



OPEN ACCESS

EDITED BY

Emin Zerman,
Mid Sweden University, Sweden

REVIEWED BY

Xiem Hoang,
University of Engineering and Technology,
Vietnam National University, Vietnam
Evangelos Alexiou,
Xiaomi Technology, Netherlands
Xuemei Zhou,
Centrum Wiskunde & Informatica, Netherlands,
in collaboration with reviewer EA

*CORRESPONDENCE

Amar Tious,
✉ amar.tious@univ-nantes.fr

RECEIVED 19 April 2024

ACCEPTED 08 October 2024

PUBLISHED 01 November 2024

CITATION

Tious A, Vigier T and Ricordel V (2024) New challenges in point cloud visual quality assessment: a systematic review. *Front. Sig. Proc.* 4:1420060. doi: 10.3389/frsip.2024.1420060

COPYRIGHT

© 2024 Tious, Vigier and Ricordel. This is an open-access article distributed under the terms of the [Creative Commons Attribution License \(CC BY\)](https://creativecommons.org/licenses/by/4.0/). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

New challenges in point cloud visual quality assessment: a systematic review

Amar Tious*, Toinon Vigier and Vincent Ricordel

École Centrale Nantes, CNRS, LS2N, UMR 6004, Nantes Université, Nantes, France

The compression, transmission and rendering of point clouds is essential for many use cases, notably immersive experience settings in eXtended Reality, telepresence and real-time communication where real world acquired 3D content is displayed in a virtual or real scene. Processing and display for these applications induce visual artifacts and the viewing conditions can impact the visual perception and Quality of Experience of users. Therefore, point cloud codecs, rendering methods, display settings and more need to be evaluated through visual Point Cloud Quality Assessment (PCQA) studies, both subjective and objective. However, the standardization of recommendations and methods to run such studies did not follow the evolution of the research field and new issues and challenges have emerged. In this paper, we make a systematic review of subjective and objective PCQA studies. We collected scientific papers from online libraries (IEEE Xplore, ACM DL, Scopus) and selected a set of relevant papers to analyze. From our observations, we discuss the progress and future challenges in PCQA toward efficient point cloud video coding and rendering for eXtended Reality. Main axes for development include the study of use case specific influential factors and the definition of new test conditions for subjective PCQA, and development of perceptual learning-based methods for objective PCQA metrics as well as more versatile evaluation of their performance and time complexity.

KEYWORDS

point cloud, volumetric video, systematic review, subjective quality assessment, objective quality metrics, QoE, extended reality

1 Introduction

Point cloud (PC) is the generalization in 3D of the principle of pixels for 2D images. More in detail, a point cloud is a set of thousands to billions of points (depending on the use case and the type of data) that each have 3D space coordinates and various attribute values (color, surface normal, transparency, etc.). Unlike in 3D meshes, there is no spatial connection between the points in a PC (Stuart, 2021), which allows the representation of non-manifold objects (Schwarz et al., 2019). Advantages to using PCs rather than meshes include a lesser time and memory complexity, making them more practical for storage and transmission. So far, meshes are preferred in mainstream and industrial applications because they are easier to manipulate, edit and render. However, the newest immersive technologies brought up numerous new use cases for PCs that do not require manipulation and editing.

Point cloud data can be saved in the same graphics file formats as meshes, by storing individual points as vertices without any faces. For colored PCs, it is generally the PLY

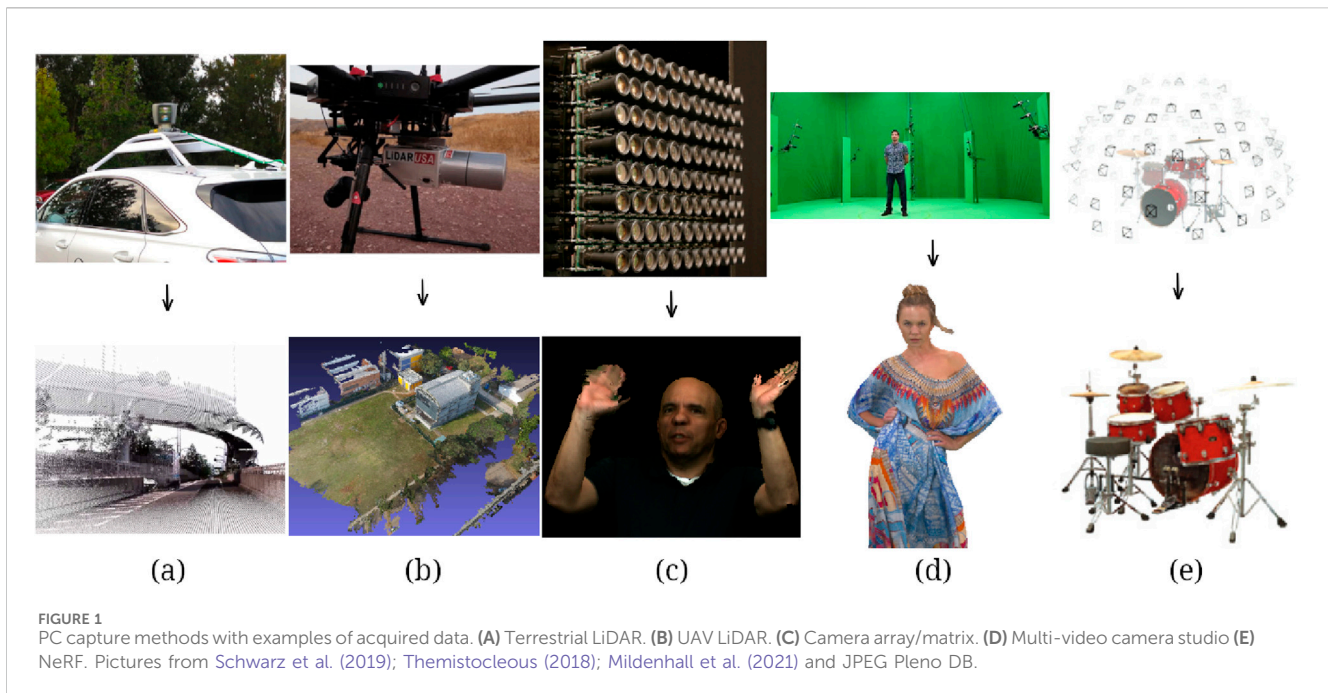


FIGURE 1
PC capture methods with examples of acquired data. (A) Terrestrial LiDAR. (B) UAV LiDAR. (C) Camera array/matrix. (D) Multi-video camera studio (E) NeRF. Pictures from Schwarz et al. (2019); Themistocleous (2018); Mildenhall et al. (2021) and JPEG Pleno DB.

format (polygon file format) that is used, despite the availability of PC specific formats (*laz/las* for LiDAR data, or *pcd* of the Point Cloud Library (PCL) project for PCs in general). This is due to the import/export capabilities and support of the common PC softwares. With PLY, each point has 3D space coordinates (x, y, z), and optionally other dimensions and properties to represent the point attributes. Common properties are the point colors (r, g, b) and the normals (n_x, n_y, n_z) which are the coordinates of the normal vector to the surface of the point. It can either be coded in ASCII or binary format.

Point clouds are relevant for representation of real life scenes, objects or places in 3D. The capture and acquisition methods, as well as the point attributes represented, are various and depend on the use case they should fit to. Laser scanners (LiDAR) are used to acquire point clouds describing 360° representation of a building or scene. They can also be dynamically acquired with LiDARs mounted on terrestrial vehicles or unmanned aerial vehicles (UAVs). This type of PC is used for 3D cartography, architecture planning, and in military operations. However, as these methods only capture the geometry, the resulting PC data has no color attributes. Such data are generally only used for machine vision tasks.

For content destined to human vision, 2D-to-3D computation methods such as photogrammetry or NeRF models (Mildenhall et al., 2021) permit to obtain photo-realistic PC representations of objects, people or scenes based on 2D content with depth or spatial information, or just on multiple 2D views. Acquisition for generation of such representations is done with RGB-D (RGD + Depth), time-of-flight, stereoscopic or regular cameras. In recent mobile hardware, the camera can be coupled with an integrated LiDAR used in place of a depth sensor (RGB + LiDAR). With these methods, the more there are input views on the content to represent, the higher the density of the resulting textured PC will be. This method is generally used for 3D modeling of real objects, but it can also be coupled with LiDAR scans from terrestrial or UAV systems

for colored representations of lands and buildings. Other use cases are cultural heritage, 3D printing and industrial quality control. Cameras can also be arranged in camera arrays or matrices to capture many viewpoints at once in video. For a complete 3D reconstruction of a moving object or person, cameras are arranged in multi-video camera studio settings. The volumetric videos are captured with such setups and stored as PC sequences, which are commonly referred to as dynamic point clouds (D-PC). Use cases for 3D PCs and D-PCs include immersive telecommunication, immersive media broadcasting, and virtual museums and theaters (Perry, 2022). These applications all induce the use of eXtended Reality (XR) displays and virtual/mixed environments in 6 degrees of freedom (DoF). Figure 1 shows the different acquisition methods mentioned with examples of captured content. XR applications have become the main motivation for development in PC processing. They require PC objects or sequences to be rendered and played in virtual/mixed scenes. The common approach for PC rendering is to use surface reconstruction Kazhdan et al. (2006) and render them as meshes (surface-based rendering). With this method, we either map the point colors to a texture or use the vertex colors. To keep the advantages of PC representation in storage and rendering, another approach is to render each vertex (a point and its attributes) as a particle or graphic object (point-based rendering). In this second approach, the size of point objects is selected to visually fill the gaps between points and make the displayed content appear as a watertight surface. When rendering large data, point-based rendering also allows control of the level of detail (LoD) in order to limit the use of computational resources.

For PCs acquired with LiDARs, the data are captured dynamically and concatenated into scans of large areas (typically 2M to 1G points Ak et al. (2024)) and are therefore more spatially voluminous. For volumetric videos and 3D reconstructions of objects or people, we need visually accurate representations that

can be rendered as seemingly watertight (typically 100 k to 2 M points) for a high visual quality, for every single frame in the case of D-PCs. Such voluminous data is costly in terms of memory space for storage and in terms of time for transmission, and this issue is even worse when using meshes instead. To address this problem, point cloud compression (PCC) methods that fit different use cases have been developed. Main approaches are based on 3D spatial division and octree coding for geometric data such as LiDAR scans, and 3D-to-2D projection and image coding for textured PCs. More recently, the field of PCC has also been taken over by AI with the emergence of compression methods using feature detection and learning-based auto-encoders. In response to a need for common ground solutions, the MPEG expert group developed and defined two standard compression schemes: geometry-based PCC (G-PCC) (ISO/IEC 23090-5, 2023) and video-based PCC (V-PCC) (ISO/IEC 23090-9, 2021). G-PCC encodes voxelized PC coordinates in an octree and uses another encoder for the attributes associated with the octree leaves. V-PCC, designed for D-PCs, generates 2D patch maps respectively for the geometry (depth map) and the attributes (texture maps), and encodes them with a state-of-the-art video codec. Other more recent standard methods such as AVS PCGC (Wang et al., 2021) and the JPEG Pleno PCC codec (Guarda et al., 2022) use learning-based coding approaches. Aside from the standards, learning-based PCC has been a very active research field in the last 5 years.

To be characterized and fit to a given use case, the performance of these compression methods, but also of the capture, transmission and rendering methods, need to be evaluated through quality assessment (QA). For geometric LiDAR scans, which are mainly used in machine vision tasks and not human vision, objective QA metrics that measure the geometric acquisition error or the compression distortion error are used. For colored PCs and D-PCs representing content destined to be visualized by human observers, optimization of the visual quality is important in order to improve the quality of experience (QoE) in use cases and applications. In this case, subjective PCQA is needed to assess the impact of capture, compression, transmission and rendering artifacts on visual perception, and to identify influential factors (IF). Subjective tests are essential in the first place to assess the human perception of quality and user expectations, and to determine better visualization and display methods, parameters and conditions. Yet, since such tests require time, material and participants, and cannot be included as quality control in production pipelines, objective PCQA for immersive media is also an important research field. Metrics are being developed to predict the visual quality of PCs. Their aim is to correlate with subjective test results in order to ultimately replace them. In PCQA, as in QA in general, objective metrics can be categorized by the computational approach and input of references. Full-reference (FR) metrics compute a quality score for a distorted stimulus by comparing it to its reference (same stimuli prior to distortion). Reduced reference (RR) metrics only use limited information about the reference, and no-reference (NR) metrics evaluate a stimulus without any comparison to a reference. This last category allows blind QA in cases where no reference is available, like during compression and after transmission. For PCQA, objective metrics either take the raw points data as input (3D-based), or compute a quality score based on 3D-to-2D projections of the PC in rotating camera videos, six viewpoint cubes, or patch maps

(projection-based). The first standardized approaches for objective PCQA are computations based on a point-by-point MSE or PSNR measure (MSE-based) for the geometry and/or color (color-based) data. The tremendous development of the research has however brought upon many new approaches. Similarly to PCC, the state-of-the-art metrics use AI principles or only feature extraction in their computation (learning- or feature-based). The learning-based category also includes metrics that consider perceptual features of the evaluated PC in the quality score computation in order to correlate with the human visual system (perceptual-based metrics). It is to be noted that these categories are not exclusive of each other and that a metric can use feature extraction or be based of perceptual features without being learning-based.

