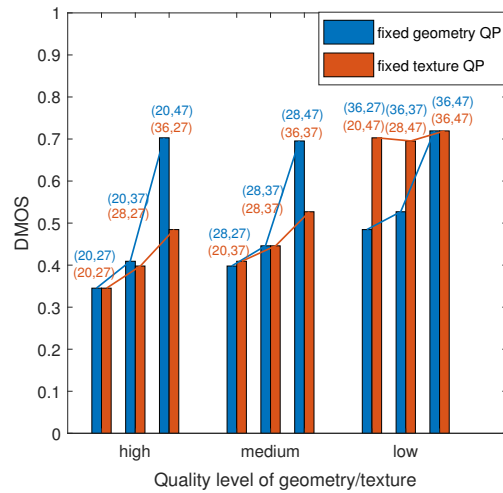


Fig. 9: The impact of different quality levels of geometry/texture.

values of F, using a confidence coefficient of 0.05 (F crit). Each F ratio is computed by dividing the MS value by another MS value. Since the test statistic F of geometry factor, texture factor and their interaction are respectively much larger than the corresponding critical value, we conclude that geometry, texture and their interaction significantly affect subjective scores. From the results above, we can see that the P values of these three factors are less than 0.01, statistically showing highly significant differences. Therefore, geometry, texture and their interaction are highly significant for visual quality of point clouds.

From another perspective, Fig. 9 shows the impact of different quality levels of geometry or texture. For gQP, the high, medium and low quality levels are defined as 20, 28 and 36. For tQP, corresponding values are 27, 37 and 47

TABLE III: The results of the multi-way ANOVA of geometry and texture factors.

Source	SS	df	MS	F	P-value	F crit
Geometry	57.17	2	28.58	716.74	2.3406E-280	2.997201
Texture	42.59	2	21.30	534.00	1.8356E-214	2.997201
Interaction	17.76	4	4.44	111.30	1.0066E-91	2.373386
Error	243.71	6111	0.04			
Total	361.23	6119				

respectively. The texts in the figure show the pairs of quantization (gQP, tQP) belonging to the corresponding cylinders below. For example, blue cylinders at a high-quality level, shown in the first group in the figure, have the same gQP , i.e., 20, and different values of tQP . When we focus on any one of the groups in the figure, we can see that the change of subjective scores with varying texture, shown in blue lines, is more drastic than that with varying geometry, shown in red lines. Severely degraded texture would be unacceptable as we can see that subjects prefer point clouds compressed with QP (36, 27) much more than those compressed with QP (20, 47). In consequence, the quality of texture has a great impact on visual quality of point clouds. While compressing point clouds for VR applicants, we can set the tQP according to the desired visual quality, and the gQP can be smaller but not too far apart from tQP in the configuration.

E. Summary

From the above discussion, we conclude some findings of human perceptual experience in the immersive VR environment which allows 6DoF.

- People prefer to detect quality degradations in flat areas of a sequence, especially in sequences belong to inanimate objects.
- Human perception has greater change amplitude with QP pairs in the interval between (28, 37) and (32, 42). The perceptual quality of point clouds declines evidently when tQP changing from 37 to 47. Severely degraded texture would be unacceptable.
- In the VR environment, the quality of texture has a great impact on visual quality of point clouds and subjects are insensitive to geometry attributes when facing intolerable texture quality. Therefore, the tQP must not be too much bigger than gQP while compressing point clouds for VR applicants.
- Distance influences people's perception of small changes in the scene, as they are more sensitive to errors from a close distance and focus more on the whole from a long distance.

While conducting the subjective experiment, we found that a normative and effective framework for subjective PCQA is necessitous but lacking now. Although experience can be learned from IQA/VQA, it is still an open problem about how to design a compelling experiment for PCQA in the VR environment. Some problems are considered in our experiment and suggestions are listed as follows.