1.1 Our contribution

PCQA is a live research topic with a very active community. Most of the progress and new proposals in the field focus on PCQA for human visualization. The number of research papers presenting subjective test results and datasets, objective QA benchmarks and novel metrics has been multiplied since 2020 after the standardization of MPEG-I PCC standards (Schwarz et al., 2019) and the first version of the JPEG Pleno common test conditions (CTC) for PCC QA (Stuart, 2021). However, with the emergence of immersive technologies and all the modern and future use cases that came along, the scope of subjective QA in terms of evaluated IFs has greatly evolved since the definition of the JPEG Pleno recommendation, and the range of objective QA metrics was also transformed. The current recommendations do not and cannot apply to all the research issues that subjective tests should investigate, and the features currently taken into account by standard objective metrics are not enough. The proposed methods and conditions for subjective PCQA are too diverse and strive away from the CTC. Objective PCQA metrics also have a much diversified range of features to consider.

Therefore, an up-to-date review of literature is much needed in order to trace the evolution path of this research topic. Previous literature reviews about this field (Fretes et al., 2019; Domic et al., 2018) review the development in PCQA only up to the standardization of the JPEG Pleno CTC, prior to the tremendous progress of the last few years, or focus mostly on the latest progress for other types of data and limited use cases (Alexiou et al., 2023a). A more recent survey (Yingjie et al., 2023) is focused only on the key papers of the literature. The authors discuss the methodologies used in the most cited subjective studies and present a benchmark of the most cited objective metrics. But they do not consider the whole picture of the research field which limits the observations. Also, they only present the distortions types used in these studies without discussing them, and do not include a discussion about the evolution and future of the field.

In this paper, we make a systematic review of the PCQA literature in order to make an overview of the tremendous progress made and amount of papers published in the last 5 years. We focus on the case of visual PCQA for representation of real-life objects or people. We explore the publications that present subjective QA experiments and datasets, new objective QA metrics, and performance benchmarks. By making statistical

analysis of a selected set of 148 relevant papers, we identify the IFs of interest and the tendencies of methodologies in subjective QA, and we review the state-of-the-art progress and current goals of objective QA metrics. In conclusion to our analysis, we discuss the next and upcoming interests that will or should be investigated by the community.

1.2 Research questions

Our topic of interest is PCQA for human vision. Our research questions are the following:

1. What aspects of PC visual quality have been considered in subjective PCQA?
2. What aspects of PC visual quality still need to be considered in objective and subjective PCQA?
3. What are the needs for new standardization of PCQA methodologies and metrics?
4. What are the next steps in optimizing the QoE of PC visualization in XR applications?

2 Methodology

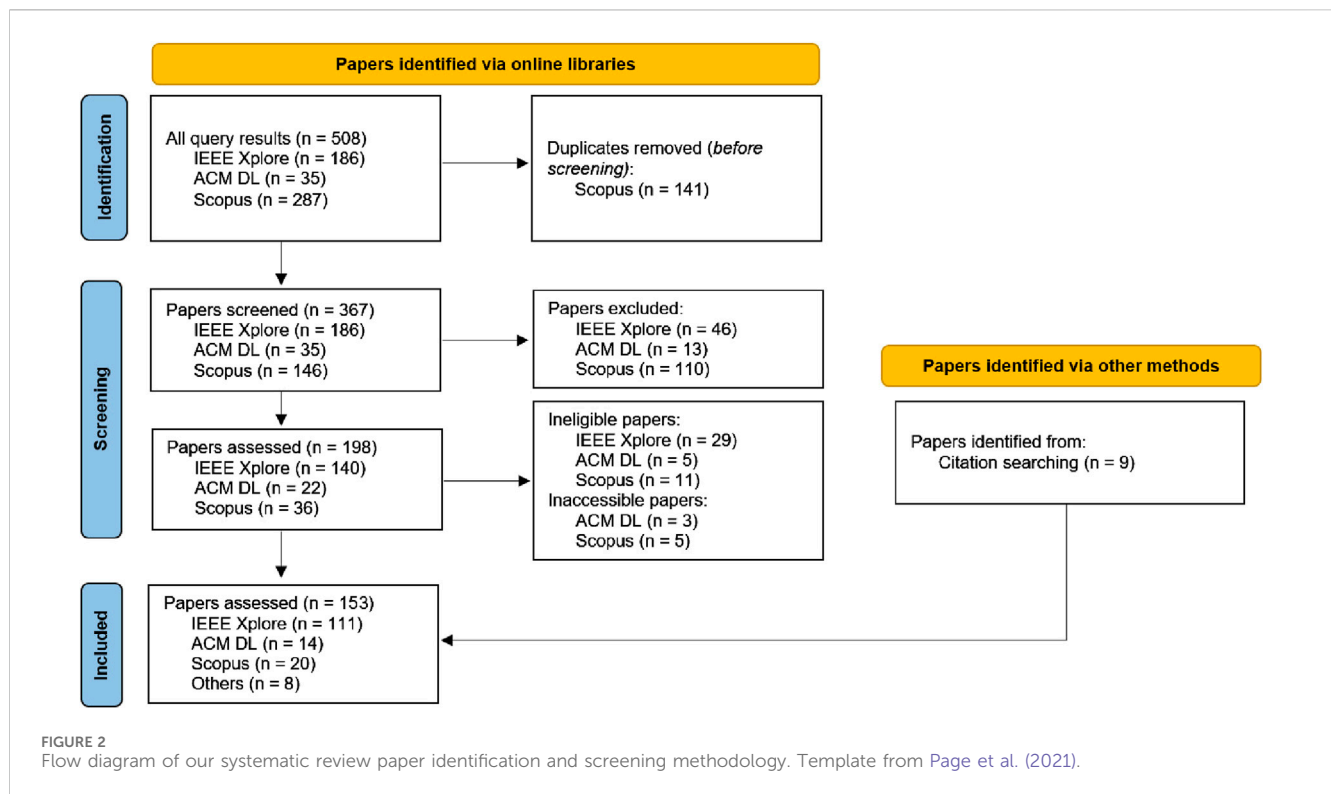
A systematic review has to apply described and published search rules and protocols. The objective is to do a review of the research field of interest that is as exhaustive as possible. It also requires precise documentation on the search tools, queries, filters and exclusion criteria for the studied papers that were used. It allows the readers to understand, validate and potentially replicate the process in the future. Therefore we detail below the steps of our method for searching, selecting, sorting and analyzing scientific papers.

1. We first selected 13 target papers that represent our prior knowledge of the studied topic (Mekuria et al., 2017; Tian et al., 2017; Alexiou and Ebrahimi, 2018c; da Silva Cruz et al., 2019; Meynet et al., 2020; Alexiou et al., 2020; Zerman et al., 2020; Viola and Cesar, 2020; Lazzarotto et al., 2021; Dumić et al., 2021; Liu et al., 2023b; Gutiérrez et al., 2023; Ak et al., 2024). The works presented in these papers include various subjective test procedures and results, datasets, objective metrics and objective benchmarks. From the titles and keywords of these papers, we define a short vocabulary that will be used in queries to search for the complete set of papers to be studied. The selected vocabulary contains the words: Point cloud, Volumetric video, Quality, Evaluation, Preference.
2. We ran a first query on only the paper titles in order to get a first large overview of the results, elaborate the next queries and identify words to exclude. We ran the query on two online libraries: IEEE Xplore and ACM Digital Library. In this query, we split the vocabulary into two sub-groups such that the paper titles have to contain at least one expression from each. The sub-groups are [point cloud, volumetric video] and [quality, evaluation, preference].
3. Based on the results of the first query, we elaborated a second vocabulary based on the titles, keywords and abstracts. We

separated it into three sub-groups of expressions with equivalent meanings: [point cloud, volumetric video], [quality assessment, quality evaluation, preference, visual quality] and [subjective, objective, metric]. In order to filter out some irrelevant results (not related to human visual PCQA, we also excluded a limited sub-group of words describing unrelated papers (PCQA for machine vision in autonomous vehicles): [vehicle, landscape]. We ran this query on the paper titles, keywords and abstracts, and included results from a third online library: Scopus. After removing the duplicates in results of both queries in each library, we got 186 papers from IEEE Xplore, 35 from ACM Digital Library, and 287 from Scopus.

4. Since the results collected from Scopus contain papers published by IEEE and ACM, we had to manually remove from the Scopus results the papers that were already found in IEEE Xplore and ACM Digital Library. Afterwards, Scopus results were narrowed down to 146, which left us 367 distinct papers in total.
5. We then did a first screening of the 367 papers based only on the paper titles and abstracts. We marked and removed all the papers where the title or abstract revealed that the type of data or focus use cases were not implying human visual tasks or visual quality assessment with PCs. The excluded topics and types of data were: machine vision tasks only, autonomous driving, uncolored LiDAR scans, volumetric videos represented only as meshes, spatial videos and light fields. After this first screening, a total of 198 papers were left with a majority of 140 from IEEE Xplore, 22 from ACM Digital Library, and only 36 left from Scopus.
6. The final step of the papers screening was an overview of all the remaining contents for eligibility in order to filter out and keep only the final set of articles to study. During this second screening, we removed all remaining articles where the content relates to the excluded topics mentioned in the previous step. We also excluded all papers that, despite being related to PCQA, were not presenting newly published subjective test results, objective metrics, or metric benchmarks. This included previous surveys, technical papers only introducing QA toolboxes, or case studies that only present results from a previous paper. In this step, we also removed all articles that we could not access a full PDF version of. After this last step of narrowing down the results, a final set of 144 papers was left to study. This includes 111 articles from IEEE Xplore, 14 from ACM Digital Library and 20 from Scopus.
7. During the paper content screening for eligibility and later, we also added 9 more papers to the final set (Viola et al., 2022; Alexiou et al., 2019; Marvie et al., 2023; Mekuria et al., 2015; Liu Y. et al., 2021; Alexiou et al., 2023b; Lazzarotto et al., 2024; Nguyen et al., 2024), that were citing or cited by our selected papers, and were included because their content was eligible and particularly relevant to the study.
8. At last, we analyzed the 154 papers of the final set that all contain at least results and protocols about subjective PCQA tests, the introduction of new objective PCQA metrics, or benchmarks of QA metrics performances. Our research process is summarized in Figure 2.

During the analysis, we extracted for each paper a set of relevant information depending on its content. For all papers, we noted the



source dataset and type of data used or presented. For subjective PCQA papers, we noted the type(s) of display (2D, 3D, VR/MR), the user interactivity (passive with 0 DoF, or active with 3/4/6 DoF), the rendering technique(s), the rating methodology, the number of observers, the investigated IFs, and whether the test was run in-lab, cross-labs or remotely. When the test results were made available, we also noted the associated dataset.

For objective PCQA papers introducing new metrics, we noted the name of the metrics, the dimensional category of the approach (3D-based or projection-based) and the reference base of the metric (full-reference (FR), no-reference (NR) or reduced-reference (RR)). We also identified, for each metric, all the categories to which its computation corresponds (MSE-based, feature-based, learning-based, perceptual-based, color-based, ...).

For all papers that present benchmark results for objective QA metrics, we noted the dataset(s) used as ground-truth and the categories of metrics evaluated (standards, image quality metrics (IQMs) and state-of-the-art FR, NR or RR). All the analyzed papers can be classified into three non-exclusive categories: subjective QA studies, objective QA metrics, and metric performance benchmarks. The queries and the collected data will be made available¹.

3 Results

Table 1 shows all the analyzed papers sorted by category of content. From the 154 papers of the final set, 69 present subjective QA

experiment protocols and/or results, all aiming to compare and evaluate experiment settings, codecs, rendering parameters, or other IFs. These 69 papers include 40 that also use their results to make a benchmark of QA metrics performances. 91 of the papers introduce new PCQA metrics, including 83 that compare its performance to other metrics in a benchmark. Between the 91 objective metrics papers and the 69 subjective QA papers, there is an intersection of 12 papers that present both, including 8 that also have metrics benchmarks. In total we have reviewed 121 benchmarks, including six from papers that present neither subjective tests, nor new metrics. Instead, they either evaluate PCQA metrics on sampled meshes (Fu et al., 2023; Alexiou and Ebrahimi, 2018a) or D-PCs with temporal subsampling/pooling (Ak et al., 2021; Freitas et al., 2022a), are cross-dataset surveys (Yingjie et al., 2023) or focus on a codec only (Dong et al., 2021). These numbers are visually described in Figure 3.

Based on the analyzed set, the go-to conferences for PCQA are IEEE QoMEX (20 papers), IEEE ICIP (13 papers), IEEE MMSP (9 papers), IEEE ICME (8 papers), ACM MM (5 papers), and EUSIPCO and IEEE ICASSP (both four papers). The highlight journals are IS&T Electronic Imaging and IEEE Transactions on Multimedia (both seven papers), IEEE Transactions on Circuits & Systems for Video Technology (6 papers), IEEE Access and IEEE Signal Processing Letters (both five papers).

3.1 Results on subjective QA

3.1.1 Participants and test conditions

From the 69 subjective QA papers we analyzed, a large majority of 63 presents tests run in-lab, including 11 cross-lab tests (same test in different labs). Single lab tests follow the CTC recommended in

1 <https://doi.org/10.5281/zenodo.13992559>

TABLE 1 All the papers of the analyzed set sorted by content. Subjective Tests are papers that present subjective test procedures and/or results. Metrics Benchmarks are papers that include performance benchmarks of QA metrics. Objective Metrics are papers that introduce new objective QA metrics.