- **Viewing distance & size of contents.** Distance is a crucial factor for the display of point clouds. However, in a VR environment, users are allowed to walk casually in

a room, which noted as 6DoF. So we set a distance of 2 meters as an initial distance and all subjects were required to keep that distance at the beginning and end of their rating, while they can observe at random in the middle. Moreover, the viewing distance also relates to the size of contents, influencing the visual perception. Therefore, we try to resize point clouds to the similar bounding box during the pre-processing and adjust the parameter in the renderer to make the contents match their sizes in reality as we mentioned before.

- **Interaction.** Different from images/videos, rendering and displaying are crucial for PCQA. For rendering, a point in the point cloud can be rendered as 2D splats, squares, 3D spheres or cubes. For displaying, we can visualize point clouds on the 2D/3D monitors or with an HMD. From a perspective of interaction, one way of no interaction is organizers design a specific path around the point clouds to make videos that will be watched by subjects. Other approaches like utilizing interactive software or an HMD supporting 6DoF are effective solutions.

In addition to the open problems, the VR environment also brings convenience to PCQA in the following aspects.

- **Experimental environment.** In the VR environment, we can expediently study the impacts of the experimental circumstance like brightness and background, since the HMD blocks out external visual stimuli and creates a better sense of space. Unity helps us readily simulate the lighting and background in reality and it will be easier to variate these factors.
- **Methodology.** The DSIS methodology was adopted in our experiment, displaying a pair of a reference point cloud and a distorted point cloud simultaneously. The interval time is fixed as the same as that in IQA. But other methodologies can also be considered. In a fully interactive VR environment, it will be more convenient to conduct other methodologies like Subjective Assessment Method for Video Image Quality (SAMVIQ) which asks subjects to give marks to all samples of a sequence in random order and subjects can go back to scrutinize and change scores of the sequence at any time.

V. PERFORMANCE OF OBJECTIVE PCQA METHODS

In this section, the performance of two categories of methods, i.e., point-based metrics and projection-based metrics, is computed, and then we propose a weighted projection-base method as described.

A. Point-based PCQA methods

In this work, we evaluated the performance of point-to-point and point-to-plane metrics by reference software *mpeg-pcc-*

dmetric version 0.13.4 [37]. In the software, a pair associated with a point in the reference point cloud is formed by finding its nearest neighbor in the distorted point cloud. Point clouds with normals are necessary for computing objective metrics. The sequences *Longdress*, *Redandblack*, *Loot*, *Soldier*, *Ricardo*, *Phil*, *Andrew*, and *Sarah* with normals are provided by the dataset providers MPEG and JPEG. As for the others, we use CloudCompareStereo software to generate the normal vector for each point. Then normal vectors of all points for each sequence are sent to the software [37] as input to compute some distortion metrics like point-to-plane.

B. Projection-based PCQA methods

For projection-based metrics, we projected the original and distorted point clouds into six planes of their bounding boxes respectively. Then six pairs of images of point clouds from different views were evaluated by different IQA metrics described follows.

- PSNR is widely used as a performance indicator for image/video quality, measuring the peak error.
- Noise Quality Measure (NQM) [38] models the nonlinear spatially varying visual effects of human visual system (HVS) by contrast pyramid.
- Universal Image Quality Index (UQI) [39] models image distortion as a combination of three factors: loss of correlation, luminance, and contrast.
- Structural Similarity Index (SSIM) [40] is a modified version of UQI, adding the assumption that HVS is highly adapted for extracting structural information. The measurement is separated into three types of comparisons: luminance, contrast, and structure.
- Multi-Scale SSIM (MS-SSIM) [41] is a variant of SSIM. MS-SSIM incorporates SSIM evaluations at different scales by down-sampling.
- Information Content Weighted SSIM (IW-SSIM) [42], an extension of SSIM, is a multi-scale information content weighted approach based upon a Gaussian scale mixture model of natural images.
- Feature Similarity Index (FSIM) [43] uses the phase congruency as the primary feature, measuring the significance of a local structure. And the image gradient magnitude is applied as the secondary feature. FSIMc is a color version of FSIM.
- Gradient Similarity Measure (GSM) [44] employs gradient similarity to measure structure, contrast, and luminance changes. Masking effect and visibility threshold are also considered.
- Gradient Magnitude Similarity Deviation (GMSD) [45] explores gradient based local quality maps and adopts the standard deviation as a novel pooling strategy.
- Visual Saliency-based Index (VSI) [46] applies visual saliency into local quality maps and the weights reflect the importance of a local region.
- Information Fidelity Criterion (IFC) [47] transforms quality assessment problems into signal source and distortion models. Mutual information between wavelet sub-bands is used to measure images.

- Visual Information Fidelity (VIF) [48] is similar to IFC, but VIF uses a HVS model in wavelet domain to measure the uncertainty in the perception of visual signals.

Based on different design philosophies, full-reference IQA methods are classified into three categories according to the comprehensive study of IQA [49]. PSNR, NQM [38] and UQI [39] are error based methods. SSIM [40], MS-SSIM [41], IW-SSIM [42], FSIM/FSIMc [43], GSM [44], GMSD [45], and VSI [46] are structural similarity based methods. IFC [47] and VIF [48] are natural scene statistics based methods.

According to the research [26], additional views do not severely improve the prediction of subjective visual quality in the interactive environment. So we study six corresponding views of the bounding box and no more views are taken into consideration. Finally, the mean scores of six pairs of images are recognized as final scores.

C. Proposed Weighted Projection-based PCQA Method

Learning from visual saliency in the VR environment [50], it can be seen that eye fixation points mostly centered around the center, which means observers seldom look down and up and prefer to explore the scenes along the horizontal direction. For example, the work [51] in stereoscopic omnidirectional IQA unevenly sampled viewpoints along the latitude with 8 viewpoints on the equator as well as 1 viewpoint at the north/south pole.

Similar to that, we proposed a new projection-based method by adding different weights to six views to generate final scores, Indicating importance of different views. The importance of the top and bottom views are acknowledged to be divergent from the front, back, left, and right views. Final scores of the weighted method are computed by

$$S_{final} = \frac{1-\gamma}{4} \cdot (S_{front} + S_{left} + S_{right} + S_{back}) + \frac{\gamma}{2} \cdot (S_{top} + S_{bottom}), \quad (5)$$

where S_{final} denotes the objective scores of the projection-based metric and $S_{front}, S_{back}, S_{left}, S_{right}, S_{top},$ and S_{bottom} denote six view of the bounding box severally. The parameter γ ($0 \leq \gamma \leq 1$) determines the importance ratio of the top and bottom views compared to other views.

According to the gaze analysis [52] by eye-tracking experiment using an HMD, the region that observers usually look at is not the center of the rectilinear area, but the space offset from the center about 12 degrees. The research [52] studied the distribution between a relative viewing angle and the aggregated probability in different visual areas. In line with the height of sequences in our dataset and the initial viewing distance in our experiment, the relative viewing angle is nearly between 6° and 21° . Thus, the parameter γ is recommended to be set within the interval $[0.13, 0.31]$. In the mean method, the parameter γ is set as $\frac{1}{3}$ to maintain the same weights for different views. In the proposed weighted method, the default of parameter γ is 0.19 in this paper to improve the consistency between observers' awareness and the importance of projected views.

D. Experimental Results

Considering the nonlinearity of subjective scores obtained from our experiments, a nonlinear regression model was applied to objective scores before evaluating the performance of objective metrics. According to the report from VQEG group [53], a logistics function was adopted as a part of the nonlinear regression model as

$$q(\mathbf{x}) = \beta_1 \left(\frac{1}{2} - \frac{1}{1 + e^{\beta_2(\mathbf{x} - \beta_3)}} \right) + \beta_4 \cdot \mathbf{x} + \beta_5, \quad (6)$$

where \mathbf{x} denotes the objective scores and $q(x)$ represents the predictive objective scores approximated by a logistic curve, which would be used to calculate the correlation with subjective scores. The parameters β_i for all $i = 1, \dots, 5$ are defined manually at first and then determined by minimizing the sum of squared differences.