Category	Count	Analyzed papers
Only subjective tests	25	Zhang et al. (2014); Mekuria et al. (2015); Alexiou et al. (2018b); Alexiou and Ebrahimi (2018b); Alexiou et al. (2020); Subramanyam et al. (2020) Zerman et al. (2020); Dumic et al. (2021); Perry et al. (2021); Lazzarotto et al. (2022b); Rossi et al. (2022); Subramanyam et al. (2022b); Subramanyam et al. (2022a) Viola et al. (2022); Chen et al. (2023); Cox et al. (2023); Fan and Gao (2023); Gutiérrez et al. (2023); Nguyen et al. (2023b) Singla et al. (2023); Van Damme et al. (2023); Vats et al. (2023); Weil et al. (2023); Zhou et al. (2023d); Nguyen et al. (2024)
Subjective tests & Metrics benchmarks	32	Alexiou et al. (2017); Alexiou and Ebrahimi (2017a,b); Javaheri et al. (2017a,b); Alexiou et al. (2018a); Torlig et al. (2018); Alexiou et al. (2019) Alexiou and Ebrahimi (2019); da Silva Cruz et al. (2019); Perry et al. (2019); Su et al. (2019); Zerman et al. (2019); Dumic and da Silva Cruz (2020) Perry et al. (2020); van der Hoof et al. (2020); Javaheri et al. (2021a); Lazzarotto et al. (2021); Liu et al. (2021c); Lazzarotto et al. (2022a) Perry et al. (2022); Prazeres et al. (2022a,b,c); Baek et al. (2023); Dumic and da Silva Cruz (2023); Nguyen et al. (2023a); Prazeres et al. (2023) Wu et al. (2023); Ak et al. (2024); Fan et al. (2024); Lazzarotto et al. (2024)
Subjective tests & Metrics benchmarks & Objective metrics	8	Alexiou and Ebrahimi (2018c); Liu et al. (2021a); Wu et al. (2021); Yang et al. (2021); He et al. (2022); Liu et al. (2022); Liu et al. (2023a); Liu et al. (2023c)
Subjective tests & Objective metrics	4	Mekuria et al. (2017); Huang et al. (2019); Cao et al. (2020); Marvie et al. (2023)
Metrics benchmarks & Objective metrics	75	Meynet et al. (2019); Alexiou and Ebrahimi (2020); Diniz et al. (2020a,b,c); Javaheri et al. (2020a,b,c); Meynet et al. (2020); Viola et al. (2020) Chen et al. (2021); Chetouani et al. (2021a,b); Diniz et al. (2021b); He et al. (2021); Hua et al. (2021); Javaheri et al. (2021b) Liu et al. (2021b); Quach et al. (2021); Zhang et al. (2021); Bourbia et al. (2022a,b); Chetouani et al. (2022); Coelho et al. (2022); Diniz et al. (2022) Fan et al. (2022); Freitas et al. (2022b); Hua et al. (2022); Javaheri et al. (2022); Laazoufi et al. (2022); Laazoufi and El Hassouni (2022) Lu et al. (2022); Tliba et al. (2022a,b); Xu et al. (2022); Yang et al. (2022a,b,c); Zhang et al. (2022); Alexiou et al. (2023b) Bourbia et al. (2023); Cheng et al. (2023); Fan et al. (2023); Freitas et al. (2023); Lazzarotto and Ebrahimi (2023); Liang et al. (2023) Liu et al. (2023b); Messai et al. (2023); Mu et al. (2023); Riache et al. (2023); Shan et al. (2023); Smitskamp et al. (2023) Su et al. (2023a,b); Tliba et al. (2023a,b); Tu et al. (2023a,b); Wang et al. (2023a,b,c,d); Watanabe et al. (2023); Xie et al. (2023) Xiong et al. (2023); Zhang et al. (2023a,b,c,d); Zhou et al. (2023a,b,c); Chai et al. (2024); Wang et al. (2024); Zhang et al. (2024)
Only objective metrics	4	Tian et al. (2017); Viola and Cesar (2020); Diniz et al. (2021a); Van Damme et al. (2022)
Only metrics benchmarks	6	Alexiou and Ebrahimi (2018a); Ak et al. (2021); Dong et al. (2021); Freitas et al. (2022a); Fu et al. (2023); Yingjie et al. (2023)

ITU-R Recommendation BT.500-14 (2019) for the experiment environment settings. They have an average of 37.1 observers for each stimuli (with a minimum of 16 and a median of 29), while cross-labs have 50.8 (with minimum of 30 and median of 46). The tests presented in the six other papers are more recent and run remotely. Even though remote tests lack control over the viewing conditions, which typically implies a higher user-bias and inter-observer standard deviation (σ), they make participation easier and satisfy a higher needed number of observers (n) in order to result in confidence intervals (CI) equivalent to those of in-lab tests (CI depends on $\frac{\sigma}{\sqrt{n}}$). Remote tests all have at least 33 valid observers, 55.4 on average and 60 on median, which is almost twice as much as for in-lab tests and results. Yet subjective QA experiments are still mostly run in-lab. Following the JPEG Pleno CTC (Stuart, 2021) for PCQA permits to control and limit the need in terms of observers (15-20 observers recommended). The flexibility in participation of remote and cross-lab tests is useful in cases where an experiment

aims to evaluate IFs that are not considered by the standard CTC and/or a more difficult task.

Studies with XR displays, where the inter-user variability is even higher and that cannot be run remotely as easily, are also run exclusively in-lab. XR QA tests in 6DoF conditions are the most demanding in terms of settings control and participation (36.5 observers on average).

3.1.2 Test methodologies

In a common subjective QA experiment, observers visualize a set of stimuli with defined distortion types, viewing conditions and interaction methods. They assess the visual quality of the stimuli on a defined rating scale, and optionally fill a questionnaire for more QoE assessment data. The methodology differs from test to test depending on the focus of the study.

The rating scale used in subjective PCQA is generally the absolute category rating-scale (ACR) where the observer rates the

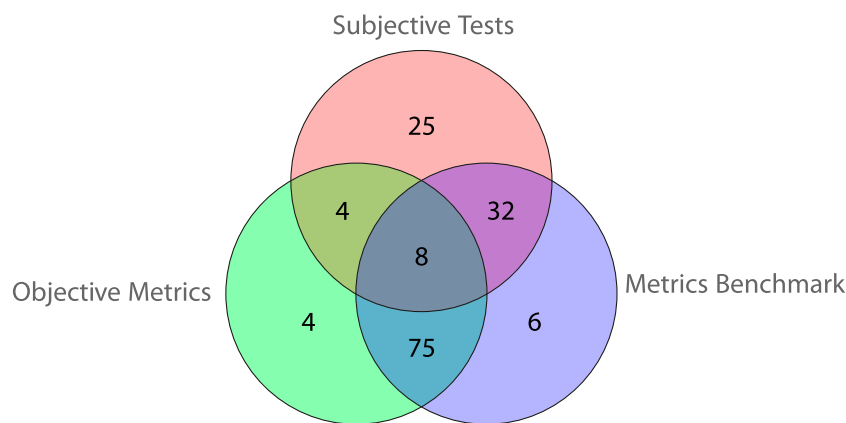


FIGURE 3
Venn Diagram of the set of selected papers.

stimuli based on a reference scale, or double stimulus impairment scale (DSIS) where the observer evaluates the distorted stimuli in comparison to their reference. We found 23 studies using ACR and 46 using DSIS, which are proportions in agreement with the observations of Yingjie et al. (2023) on a smaller set of papers. For at least 12 of them, the paper mentions the use of a hidden reference (HR) in the stimuli set as a high quality anchor. But since this inclusion is recommended in ITU-R Recommendation BT.500-14 (2019), it is likely that much more than these 12 papers use it without mention. Most experiments on 2D display with static PCs use DSIS (40 out of 46) as it is the recommended methodology in the CTC. But studies in XR are more varied (8 with ACR and 11 with DSIS). ACR is shown to be just as efficient in XR by the latest studies (Gutiérrez et al., 2023) than DSIS. It is also more fit to the use cases and the evaluation of dynamic content than a double stimuli displaying method.

Prior to the standardization of MPEG codecs, PCQA studies were using only texture and geometry noise and down-sampling in order to create different quality levels for the stimuli (14 out of 22 studies before 2020, and the other 8 are either using no distortion or QA of codecs for standardization). Since the release of the MPEG-I PCC standards in 2020, almost every PCQA study has been about compression distortion. 28 studies use G-PCC, 36 use V-PCC, 5 use Google Draco, 14 use more recent learning-based codecs, 5 use the CWI-PL codec for tele-immersive communication.

A few studies evaluate the visual quality and QoE of point clouds in real time streaming applications (Subramanyam et al. (2022b; a)). The MPEG standards and popular AI codecs (including the recent JPEG Pleno codec (Guarda et al., 2022)) are not yet optimized for this use case, so the compression methods used in this scenario are Draco or CWI-PL. However, results of the subjective studies we analyzed tend to suggest that these two codecs are also those with the lesser visual quality. V-PCC, the most often used, is shown to offer the best ratio between bitrate and visual quality (Wu et al., 2023; Perry et al., 2022). It is also shown to be the most fit for visual content and D-PCs (Zerman et al., 2020), and is therefore the most used in recent studies and XR experiments (10 out of 18 XR studies use V-PCC).

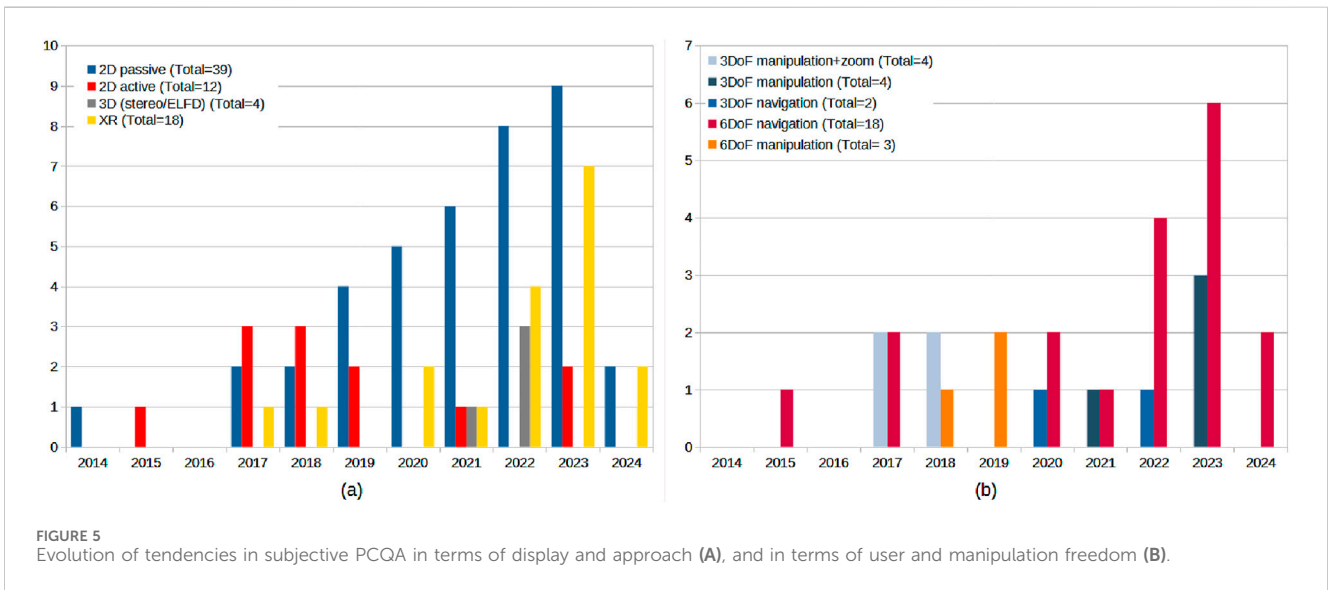
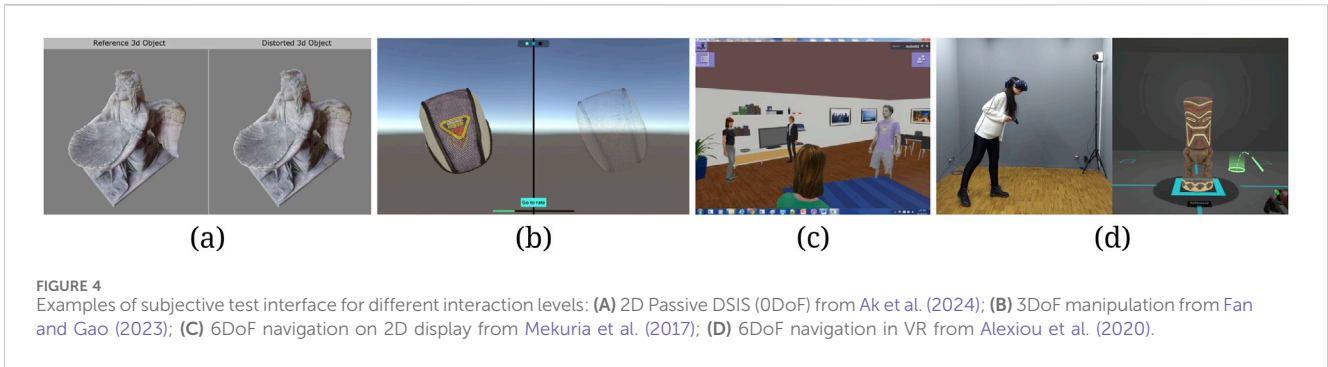
For the standard codecs, the different quality levels for the stimuli are those defined by JPEG Pleno CTC, despite there

being no study to justify these parameters as optimal (Lazzarotto et al., 2024). In large experiments comparing and evaluating many codecs, the many types and levels of distortions make the set of stimuli too large for a single session test. In such cases, tests are split into sessions with 20–30 stimuli per session in general. For each observer, participating in an experiment is never longer than 30 min.

3.1.3 Interaction, display and rendering

Figure 4 shows examples of subjective test interfaces for different interaction levels and methodologies. 53 out of 69 studies use 2D displays. For 39 of them, a passive approach is used, in which the stimuli are shown to the observers either as static images (5 out of 39) or videos with a rotating viewpoint around the objects (34 out of 39). For only 12 of them we could confirm an active assessment approach where users were free to manipulate the object and choose their point of view. For the last two studies with 2D display, no information was given about the interactivity of the interface. The large superiority in popularity of the passive approach was not shown in previous surveys and reviews. For studies using the active approach, depending on the interface, observers are either only able to rotate the stimuli (3DoF manipulation), also allowed to zoom in and out (3DoF manipulation + zoom), or free to translate its position in 3D space (6DoF manipulation). Another interactive method is to have the observer control an avatar to move around the stimuli in a virtual room (6DoF navigation). This last approach is used with a 2D screen in a few early papers (Mekuria et al. (2015; 2017)), leading to the use of HMDs later. As can be seen on Figure 5B, the rise of XR in QA has almost totally replaced 2D displays in studies focused on interactivity or specific use cases.

The passive approach reportedly allows better inter-user consistency and confidence interval (Perry et al., 2022), which is why it has been selected for standardization. But it is not reflective of real in-context viewing conditions, and does not fit the evaluation of dynamic content. Four experiments studying user preferences and display as an IF have users view PCs on 3D stereo displays or eye sensing light-field displays (ELFD) (Dumic et al. (2021); Prazeres et al. (2022b); Lazzarotto et al. (2022b; a)), but no significant difference with using 2D screens was found. With HMDs (head-mounted displays) however, differences in freedom and effort



influence the ratings. We found 18 papers presenting subjective studies in VR, MR or AR (including two that also present a test with 2D display). From these 18, 16 present experiments in 6DoF navigation. These studies show an important inter-observer variability and aim to demonstrate a significant impact of the display and task on user behavior and ratings. The amount of PCQA studies in XR is growing each year as can be seen on Figure 5A and will likely keep going as they are closer to the expected application for the evaluated content. For the same reason, most XR studies (11 out of 18) are about the quality of volumetric videos represented as D-PCs. In total, 21 of the 69 analyzed subjective PCQA experiments assess D-PCs, and this proportion is also expected to grow.

Another IF that has been evaluated in subjective PCQA is the PC rendering approach. While early studies used sparse PCs rendered only as sets of pixel-sized points (Alexiou and Ebrahimi (2018c; 2017a); Zhang et al. (2014); Alexiou and Ebrahimi (2018b); Alexiou et al. (2017)), the majority of subjective experiments (48 out of 69) use vertex-based rendering. Points are rendered either as squares (Alexiou et al., 2020), cubes (Torlig et al., 2018), disks (Lazzarotto et al., 2022b) or spheres (Chen et al., 2023). Since the industrial approach for volumetric content mostly considers meshes, 12 studies use surface-based rendering and compare it to point-based rendering. Results of these studies conclude on the same

observations (Dumic et al., 2021; Zerman et al., 2020): for highly distorted objects, point-based rendering is better than surface-based; it is also preferred for any distortion level except when the viewing distance (distance between the object and the viewpoint) is too short. A few studies using surface-based rendering (Alexiou et al., 2018a; Javaheri et al., 2017a; Dumic et al., 2021) also include object shading and dynamic lighting, allowed by mesh rendering engines. (Javaheri et al., 2021a). is the first study that considers lighting in point-based rendering, and compares it to mesh surface shading. However, the points shading is based on their normals. In this experiment, rather than being processed as a point attribute like the color, the normals are estimated from the distorted geometry of the stimuli. As a consequence, the addition of lighting has a negative revealing effect on the geometry quality.

3.1.4 Sources and PCQA datasets

For subjective QA, the available source PCs are not as numerous as for video or mesh QA. Out of 39 studies on static colored PCs, 28 use stimuli from the MPEG and JPEG Pleno repositories. For D-PCs, only a handful of PC sequences are available. Stimuli from the MPEG database (8i and OwlII) (Krivokuća et al., 2018; Xu et al., 2017) are used in almost every (all except three (Zerman et al., 2019; Subramanyam et al., 2022a; Nguyen et al., 2024)) subjective PCQA study on D-PCs. The only other used source for D-PCs is the Vsense

TABLE 2 Summary of the identified methodologies and distortions for each type of display and task in subjective PCQA.

Display (task)	Stimuli	Papers	Distortions	Methodologies	Dataset example
2D (Passive)	PC	31	V-PCC (18),G-PCC (19),other codec (13),Noise and scaling (5),other (5)	DSIS (4),PWC (2),ACR (1),SAMVIQ (1)	IRPC (Javaheri et al., 2021a)
	D-PC	11	V-PCC (8),G-PCC (2),other codec (4),Noise and scaling (2),other (4)	DSIS (4),PWC (2),ACR (6)	VVDB2 (Zerman et al., 2020)
2D (Interactive)	PC	12	V-PCC (2),G-PCC (2),other codec (6),Noise and scaling (6),other (1)	DSIS (9), ACR (4)	SJTU-PCQA (Yang et al., 2021)
3D (Passive)	PC	5	V-PCC (1),G-PCC (3),other codec (3),Noise and scaling (1)	DSIS (4), ACR (1)	ICIP22 (Prazeres et al., 2022b)
XR	PC	7	V-PCC (2),G-PCC (2),Noise and scaling (2),other (1)	DSIS (6), ACR (1)	PointXR (Alexiou et al., 2020)
	D-PC	11	V-PCC (8),G-PCC (2),other codec (4),Noise and scaling (1),other (2)	DSIS (11), ACR (1)	QAVA-DPC (Zhou et al., 2023d)

VVDB2.0 dataset (Zerman et al., 2020). Other datasets of source point cloud sequences (Gautier et al., 2023; Reimat et al., 2021) offer more diversity and range, but have not been used in as much studies so far. All these sequences were also captured in studios with limited space for the models, and therefore all represent humans doing short movements.

Finally, 31 of the analyzed papers have their stimuli and results (mean opinion scores, MOS) publicly available as PCQA datasets, and seven of them are from XR studies. These datasets are used in other studies as ground-truth for evaluating the performances of objective QA metrics or, for the largest and most diverse of them, to train learning-based PCQA models. The most used datasets in the 119 metric performance benchmarks are SJTU-PCQA (Yang et al. (2021): used in 40), WPC (Liu et al. (2023b): used in 31), ICIP 2020 (Perry et al. (2020): used in 19), IRPC (Javaheri et al. (2021a): used in 13) and M-PCCD (Alexiou et al. (2019): used in 11). For metrics performances on D-PCs, there are 8 benchmarks, with four using the VsenseVVDB datasets (Zerman et al. (2019; 2020)), and four others using ground-truth ratings collected in their own subjective experiment. About datasets built from studies in XR, the most popular are PointXR (Alexiou et al. (2020): used in four benchmarks) and SIAT-PCQD (Wu et al. (2021): used in 2). The largest datasets for model training are LS-PCQA (Liu Y. et al. (2023): used in 7) and the most recent BASICS (Ak et al. (2024): used in three already). The last two are very recent and will likely also be very popular as ground truth for benchmarks. Other recent and innovative databases are the QAVA-DPC and ComPEQ-MR datasets (Zhou et al., 2023d; Nguyen et al., 2024) that also contain the observers behavioral and gaze data from a 6DoF experiment in XR. Table 2 gives a summary of all the subjective test scenarios we found, with an example of dataset for each.

3.2 Results on objective QA metrics

3.2.1 Types of PCQA metrics

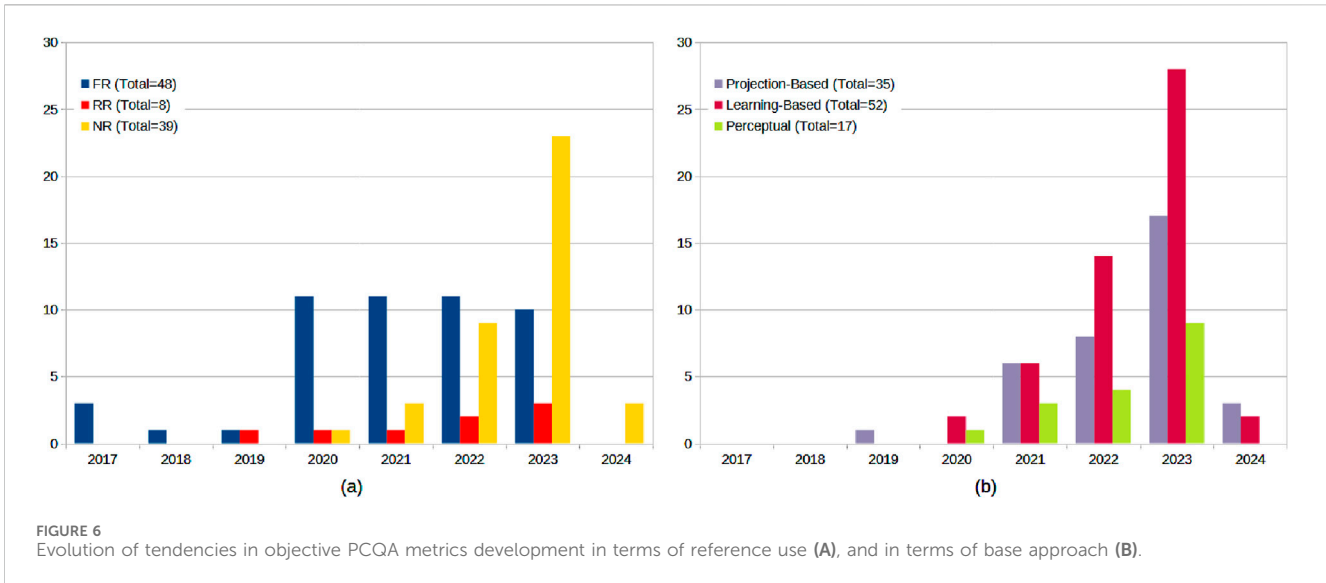
In the 91 papers presenting objective PCQA metrics we identified, 95 metrics are introduced in total (Viola et al. (2020); Javaheri et al. (2020b); Watanabe et al. (2023); Tian et al. (2017) each present not one but two metrics). 62 of these metrics are 3D-based

and 35 are projection-based. Among them, seven are hybrid metrics using both approaches and counted in both categories. Generally for this last category, the geometry is evaluated in 3D space and the texture (color attributes) on projection maps. The projection-based approach is justified by the fact that, unlike 3D-based metrics, it can easily take into account more IFs that are not noticeable from just the raw point data, like rendering artifacts and conditions. The analyzed metrics also include five others that are neither based on 3D or 2D data. Two of them (Liu et al., 2023a; Su et al., 2023a) are designed to assess the quality of an encoded point cloud during transmission, based on the distorted bitstream prior to decoding (bitstream-based). Two others (Liu et al. (2022; 2021a)) are AI-based metrics, trained with subjective test MOS, that computes a quality score based on input subjective experiment parameters (condition-based). The last metric of the analyzed set (Cao et al., 2020) uses a combination of these two approaches.

Bitstream-based and condition-based metrics are also NR metrics. Before the MPEG PCC standardization, all metrics were FR (48 in total presented in 45 papers of the set). We also identified 8 RR metrics, and 39 NR metrics. One of the selected papers (Watanabe et al., 2023) presents two metrics that are FR and NR versions of a same method. From the NR metrics, 35 were also learning- and/or feature-based. Learning-based PCQA is the most active research sub-field of PCQA today. 52 of the 95 metrics we identified are learning-based, including 29 that were published just in 2023 and early 2024. We also found 17 perceptual-based metrics from which 13 are also learning-based. Here, we count as perceptual-based the feature-based metrics who extract perceptual features, and the learning-based metrics that visual attention prediction models (saliency-based). Among perceptual-based metrics, six are saliency-based and use the predicted saliency of individual points and regions to compute a weighted score. Figure 6B shows the evolution of interest in the development of different categories of metrics over the years.

3.2.2 Existing benchmarks for metric performance

The performances of metrics are evaluated and compared through benchmark studies. From the 121 objective PCQA benchmarks we analyzed, almost all were using Pearson's linear correlation coefficient (PLCC) and Spearman's rank-



order correlation coefficient (SROCC) to assess the performance of metrics. More than half (70 out of 121) also use the root mean square error (RMSE), 23 use Kendall's rank-order correlation coefficient (KROCC), and 21 use the outlier ratio (OR). The most often assessed metrics in these benchmarks are either standardized point-based metrics (Alexiou and Ebrahimi, 2018c; Tian et al., 2017) not well performing but used as references, or state-of-the-art metrics that were shown to have high correlation with subjective ratings. These non-standard most assessed metrics are PCQM (Meynet et al., 2020), PointSSIM (Alexiou and Ebrahimi, 2020) and GraphSIM (Yang et al., 2022b) (Graph-based metric using Graph Signal Processing to connect the points and define local regions to evaluate). These are all FR metrics. Despite the presence of inconsistencies in benchmarks on the same datasets, these three metrics are shown to be among the best on average. For NR and RR metrics, the most often used are BQE-CVP (Hua et al., 2021), PCM-RR (Viola and Cesar, 2020), 3D-NSS (Zhang et al., 2022), IT-PCQA (Yang et al., 2022a) and MM-PCQA (Zhang et al., 2023b), with the best performing being BQE-CVP and 3D-NSS. They have been shown to not be inferior to FR metrics. Some more recent metrics among the new best performing will likely be used often in future studies are MS-PointSSIM (Lazzarotto and Ebrahimi, 2023) and MS-GraphSIM (Zhang et al., 2021) (multi-scale versions of previously cited metrics), MPED (Yang et al., 2022c), and GMS-3DQA (NR metric). Table 3 lists the best performing metrics according to the literature with the ratio of datasets on which they were shown to perform well by benchmarks and the categories they correspond to.