Based on the Recommendation ITU-T P.1401 [54], the following performance evaluation metrics are used to compare the performance of different PCQA methods. The Pearson's Linear Correlation Coefficient (PLCC) is the linear correlation coefficient between subjective scores and predictive objective scores, and Root Mean Square Error (RMSE) is the average error between them. Spearman Rank Order Correlation Coefficient (SROCC) measures the prediction of monotonicity between predictive DMOS and subjective DMOS. Kendall Rank Order Correlation Coefficient (KROCC) shows the similarities of data in the ordering. SROCC and KROCC indicate the nonmonotonic relationship, while PLCC and RMSE indicate the nonlinear relationship.

For point-based methods, Table IV shows the correlation between subjective scores and predictive objective scores of different point-based PCQA methods. As we can see, D1, i.e., point-to-plane metric, surpasses D2, i.e., point-to-point metric, a little in both sessions, where the priority derives from the association between local plane properties and human vision. Besides, the evaluation of YUV, i.e. texture attributes, shows a higher correlation with subjective scores than that of D1/D2, i.e., geometry attributes. Different from the traditional 2D screen, the interactive VR environment focuses more on the whole of point clouds. According to the response from subjects in our subjective experiment, subjects are more sensitive to texture information and they might ignore the slight changes of geometry information, especially in the flat region. Specifically, since geometry attributes are lossless in some pairs of QP, the PSNR values of geometric metrics are infinite, causing troubles when performance evaluation metrics are calculated. To fairly compare the performance of metrics, we ignored samples corresponding to these pairs like (0, 27), (0, 37), and (0, 47) while computing the correlation between 3D metric of PCQA and subjective scores.

For projection-based methods, Table V shows the correlation between subjective scores and predictive objective scores of different projection-based PCQA methods. Various image quality methods were used to evaluate images generated from projection as we described above. IFC [47] achieves the best performance in both methods of mean and weighted views with 0.5296 and 0.5462 in PLCC and 0.5312 and 0.5516 in SROCC respectively. Regardless of computational efficiency,

we can see that IQA methods using natural scene statistics like IFC [47] and VIF [48] and methods using structure similarity like IW-SSIM [42] and VSI [46] perform a bit better than error based methods like PSNR and UQI [39]. IFC [47] and VIF [48] model natural images in the wavelet domain using Gaussian Scale Mixtures models, using steerable pyramid decomposition. Both of them perform well in the the correlation between subjective scores and predictive objective scores of projected images. It provides a novel thinking that IQA methods utilizing wavelet domain are able to evaluate constructed point clouds in a way of projection. In addition to that, it is no surprise that the proposed method of weighted views outperforms the mean method with an increase of 0.0536 and 0.0296 in PLCC and SROCC respectively on average since our method takes human awareness into consideration. In particular, the ratio, shown as percentages, denotes the average of the original correlation scores divided by the gains. The method of projection considers texture attributes with a slight awareness of geometry attributes as the geometric distortions reflect on the shift of pixels on projected images.

For different sessions, diverse IQA metrics in the human figure session show a higher correlation with subjective quality scores than those metrics in the inanimate object session as shown in Table IV and Table V. The reason for the difference may lie in that some point clouds in the inanimate object session are a little sparse and show lower perceptual quality, causing the deviation from rating.

VI. CONCLUSION

In this paper, we concentrated on subjective point cloud quality assessment in an immersive environment and studied the effect of geometry and texture attributes in compression distortion. We conducted an interactive subjective point cloud assessment experiment with a head-mounted display and interactive controllers. The impacts of different contents, geometry and texture quantization parameters were discussed in the work. Finally, we evaluated the performance of current objective quality metrics and proposed an objective weighted projection-based method. Point cloud assessment is still an intricate and challenging problem involved with excessive elements. Our subjective database and findings can be used in perception-based point cloud processing, transmission, and coding, especially for the Virtual Reality applications.

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