Among the aforementioned NR metrics, there are also projection-based metrics (Hua et al., 2021; Yang et al., 2022a). But for FR metrics, the most popular state-of-the-art methods are all 3D-based despite an important number of well performing projection-based methods that have equivalent performance (Liu et al., 2023b; Wu et al., 2021; Yang et al., 2021). This is because, for FR PCQA, objective studies were using image-quality metrics (IQM) computed on self-defined projections in early studies and still tend to do so because they were shown to rival the

best 3D-based PCQA metrics. The most efficient and popular IQMs used in PCQA studies are VIF (Sheikh and Bovik, 2006) and IW-SSIM (Wang and Li, 2010). VMAF, not mentioned in the survey of Yingjie et al. (2023), is a weighted combination of several IQMs and a state-of-the-art tool that performs well for video QA. In PCQA, it also outperforms most state-of-the-art 3D-based methods in a recent benchmark (Ak et al., 2024). The performance of these IQM for PCQA still depends on the selected viewpoints to assess (Alexiou and Ebrahimi, 2017b) and the score pooling method (Freitas et al. (2022b; a)). It has also been observed that IQMs and projection-based metrics in general are better at predicting the quality of PCs when they represent inanimate objects (Ak et al., 2024; Wang and Li, 2010). For virtual humans content, saliency and spatial features play a too important role in subjective QA, which is why the best performing metrics for this category are 3D feature-based perceptual metrics. For colored PCs representing buildings or places (captured with LiDARs + photogrammetry), projection-based metrics performances are not satisfying enough, and should not be considered for such large and sparse geometric data.

Because to consider the scope of a metric in its performance assessment is essential, some of the benchmarks, to this end and to avoid bias, use cross-dataset evaluation. However, out of 54 cross-dataset benchmarks, 36 oppose datasets with various reference stimuli. For the others, the ground-truth ratings of all used datasets are for stimuli of the same sources (MPEG and JPEG repositories). Among the 36 benchmarks that use datasets with varied sources, 33 include ground-truth scores collected in different interaction conditions (passive and active tasks, 2D and XR displays). However, no benchmark assesses the performance of metrics on XR datasets for D-PCs.

4 Discussion

Based on the results of our analysis, we identify the current progress and tendencies in subjective and objective PCQA, and discuss our research questions listed in the Introduction.

TABLE 3 Most cited and well performing objective quality metrics from different categories. The last column is the ratio of datasets validating the metrics (where $PLCC > 0.7$ and $SROCC > 0.7$ on average) among the 12 most popular.

Metric	References	Categories	Performance
p2poMSE (Tian et al., 2017)	FR	3D-based, MSE-based	7/12
PCQM (Meynet et al., 2020)	FR	3D-based, Learning-based, Perceptual-based	7/10
GraphSIM (Yang et al., 2022b)	FR	3D-based, Graph-based	6/8
PointSSIM (Geom) (Alexiou and Ebrahimi, 2020)	FR	3D-based	6/8
MS-GraphSIM (Zhang et al., 2021)	FR	3D-based, Graph-based, Learning-based	2/3
MS-PointSSIM (Lazzarotto and Ebrahimi, 2023)	FR	3D-based, Learning-based	2/2
PCM-RR (Viola and Cesar, 2020)	RR	3D-based, Learning-based	2/6
IT-PCQA (Yang et al., 2022a)	NR	Projection-based, Learning-based	4/7
3D-NSS (Zhang et al., 2022)	NR	3D-based, Learning-based	2/4
BQE-CVP (Hua et al., 2021)	NR	3D-based, Projection-based, Perceptual-based	6/7
IW-SSIM (Liu et al., 2023b)	FR	IQM	4/5
VIF (Sheikh and Bovik, 2006)	FR	IQM	3/6
VMAF (Li et al., 2016)	FR	IQM, Learning-based	2/2

4.1 Considering XR and more IFs in subjective PCQA

From our observations on subjective PCQA, we can deduce that experiments have evolved toward two main categories: passive tasks with 2D display, and active tasks with HMDs. In both cases, it is mostly compression distortion that is studied and evaluated. For 2D experiments, the CTC of JPEG Pleno are followed. They have the advantage of resulting in less outliers and are less demanding in observers to achieve significant results. They can also be conducted through crowdsourcing, which led to an interest and increase in remote experiments during and after the covid-19 pandemic and lockdowns. 2D tests are less demanding in observers to achieve significant results, thanks to the well defined conditions and simple tasks. Such experiments allow to easily obtain meaningful and exploitable MOS, but are very limiting in terms of context. The CTC do not allow consideration of all IFs exclusive to the target applications. With 2D displays, the CTC imply a passive rating task, with no observer interaction. Tests with interactive interfaces in 2D are becoming less and less popular, as the influence of interaction is being studied with immersive displays instead. Tests in XR environments do not have the limits of passive 2D experiments and have conditions closer to the target use cases, which allows to study dynamic content and the influence of real viewing conditions on the perceived quality. However, the freedom (mostly 6DoF) it gives to users results in a higher inter-observers variability and a more important need in participants. PCQA (and 3DQA in general) in XR do not have any CTC to follow, since they have yet to be defined. Tests in XR have become essential to identify and investigate numerous IFs that have only recently become research interests.

In subjective QoE assessment, experiments have to target specific IFs to evaluate. In regards of our Research Question n°1, the investigated IFs in subjective PCQA so far are:

1. The semantic category of content represented in the stimuli: people (dynamic or static), animals, objects, buildings, landscapes. . .
2. The type of display (2D screen, 3D stereo, ELFD, or HMD).
3. The quality level (from compression or other types of distortion) of the stimulus, and quality switches (for PC streaming).
4. The viewing distance between the observer and the display (for 2D display experiments) and/or between the viewpoint and the stimulus.
5. The rendering method (point-based or surface-based, with or without shading, point size, . . .).

Considering Research Question n°2, there are other and new found IFs that have just recently become subjects of evaluation or have not yet been investigated. The lighting of the environment and shading of the stimuli with point-based rendering (Javaheri et al., 2021a; Tious et al., 2023) have been looked into only in very few studies, and not enough to draw conclusions. The orientation (Vanhoeve et al., 2017) and intensity (Gutiérrez et al., 2020) of lighting were shown to have an impact on the visual quality in mesh QA. The shading for point-based rendering is computed and executed differently than for standard surface shading. To compute the lighting intensity of points, the normals (3D normal vector to the points surface) are necessary attributes. As mentioned in the results, Javaheri et al. (2021a) compares the subjective QA of PCs rendered with a reconstructed shaded surface and rendered as lit points, but uses normals that were re-estimated after the compression distortion to light the points. It does not consider the case of decoded normals distorted by compression as an attribute, like the point cloud colors. To consider more attributes in PCC in order to improve the quality of rendered point clouds (Tious et al., 2024), as well as evaluating such compression and render pipelines, is therefore a new coming challenge in PCQA.

Other surface properties could be set as attributes in a PC just as the normals (like the metalness, smoothness, transparency, or emission of points) and could also be used to optimize point-based rendering. Therefore their transmission or estimation could also be investigated and considered in future PCQA studies. The compression distortion of these attributes having an impact on point-based rendering also implies that further comparisons with mesh rendering (surface-based) are needed. Evaluating PCs with attributes and geometry distorted by PCC and meshes distorted by mesh codecs in this context will allow us to compare them as 3D representations of data and go toward optimization of volumetric objects and video rendering.

Another IF that has just recently become a focus and constitutes a current challenge is the observers behavior and gaze data. The results of experiments in which such data were collected (Gutiérrez et al., 2023; Rossi et al., 2022; Zhou et al., 2023d) have yet to be exploited. As concluded in these papers, further studies are needed to understand the impact of the QA task on the exploration behavior of observers. Tests with more semantic categories of content and spatial exploration are also needed as, so far, gaze and behavior data were only collected for the D-PCs of MPEG-I.

4.2 Developing and evaluating versatile QA metrics

In this subsection, we bring elements of answers to our Research Question n°2 about objective PCQA. As mentioned, objective QA performance studies tend to use IQMs rather than objective metrics designed for PCQA. The metric considered and shown to be the best performing, in correlation with standard subjective QA scores, is the learning-based PCQM (Meynet et al., 2020). However, this metric only accounts for the raw point cloud data (point coordinates and colors) in its score computation and can therefore not consider IFs such as rendering and display distortions. To consider various types of distortions and factors other than coding artifacts, IQMs or projection-based PCQA metrics should be used. The difference between IQMs and projection-based PCQA metrics is actually just that in projection-based PCQA, the type of projection is defined and generated as part of the metric score computation. The performance of IQMs can still vary depending on the type of projection used. Alexiou and Ebrahimi (2017b) study the number and type of viewpoints needed for IQMs to perform well in correlation with subjective QA scores. They conclude with suggestions that fit different semantic content categories but are not exhaustive, and do not consider D-PCs. Further and more complete benchmark studies for IQMs and projection-based metrics, notably including VMAF, will therefore help in improving PCQA for more IFs and types of distortion.

Development of learning-based metrics has brought tremendous improvement to PCQA, and the recent release of large-scale PCQA datasets for QA model training (Ak et al., 2024; Liu Y. et al., 2023) is encouraging further progress. Among the best performing learning-based examples are metrics that are also perceptual-based, another important category and axis for development. Examples of the most common extracted visual features (Meynet et al., 2020; Alexiou et al., 2023b) in the computation of these metric scores are: the chroma, hue and

lightness of points in order to characterize the texture; and the surface normals, the curvature, the roughness, the omni-variance, the planarity, and the sphericity in order to characterize the geometry. Those features are evaluated and weighted in a global quality score. Another important perceptual feature that can be used to weigh the points or faces of the assessed objects is their saliency, predicted by visual attention models (Zhou W. et al., 2023; Wang et al., 2023c). Predicting visual attention to improve objective QA is already a challenging focus for other types of media. Only few PCQA metrics use this perceptual feature, yet it could be efficient in order to increase correlation with subjective QA scores using interactive display or XR, and therefore closer to a description of the visual quality as would be experienced in context of application.

Besides, regarding the quality of objective prediction, we have noticed that no benchmark assesses the state-of-the-art metrics when compared to data from a test in XR for D-PCs. With the recent release of such datasets (Zhou et al., 2023d; Nguyen et al., 2024; 2023a), more benchmarks filling this gap should soon be published and potentially reveal a new challenge for objective PCQA. Another not yet much explored aspect of the performance of metrics is not only their prediction accuracy, but also their runtime. In-pipeline QA for real-time transmission is a hot research topic that motivates the development of new NR metrics. There are nearly as many NR metrics than FR metrics and, as can be seen in Figure 6, the large majority of developed metrics in the latest years are NR. The challenge of performant NR PCQA, as can be shown by the numerous metrics of this type from the last few years, is an active focus for the research community. However, to fit the target use cases, it should bring about a next challenge, which is timely efficient quality predictions.

Objective PCQA metrics, in general, should also be more diligently assessed in terms of prediction accuracy in order to identify and account for their scope. To this end, more versatile ground-truth datasets should be used and developed.

4.3 Standardizing new CTC

The most used experiment parameters and tools in practice that we identified from the results of our analysis are the CTC and recommendations of JPEG Pleno (Stuart, 2021). Indeed, the majority of subjective PCQA studies were using 2D displays with rotating camera videos of the stimuli rendered as watertight points, and the DSIS rating methodology. The reference PCs, static or dynamic, were taken from the MPEG and JPEG Pleno repositories and were distorted using the MPEG PCC standards using quality parameters defined in (Stuart, 2021). For objective QA, the most cited and assessed metrics are the point-to-point, point-to-plane (Tian et al., 2017) and plane-to-plane (Alexiou and Ebrahimi, 2018c) measures which are also recommended by JPEG. These metrics are however always shown to be among the least efficient and only measure geometry (or only texture for the attribute point-to-point) distortions.

These CTC do not fit to the evaluation of all IFs, and particularly not to the experiments in XR. The interactivity and 6DoF that XR applications offer cannot and should not be neglected in PCQA. Until now, such experiments followed only a few recommendations from standards for other types of tests (ITU-T Recommendation

P.919 (2020); ITU-R Recommendation BT.500-14 (2019)) but these cannot exhaustively define CTC for all immersive QA experiments. To answer Research Question n°3, all parameters that are not given by the current standards or are unfit for PCQA have yet to be defined (rendering, virtual scene, rating methodology). So far, popular conditions for PCQA in XR seem to be a 6DoF environment, using the ACR methodology (Gutiérrez et al., 2023). But more tests in XR are needed to go toward the definition of a standard. Parameters such as the visual settings of HMDs, and the boundaries of user-freedom have not been addressed in studies. Further experiments are needed to compare all possible conditions and eventually establish new CTC for subjective PCQA in XR.

Regarding objective QA standards, PCQM (the best performing and most versatile FR PCQA metric) has recently been added to a JPEG recommendation (Cruz, 2024). Judging from the latest trends in objective PCQA studies, The next challenge in standardization should be going toward another CTC definition specific to blind PCQA, which would include NR metrics to be used in use case applications. As mentioned earlier, there is still progress to make in the evaluation of such metrics. A call for proposals would encourage further progress and assessment in the field.

4.4 Considering a larger range of use cases in QoE assessment

Finally, in this subsection, we consider Research Question n°4. In this systematic review, we wrote an overview of the results and observations made in subjective PCQA studies, including a regard on the performance of PCC standards and learning-based schemes. As we noted previously, the PCC codecs that offer the best visual quality are not designed and optimized for real-time transmission (Subramanyam et al., 2022a). However, the codecs used instead in a real-time scenario (Draco and CWI-PL) result in significantly less visual quality than V-PCC for the same bitrates (Zhou et al., 2023; Wu et al., 2023). The most recent standardized learning-based PCC schemes are not yet out-performing V-PCC either (Lazzarotto et al., 2024). There is a need thus for new or updated codecs that allow real-time transmission and state-of-the-art visual quality, which is a challenge currently addressed by standardization groups. Emerging PCC schemes, like the recent JPEG Pleno PCC standard Guarda et al. (2022), could also aim to fulfill this need.

Additionally, we have mentioned that rendering options for PCs could be improved by using new attributes such as the normals that could be encoded and decoded like the colors. Most learning-based PCC methods (Wang et al., 2021; Ak et al., 2024) only encode the geometry, and the reference softwares of standards only consider the colors as attributes. Implementing the encoding and decoding of more PC attributes is another horizon of progress that could improve PCs as a representation for 3D data. However, the possible steps forward in PCC need to be identified as first, which is already an upcoming challenge. Codec prototypes and their evaluation through PCQA is first needed to identify the attributes to consider for these upgrades.

Finally, another noticeable loophole in PCQA is the availability of diverse sources of content and materials. For QA of static and single frame PCs, there are many large datasets with PCs representing content from a great variety of semantic categories

and with a large range of textures and geometries. The same observation cannot be made for D-PCs. All freely available source sequences for QA of D-PCs represent single virtual humans with limited movement in space and time (generally stationary and only 10 s). The test sequences from 8i and Vsense are the same sources that are used in almost subjective QA studies on D-PCs. Volumetric videos in XR do not have to be limited to representing only humans. Immersive and interactive movies have complex dynamic scenes with accessories and scenery that virtual humans interact with. Other sources, such as UVG-VPC (Gautier et al., 2023) and CWIPC-SXR (Reimat et al., 2021) have yet to be used in more experiments, to bring diversity to dynamic test data and prevent content bias. More content is needed to assess the performance of PCC codecs and PCQA methods and tools for the future. Additionally, the capture and publication of new open access point cloud sequences that represent more various scenes, people interacting with each other or with objects, or moving objects alone, would fill this hole and allow research in PCC and PCQA in context of a greater variety of use cases.

5 Conclusion

In this paper, we made an overview and analysis of subjective and objective point cloud visual quality assessment. To this end, we conducted a systematic review of 154 selected papers presenting experiments, tools and methods in the research field, representing its evolution and history throughout the last decade. After a statistical analysis of our set of selected papers, we discussed the trends, further improvements and challenges they imply.

The field of PCQA has come a long way since the first versions of its related standards. The current CTC for subjective experiments, even though massively adopted and efficient in terms of cost and methodology, are not up to date anymore and cannot apply to the testing of new scenarios and IFs of interest, notably for QA in XR. The standard objective PCQA metrics have been by far surpassed in performance by recent alternatives, among which the most promising are learning-based, perceptual-based and no-reference metrics. Ideally, new standardization efforts in both PCQA and PCC for XR and real-time applications should be considered.

Ongoing and next steps in PCQA toward high quality volumetric content in XR applications could be further works with subjective studies in order to investigate influential factors such as: the exploration behavior and visual attention of observers; the rendering methods and the shading of PCs; and to evaluate new PCC codecs, notably learning-based methods (including the recently standardized JPEG Pleno codec (Guarda et al., 2022)), in terms of visual quality and efficiency. Regarding objective PCQA, the focus is and will be on feature selection and weighting (using visual attention data for instance) for perceptual learning-based metrics. Progress is also needed in PCQA metric performance evaluation, in terms of runtime for NR metrics that aim at fitting the case of real-time transmission and in-pipeline QA, and in terms of prediction accuracy. For the latter, more versatile and diverse subjective QA ground-truth data, such as BASICS dataset, need to be collected and made freely available, cultivating the circle of dependency between research in subjective and objective PCQA.

Author contributions

AT: Conceptualization, Data curation, Formal Analysis, Investigation, Visualization, Writing—original draft, Writing—review and editing. TV: Funding acquisition, Supervision, Validation, Writing—review and editing. VR: Funding acquisition, Supervision, Validation, Writing—review and editing.

Funding

The author(s) declare that no financial support was received for the research, authorship, and/or publication of this article.

References

- Ak, A., Zerman, E., Ling, S., Le Callet, P., and Smolic, A. (2021). "The effect of temporal sub-sampling on the accuracy of volumetric video quality assessment," in *2021 picture coding symposium (PCS)*, 1–5. doi:10.1109/PCS50896.2021.9477449
- Ak, A., Zerman, E., Quach, M., Chetouani, A., Smolic, A., Valenzise, G., et al. (2024). BASICS: broad quality assessment of static point clouds in a compression scenario. *IEEE Trans. Multimedia* 26, 6730–6742. doi:10.1109/TMM.2024.3355642
- Alexiou, E., and Ebrahimi, T. (2017a). "On subjective and objective quality evaluation of point cloud geometry," in *2017 ninth international conference on quality of Multimedia experience (QoMEX)*, 1–3. doi:10.1109/QoMEX.2017.7965681
- Alexiou, E., and Ebrahimi, T. (2017b). On the performance of metrics to predict quality in point cloud representations. *Appl. Digital Image Process. XL (SPIE)* 10396, 53–297. doi:10.1117/12.2275142
- Alexiou, E., and Ebrahimi, T. (2018a). "Benchmarking of objective quality metrics for colorless point clouds," in *2018 picture coding symposium (PCS)*, 51–55. doi:10.1109/PCS.2018.8456252
- Alexiou, E., and Ebrahimi, T. (2018b). "Impact of visualisation strategy for subjective quality assessment of point clouds," in *2018 IEEE international conference on Multimedia and expo workshops (ICMEW)*, 1–6. doi:10.1109/ICMEW.2018.8551498
- Alexiou, E., and Ebrahimi, T. (2018c). "Point cloud quality assessment metric based on angular similarity," in *2018 IEEE international conference on Multimedia and expo (ICME)*, 1–6. doi:10.1109/ICME.2018.8486512
- Alexiou, E., and Ebrahimi, T. (2019). "Exploiting user interactivity in quality assessment of point cloud imaging," in *2019 eleventh international conference on quality of Multimedia experience (QoMEX)*, 1–6. doi:10.1109/QoMEX.2019.8743277
- Alexiou, E., and Ebrahimi, T. (2020). "Towards a point cloud structural similarity metric," in *2020 IEEE international conference on Multimedia and expo workshops (ICMEW)*, 1–6. doi:10.1109/ICMEW46912.2020.9106005
- Alexiou, E., Ebrahimi, T., Bernardo, M. V., Pereira, M., Pinheiro, A., Da Silva Cruz, L. A., et al. (2018a). "Point cloud subjective evaluation methodology based on 2D rendering," in *2018 tenth international conference on quality of Multimedia experience (QoMEX)*, 1–6. doi:10.1109/QoMEX.2018.8463406
- Alexiou, E., Nehmé, Y., Zerman, E., Viola, I., Lavoué, G., Ak, A., et al. (2023a). "Subjective and objective quality assessment for volumetric video," in *Immersive video technologies* (Elsevier), 501–552.
- Alexiou, E., Pinheiro, A. M. G., Duarte, C., Matković, D., Dumić, E., Cruz, L. A. d. S., et al. (2018b). Point cloud subjective evaluation methodology based on reconstructed surfaces. *Appl. Digital Image Process. XLI (SPIE)* 10752, 160–173. doi:10.1117/12.2321518
- Alexiou, E., Upenik, E., and Ebrahimi, T. (2017). "Towards subjective quality assessment of point cloud imaging in augmented reality," in *2017 IEEE 19th international workshop on Multimedia signal processing (MMSP)*, 1–6. doi:10.1109/MMSP.2017.8122237
- Alexiou, E., Viola, I., Borges, T. M., Fonseca, T. A., Queiroz, R. L. d., and Ebrahimi, T. (2019). A comprehensive study of the rate-distortion performance in MPEG point cloud compression. *APSIPA Trans. Signal Inf. Process.* 8, e27. doi:10.1017/ATSIP.2019.20
- Alexiou, E., Yang, N., and Ebrahimi, T. (2020). "PointXR: a toolbox for visualization and subjective evaluation of point clouds in virtual reality," in *2020 twelfth international conference on quality of Multimedia experience (QoMEX)*, 1–6. doi:10.1109/QoMEX48832.2020.9123121
- Alexiou, E., Zhou, X., Viola, I., and Cesar, P. (2023b). PointPCA: point cloud objective quality assessment using PCA-based descriptors. doi:10.48550/arXiv.2111.12663
- Baek, A., Kim, M., Son, S., Ahn, S., Seo, J., Kim, H. Y., et al. (2023). Visual quality assessment of point clouds compared to natural reference images. *J. Web Eng.* 22, 405–432. doi:10.13052/jwe1540-9589.2232
- Bourbia, S., Karine, A., Chetouani, A., and El Hassouni, M. (2022a). "Blind projection-based 3D point cloud quality assessment method using a convolutional neural network," in *Proceedings of the 17th international joint Conference on computer vision, Imaging and computer graphics Theory and applications online streaming — select a country — (Lisboa, Portugal: SCITEPRESS - Science and Technology Publications)*, 518–525. doi:10.5220/0010872700003124
- Bourbia, S., Karine, A., Chetouani, A., El Hassouni, M., and Jridi, M. (2022b). "No-Reference point clouds quality assessment using transformer and visual saliency," in *Proceedings of the 2nd Workshop on Quality of Experience in visual Multimedia applications (lisboa Portugal: ACM)* (Lisboa, Portugal: QoEVMA '22), 57–62. doi:10.1145/3552469.3555713
- Bourbia, S., Karine, A., Chetouani, A., Hassouni, M. E., and Jridi, M. (2023). No-reference 3D point cloud quality assessment using multi-view projection and deep convolutional neural network. *IEEE Access* 11, 26759–26772. doi:10.1109/ACCESS.2023.3247191
- Cao, K., Xu, Y., and Cosman, P. (2020). Visual quality of compressed mesh and point cloud sequences. *IEEE Access* 8, 171203–171217. doi:10.1109/ACCESS.2020.3024633
- Chai, X., Shao, F., Mu, B., Chen, H., Jiang, Q., and Ho, Y.-S. (2024). Plain-PCQA: No-reference point cloud quality assessment by analysis of Plain visual and geometrical components. *IEEE Trans. Circuits Syst. Video Technol.* 34, 6207–6223. doi:10.1109/TCSVT.2024.3350180
- Chen, T., Long, C., Su, H., Chen, L., Chi, J., Pan, Z., et al. (2021). Layered projection-based quality assessment of 3D point clouds. *IEEE Access* 9, 88108–88120. doi:10.1109/ACCESS.2021.3087183
- Chen, Z., Wan, S., and Yang, F. (2023). "Impact of geometry and attribute distortion in subjective quality of point clouds for G-PCC," in *2023 IEEE international conference on visual communications and image processing (VCIP)*, 1–5. doi:10.1109/VCIP59821.2023.10402708
- Cheng, J., Su, H., and Korhonen, J. (2023). "No-reference point cloud quality assessment via weighted patch quality prediction," in *35th international conference on software engineering and knowledge engineering, SEKE 2023*, 298–303. doi:10.18293/SEKE2023-185
- Chetouani, A., Quach, M., Valenzise, G., and Dufaux, F. (2021a). "Convolutional neural network for 3D point cloud quality assessment with reference," in *2021 IEEE 23rd international workshop on Multimedia signal processing (MMSP)*, 1–6. doi:10.1109/MMSP53017.2021.9733565
- Chetouani, A., Quach, M., Valenzise, G., and Dufaux, F. (2021b). "Deep learning-based quality assessment of 3d point clouds without reference," in *2021 IEEE international conference on Multimedia and expo workshops (ICMEW)*, 1–6. doi:10.1109/ICMEW53276.2021.9455967
- Chetouani, A., Quach, M., Valenzise, G., and Dufaux, F. (2022). Learning-based 3D point cloud quality assessment using a support vector regressor. *Electron. Imaging* 34, 385-1–385-5. doi:10.2352/EI.2022.34.9.IQSP-385
- Coelho, L., Guarda, A. F. R., and Pereira, F. (2022). "Deep learning-based point cloud joint geometry and color coding: designing a perceptually-driven differentiable training distortion metric," in *2022 IEEE eighth international conference on Multimedia big data (BigMM)*, 21–28. doi:10.1109/BigMM55396.2022.00011
- Cox, S. R., Lim, M., and Ooi, W. T. (2023). "VOLVQAD: an MPEG V-PCC volumetric video quality assessment dataset," in *Proceedings of the 14th conference*

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

on *ACM Multimedia systems* (New York, NY, USA: Association for Computing Machinery), MMSys '23), 357–362. doi:10.1145/3587819.3592543

Cruz, L. A. d. S. (2024). JPEG pleno point cloud coding common training and test conditions v2.0. *ISO/IEC JTC 1/SC 29/WG1 100738*

da Silva Cruz, L. A., Dumić, E., Alexiou, E., Prazeres, J., Duarte, R., Pereira, M., et al. (2019). “Point cloud quality evaluation: towards a definition for test conditions,” in *2019 eleventh international conference on quality of Multimedia experience (QoMEX)*, 1–6. doi:10.1109/QoMEX.2019.8743258

Diniz, R., Freitas, P. G., and Farias, M. (2021a). A novel point cloud quality assessment metric based on perceptual color distance patterns. *Electron. Imaging* 33, 256–1–256–11. doi:10.2352/ISSN.2470-1173.2021.9.IQSP-256

Diniz, R., Freitas, P. G., and Farias, M. C. (2020a). “Local luminance patterns for point cloud quality assessment,” in *2020 IEEE 22nd international workshop on Multimedia signal processing (MMSP)*, 1–6. doi:10.1109/MMSP48831.2020.9287154

Diniz, R., Freitas, P. G., and Farias, M. C. (2020b). “Multi-distance point cloud quality assessment,” in *2020 IEEE international conference on image processing (ICIP)*, 3443–3447. doi:10.1109/ICIP40778.2020.9190956

Diniz, R., Freitas, P. G., and Farias, M. C. Q. (2020c). “Towards a point cloud quality assessment model using local binary patterns,” in *2020 twelfth international conference on quality of Multimedia experience (QoMEX)*, 1–6. doi:10.1109/QoMEX48832.2020.9123076

Diniz, R., Freitas, P. G., and Farias, M. C. Q. (2021b). Color and geometry texture descriptors for point-cloud quality assessment. *IEEE Signal Process. Lett.* 28, 1150–1154. doi:10.1109/LSP.2021.3088059

Diniz, R., Garcia Freitas, P., and Farias, M. C. Q. (2022). Point cloud quality assessment based on geometry-aware texture descriptors. *Comput. and Graph.* 103, 31–44. doi:10.1016/j.cag.2022.01.003

Dong, T., Kim, K., and Jang, E. S. (2021). Performance evaluation of the codec agnostic approach in MPEG-I video-based point cloud compression. *IEEE Access* 9, 167990–168003. doi:10.1109/ACCESS.2021.3137036

Dumić, E., Battisti, F., Carli, M., and da Silva Cruz, L. A. (2021). “Point cloud visualization methods: a study on subjective preferences,” in *2020 28th European signal processing conference (EUSIPCO)*, 595–599. doi:10.23919/Eusipco47968.2020.9287504

Dumić, E., and da Silva Cruz, L. A. (2020). Point cloud coding solutions, subjective assessment and objective measures: a case study. *Symmetry* 12, 1955. doi:10.3390/sym12121955

Dumić, E., and da Silva Cruz, L. A. (2023). Subjective quality assessment of V-PCC-Compressed dynamic point clouds degraded by packet losses. *Sensors* 23, 5623. doi:10.3390/s23125623

Dumić, E., Duarte, C. R., and da Silva Cruz, L. A. (2018). “Subjective evaluation and objective measures for point clouds — state of the art,” in *2018 first international colloquium on smart grid metrology (SmaGriMet)*, 1–5. doi:10.23919/SMAGRIMET.2018.8369848

Fan, C., Zhang, Y., Zhu, L., and Wu, X. (2024). PCQD-AR: subjective quality assessment of compressed point clouds with head-mounted augmented reality. *Electron. Lett.* 60, e13134. doi:10.1049/ell2.13134

Fan, S., and Gao, W. (2023). “Screen-based 3D subjective experiment software,” in *Proceedings of the 31st ACM international conference on Multimedia* (New York, NY, USA: Association for Computing Machinery), MM '23), 9672–9675. doi:10.1145/3581783.3613457

Fan, Y., Zhang, Z., Sun, W., Min, X., Lin, J., Zhai, G., et al. (2023). “MV-VVQA: multi-view learning for No-reference volumetric video quality assessment,” in *2023 31st European signal processing conference (EUSIPCO)*, 670–674. doi:10.23919/EUSIPCO58844.2023.10290018

Fan, Y., Zhang, Z., Sun, W., Min, X., Liu, N., Zhou, Q., et al. (2022). “A No-reference quality assessment metric for point cloud based on captured video sequences,” in *2022 IEEE 24th international workshop on Multimedia signal processing (MMSP)*, 1–5. doi:10.1109/MMSP55362.2022.9949359

Freitas, P. G., Gonçalves, M., Homonnai, J., Diniz, R., and Farias, M. C. (2022a). “On the performance of temporal pooling methods for quality assessment of dynamic point clouds,” in *2022 14th international conference on quality of Multimedia experience (QoMEX)*, 1–6. doi:10.1109/QoMEX55416.2022.9900906

Freitas, P. G., Lucafo, G. D., Gonçalves, M., Homonnai, J., Diniz, R., and Farias, M. C. (2022b). “Comparative evaluation of temporal pooling methods for No-reference quality assessment of dynamic point clouds,” in *Proceedings of the 1st workshop on photorealistic image and environment synthesis for Multimedia experiments (lisboa Portugal: ACM)* (Lisboa, Portugal: PIES-ME '22), 35–41. doi:10.1145/3552482.3556552

Freitas, X. G., Diniz, R., and Farias, M. C. Q. (2023). Point cloud quality assessment: unifying projection, geometry, and texture similarity. *Vis. Comput.* 39, 1907–1914. doi:10.1007/s00371-022-02454-w

Fretes, H., Gomez-Redondo, M., Paiva, E., Rodas, J., and Gregor, R. (2019). “A review of existing evaluation methods for point clouds quality,” in *2019 workshop on research, education and development of unmanned aerial systems (RED UAS)*, 247–252. doi:10.1109/REDUAS47371.2019.8999725

Fu, C., Zhang, X., Nguyen-Canh, T., Xu, X., Li, G., and Liu, S. (2023). “Surface-sampling based objective quality assessment metrics for meshes,” in *Icassp 2023 -*

2023 IEEE international conference on acoustics, speech and signal processing (ICASSP), 1–5. doi:10.1109/ICASSP49357.2023.10096048

Gautier, G., Mercat, A., Fréneau, L., Pitkänen, M., and Vanne, J. (2023). “Uvg-vpc: voxelized point cloud dataset for visual volumetric video-based coding,” in *2023 15th international conference on quality of Multimedia experience (QoMEX)* (IEEE), 244–247.

Guarda, A. F., Rodrigues, N. M., Ruivo, M., Coelho, L., Selem, A., and Pereira, F. (2022). It/ist/ipleiria response to the call for proposals on jpeg pleno point cloud coding. *arXiv Prepr. arXiv:2208.02716*.

Gutiérrez, J., Dandyyeva, G., Magro, M. D., Cortés, C., Brizzi, M., Carli, M., et al. (2023). “Subjective evaluation of dynamic point clouds: impact of compression and exploration behavior,” in *2023 31st European signal processing conference (EUSIPCO)*, 675–679. doi:10.23919/EUSIPCO58844.2023.10290086

Gutiérrez, J., Vigier, T., and Le Callet, P. (2020). Quality evaluation of 3D objects in mixed reality for different lighting conditions. *Electron. Imaging* 32, 128–1–128–7. doi:10.2352/ISSN.2470-1173.2020.11.HVEI-128

He, Z., Jiang, G., Jiang, Z., and Yu, M. (2021). “Towards A colored point cloud quality assessment method using colored texture and curvature projection,” in *2021 IEEE international conference on image processing (ICIP)*, 1444–1448. doi:10.1109/ICIP42928.2021.9506762

He, Z., Jiang, G., Yu, M., Jiang, Z., Peng, Z., and Chen, F. (2022). TGP-PCQA: texture and geometry projection based quality assessment for colored point clouds. *J. Vis. Commun. Image Represent.* 83, 103449. doi:10.1016/j.jvcir.2022.103449

Hua, L., Jiang, G., Yu, M., and He, Z. (2021). “BQE-CVP: blind quality evaluator for colored point cloud based on visual perception,” in *2021 IEEE international symposium on broadband Multimedia systems and broadcasting (BMSB)*, 1–6. doi:10.1109/BMSB53066.2021.9547070

Hua, L., Yu, M., He, Z., Tu, R., and Jiang, G. (2022). CPC-GSCT: visual quality assessment for coloured point cloud based on geometric segmentation and colour transformation. *IET Image Process.* 16, 1083–1095. doi:10.1049/ipr2.12211

Huang, Q., He, L., Xie, S., Xu, Y., and Song, J. (2019). “Rate allocation for unequal error protection in dynamic point cloud,” in *2019 IEEE international symposium on broadband Multimedia systems and broadcasting (BMSB)*, 1–5. doi:10.1109/BMSB47279.2019.8971855

ISO/IEC 23090-5 (2023). Information technology—coded representation of immersive media—part 5: visual volumetric video-based coding (V3C) and video-based point cloud compression (V-PCC). International Organization for Standardization.

ISO/IEC 23090-9 (2021). Information technology—coded representation of 3D point clouds—part 9: geometry-based point cloud compression (G-PCC). International Organization for Standardization

ITU-R Recommendation BT (2019). *Methodology for the subjective assessment of the quality of television pictures*, 500–14.

ITU-T Recommendation P (2020). Subjective test methodologies for 360° video on head-mounted displays

Javaheri, A., Brites, C., Pereira, F., and Ascenso, J. (2017a). “Subjective and objective quality evaluation of 3D point cloud denoising algorithms,” in *2017 IEEE international conference on Multimedia and expo workshops (ICMEW)*, 1–6. doi:10.1109/ICMEW.2017.8026263

Javaheri, A., Brites, C., Pereira, F., and Ascenso, J. (2017b). “Subjective and objective quality evaluation of compressed point clouds,” in *2017 IEEE 19th international workshop on Multimedia signal processing (MMSP)*, 1–6. doi:10.1109/MMSP.2017.8122239

Javaheri, A., Brites, C., Pereira, F., and Ascenso, J. (2020a). “A generalized hausdorff distance based quality metric for point cloud geometry,” in *2020 twelfth international conference on quality of Multimedia experience (QoMEX)*, 1–6. doi:10.1109/QoMEX48832.2020.9123087

Javaheri, A., Brites, C., Pereira, F., and Ascenso, J. (2020b). “Improving psnr-based quality metrics performance for point cloud geometry,” in *2020 IEEE international conference on image processing (ICIP)*, 3438–3442. doi:10.1109/ICIP40778.2020.9191233

Javaheri, A., Brites, C., Pereira, F., and Ascenso, J. (2020c). Mahalanobis based point to distribution metric for point cloud geometry quality evaluation. *IEEE Signal Process. Lett.* 27, 1350–1354. doi:10.1109/LSP.2020.3010128

Javaheri, A., Brites, C., Pereira, F., and Ascenso, J. (2021a). Point cloud rendering after coding: impacts on subjective and objective quality. *IEEE Trans. Multimedia* 23, 4049–4064. doi:10.1109/TMM.2020.3037481

Javaheri, A., Brites, C., Pereira, F., and Ascenso, J. (2021b). “A point-to-distribution joint geometry and color metric for point cloud quality assessment,” in *2021 IEEE 23rd international workshop on Multimedia signal processing (MMSP)*, 1–6. doi:10.1109/MMSP53017.2021.9733670

Javaheri, A., Brites, C., Pereira, F., and Ascenso, J. (2022). Joint geometry and color projection-based point cloud quality metric. *IEEE Access* 10, 90481–90497. doi:10.1109/ACCESS.2022.3198995

Kazhdan, M., Bolitho, M., and Hoppe, H. (2006). “Poisson surface reconstruction,” in *Proceedings of the fourth Eurographics symposium on Geometry processing* (Goslar, Germany: SGP '06), 61–70.

- Krivokuća, M., Chou, P. A., and Savill, P. (2018). 8i voxelized surface light field 8ivslf
- Laazoufi, A., and El Hassouni, M. (2022). "Saliency-based point cloud quality assessment method using Mahalanobis distance," in *2022 9th international conference on wireless networks and mobile communications (WINCOM)*, 1–5. doi:10.1109/WINCOM55661.2022.9966464
- Laazoufi, A., Hassouni, M. E., and Cherifi, H. (2022). "3D point cloud quality assessment method using Mahalanobis distance," in *2022 16th international conference on signal-image Technology and internet-based systems (SITIS)*, 616–621. doi:10.1109/SITIS57111.2022.00097
- Lazarotto, D., Alexiou, E., and Ebrahimi, T. (2021). "Benchmarking of objective quality metrics for point cloud compression," in *2021 IEEE 23rd international workshop on Multimedia signal processing (MMSP)*, 1–6. doi:10.1109/MMSP53017.2021.9733538
- Lazarotto, D., and Ebrahimi, T. (2023). "Towards a multiscale point cloud structural similarity metric," in *2023 IEEE 25th international workshop on Multimedia signal processing (MMSP)*, 1–6. doi:10.1109/MMSP59012.2023.10337634
- Lazarotto, D., Testolina, M., and Ebrahimi, T. (2022a). "Influence of spatial rendering on the performance of point cloud objective quality metrics," in *2022 10th European workshop on visual information processing (EUVIP)*, 1–6. doi:10.1109/EUVIP53989.2022.9922737
- Lazarotto, D., Testolina, M., and Ebrahimi, T. (2022b). "On the impact of spatial rendering on point cloud subjective visual quality assessment," in *2022 14th international conference on quality of Multimedia experience (QoMEX)* (Lippstadt, Germany: IEEE), 1–6. doi:10.1109/QoMEX55416.2022.9900898
- Lazarotto, D., Testolina, M., and Ebrahimi, T. (2024). Subjective performance evaluation of bitrate allocation strategies for MPEG and JPEG Pleno point cloud compression. *J. Image Video Process.* 2024, 14. doi:10.1186/s13640-024-00629-0
- Li, Z., Aaron, A., Katsavounidis, I., Moorthy, A., and Manohara, M. (2016). Toward a practical perceptual video quality metric. *Netflix Tech Blog* 6, 2.
- Liang, Q., He, Z., Yu, M., Luo, T., and Xu, H. (2023). MFE-net: a multi-layer feature extraction network for No-reference quality assessment of 3-D point clouds. *IEEE Trans. Broadcast.* 70, 265–277. doi:10.1109/TBC.2023.3311339
- Liu, Q., Su, H., Chen, T., Yuan, H., and Hamzaoui, R. (2023a). No-reference bitstream-layer model for perceptual quality assessment of V-PCC encoded point clouds. *IEEE Trans. Multimedia* 25, 4533–4546. doi:10.1109/TMM.2022.3177926
- Liu, Q., Su, H., Duanmu, Z., Liu, W., and Wang, Z. (2023b). Perceptual quality assessment of colored 3D point clouds. *IEEE Trans. Vis. Comput. Graph.* 29, 3642–3655. doi:10.1109/TVCG.2022.3167151
- Liu, Q., Yuan, H., Hamzaoui, R., Su, H., Hou, J., and Yang, H. (2021a). Reduced reference perceptual quality model with application to rate control for video-based point cloud compression. *IEEE Trans. Image Process.* 30, 6623–6636. doi:10.1109/TIP.2021.3096060
- Liu, Q., Yuan, H., Su, H., Liu, H., Wang, Y., Yang, H., et al. (2021b). PQA-net: deep No reference point cloud quality assessment via multi-view projection. *IEEE Trans. Circuits Syst. Video Technol.* 31, 4645–4660. doi:10.1109/TCSVT.2021.3100282
- Liu, Y., Yang, Q., and Xu, Y. (2022). "Reduced reference quality assessment for point cloud compression," in *2022 IEEE international conference on visual communications and image processing (VCIP)*, 1–5. doi:10.1109/VCIP56404.2022.10008813
- Liu, Y., Yang, Q., Xu, Y., and Ma, Z. (2021c). Which one is better: assessing objective metrics for point cloud compression. doi:10.48550/arXiv.2109.07158
- Liu, Y., Yang, Q., Xu, Y., and Yang, L. (2023c). Point cloud quality assessment: dataset construction and learning-based No-reference metric. *ACM Trans. Multimedia Comput. Commun. Appl.* 19 (80), 1–26. doi:10.1145/3550274
- Lu, Z., Huang, H., Zeng, H., Hou, J., and Ma, K.-K. (2022). Point cloud quality assessment via 3D edge similarity measurement. *IEEE Signal Process. Lett.* 29, 1804–1808. doi:10.1109/LSP.2022.3198601
- Marvie, J.-E., Nehmé, Y., Graziosi, D., and Lavoué, G. (2023). Crafting the MPEG metrics for objective and perceptual quality assessment of volumetric videos. *Qual. User Exp.* 8, 4. doi:10.1007/s41233-023-00057-4
- Mekuria, R., Blom, K., and Cesar, P. (2017). Design, implementation, and evaluation of a point cloud codec for tele-immersive video. *IEEE Trans. Circuits Syst. Video Technol.* 27, 828–842. doi:10.1109/TCSVT.2016.2543039
- Mekuria, R., Cesar, P., Doumanis, I., and Frisliello, A. (2015). Objective and subjective quality assessment of geometry compression of reconstructed 3D humans in a 3D virtual room. *Appl. Digital Image Process. XXXVIII (SPIE)* 9599, 537–549. doi:10.1117/12.2203312
- Messai, O., Bentamou, A., Zein-Eddine, A., and Gavet, Y. (2023). "Activating frequency and VIT for 3D point cloud quality assessment without reference," in *2023 IEEE international conference on image processing challenges and workshops (ICIPCW)*, 3636–3640. doi:10.1109/ICIPCW59416.2023.10328373
- Meynet, G., Digne, J., and Lavoué, G. (2019). "PC-MSDM: a quality metric for 3D point clouds," in *2019 eleventh international conference on quality of Multimedia experience (QoMEX)*, 1–3. doi:10.1109/QoMEX.2019.8743313
- Meynet, G., Nehmé, Y., Digne, J., and Lavoué, G. (2020). "PCQM: a full-reference quality metric for colored 3D point clouds," in *2020 twelfth international conference on quality of Multimedia experience (QoMEX)*, 1–6. doi:10.1109/QoMEX48832.2020.9123147
- Mildenhall, B., Srinivasan, P. P., Tancik, M., Barron, J. T., Ramamoorthi, R., and Ng, R. (2021). NeRF: representing scenes as neural radiance fields for view synthesis. *Commun. ACM* 65, 99–106. doi:10.1145/3503250
- Mu, B., Shao, F., Chai, X., Liu, Q., Chen, H., and Jiang, Q. (2023). Multi-view aggregation transformer for no-reference point cloud quality assessment. *Displays* 78, 102450. doi:10.1016/j.displa.2023.102450
- Nguyen, M., Vats, S., van Damme, S., van der Hooft, J., Vega, M. T., Wauters, T., et al. (2023a). Characterization of the quality of experience and immersion of point cloud videos in augmented reality through a subjective study. *IEEE Access* 11, 128898–128910. doi:10.1109/ACCESS.2023.3326374
- Nguyen, M., Vats, S., Van Damme, S., Van Der Hooft, J., Vega, M. T., Wauters, T., et al. (2023b). "Impact of quality and distance on the perception of point clouds in mixed reality," in *2023 15th international conference on quality of Multimedia experience (QoMEX)*, 87–90. doi:10.1109/QoMEX58391.2023.10178491
- Nguyen, M., Vats, S., Zhou, X., Viola, I., Cesar, P., Timmerer, C., et al. (2024). "Compeq-mr: compressed point cloud dataset with eye tracking and quality assessment in mixed reality," in *Proceedings of the 15th ACM Multimedia systems conference*, 367–373.
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ* 372, n71. doi:10.1136/bmj.n71
- Perry, S. (2022). JPEG pleno point cloud use cases and requirements, v1.6. *ISO/IEC JTC 1/SC 29/WG1* 100096
- Perry, S., Cong, H. P., da Silva Cruz, L. A., Prazeres, J., Pereira, M., Pinheiro, A., et al. (2020). "Quality evaluation of static point clouds encoded using MPEG codecs," in *2020 IEEE international conference on image processing (ICIP)*, 3428–3432. doi:10.1109/ICIP40778.2020.9191308
- Perry, S., Da Silva Cruz, L. A., Dumic, E., Thi Nguyen, N. H., Pinheiro, A., and Alexiou, E. (2021). "Comparison of remote subjective assessment strategies in the context of the JPEG pleno point cloud activity," in *2021 IEEE 23rd international workshop on Multimedia signal processing (MMSP)*, 1–6. doi:10.1109/MMSP53017.2021.9733709
- Perry, S., Da Silva Cruz, L. A., Prazeres, J., Pinheiro, A., Dumic, E., Lazarotto, D., et al. (2022). "Subjective and objective testing in support of the JPEG pleno point cloud compression activity," in *2022 10th European workshop on visual information processing (EUVIP)*, 1–6. doi:10.1109/EUVIP53989.2022.9922803
- Perry, S., Pinheiro, A., Dumic, E., and da Silva Cruz, L. A. (2019). Study of subjective and objective quality evaluation of 3D point cloud data by the JPEG committee. *Image Qual. Syst. Perform.* XVI 31, 312-1–312-7. doi:10.2352/issn.2470-1173.2019.10.iqsp-312
- Prazeres, J., Luo, Z., Pinheiro, A. M. G., da Silva Cruz, L. A., and Perry, S. (2023). "JPEG pleno call for proposals responses quality assessment," in *Icassp 2023 - 2023 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, 1–5. doi:10.1109/ICASSP49357.2023.10094713
- Prazeres, J., Pereira, M., and Pinheiro, A. M. G. (2022a). Quality analysis of point cloud coding solutions. *IET Image Process. IS&T Int. Symposium Electron. Imaging* 34, 225-1–225-6. doi:10.2352/EI.2022.34.17.3DIA-225
- Prazeres, J., Pereira, M., and Pinheiro, A. M. G. (2022b). "Subjective quality evaluation of point clouds with 3D stereoscopic visualization," in *2022 IEEE international conference on image processing (ICIP)*, 2861–2865. doi:10.1109/ICIP46576.2022.9897937
- Prazeres, J., Rodrigues, R., Pereira, M., and Pinheiro, A. M. G. (2022c). "Quality evaluation of machine learning-based point cloud coding solutions," in *Proceedings of the 1st international workshop on advances in point cloud compression, processing and analysis (lisboa Portugal: ACM) (APCCPA '22)*, 57–65. doi:10.1145/3552457.3555730
- Quach, M., Chetouani, A., Valenzise, G., and Dufaux, F. (2021). A deep perceptual metric for 3D point clouds. *Electron. Imaging* 33, 257-1–257-7. doi:10.2352/issn.2470-1173.2021.9.iqsp-257
- Reimat, I., Alexiou, E., Jansen, J., Viola, I., Subramanyam, S., and Cesar, P. (2021). "Cwpc-sxr: point cloud dynamic human dataset for social xr," in *Proceedings of the 12th ACM Multimedia systems conference* (New York, NY, USA: Association for Computing Machinery, MMSys '21), 300–306. doi:10.1145/3458305.3478452
- Riache, S., Larabi, M., and Deriche, M. (2023). "Blind quality assessment of point clouds based on 3D Co-occurrence statistics," in *2023 IEEE international conference on Multimedia and expo workshops (ICMEW)*, 452–457. doi:10.1109/ICMEW59549.2023.00084
- Rossi, S., Viola, I., and Cesar, P. (2022). "Behavioural analysis in a 6-DoF VR system: influence of content, quality and user disposition," in *Proceedings of the 1st workshop on interactive eXtended reality* (New York, NY, USA: Association for Computing Machinery, IXR '22), 3–10. doi:10.1145/3552483.3556454
- Schwarz, S., Preda, M., Baroncini, V., Budagavi, M., Cesar, P., Chou, P. A., et al. (2019). Emerging MPEG standards for point cloud compression. *IEEE J. Emerg. Sel. Top. Circuits Syst.* 9, 133–148. doi:10.1109/JETCAS.2018.2885981

- Shan, Z., Yang, Q., Ye, R., Zhang, Y., Xu, Y., Xu, X., et al. (2023). GPA-Net: No-Reference point cloud quality assessment with multi-task Graph convolutional network. *IEEE Trans. Vis. Comput. Graph.* 30, 4955–4967. doi:10.1109/TVCG.2023.3282802
- Sheikh, H. R., and Bovik, A. C. (2006). Image information and visual quality. *IEEE Trans. Image Process.* 15, 430–444. doi:10.1109/tip.2005.859378
- Singla, A., Wang, S., Göring, S., Rao, R. R. R., Viola, I., Cesar, P., et al. (2023). “Subjective quality evaluation of point clouds using remote testing,” in *Proceedings of the 2nd international workshop on interactive eXtended reality* (New York, NY, USA: Association for Computing Machinery), 21–28. doi:10.1145/3607546.3616803
- Smitskamp, G., Viola, I., and Cesar, P. (2023). “Evaluation of point cloud features for no-reference visual quality assessment,” in *2023 15th international conference on quality of Multimedia experience (QoMEX)*, 147–152. doi:10.1109/QoMEX58391.2023.10178459
- Stuart, P. (2021). JPEG pleno point cloud coding common test conditions v3.6
- Su, H., Duanmu, Z., Liu, W., Liu, Q., and Wang, Z. (2019). “Perceptual quality assessment of 3d point clouds,” in *2019 IEEE international conference on image processing (ICIP)*, 3182–3186. doi:10.1109/ICIP.2019.8803298
- Su, H., Liu, Q., Liu, Y., Yuan, H., Yang, H., Pan, Z., et al. (2023a). Bitstream-based perceptual quality assessment of compressed 3D point clouds. *IEEE Trans. Image Process.* 32, 1815–1828. doi:10.1109/TIP.2023.3253252
- Su, H., Liu, Q., Yuan, H., Cheng, Q., and Hamzaoui, R. (2023b). Support vector regression-based reduced-reference perceptual quality model for compressed point clouds. *IEEE Trans. Multimedia* 26, 6238–6249. doi:10.1109/TMM.2023.3347638
- Subramanyam, S., Li, J., Viola, I., and Cesar, P. (2020). “Comparing the quality of highly realistic digital humans in 3DoF and 6DoF: a volumetric video case study,” in *2020 IEEE conference on virtual reality and 3D user interfaces (VR)*, 127–136. doi:10.1109/VR46266.2020.00031
- Subramanyam, S., Viola, I., Jansen, J., Alexiou, E., Hanjalic, A., and Cesar, P. (2022a). “Evaluating the impact of tiled user-adaptive real-time point cloud streaming on VR remote communication,” in *Proceedings of the 30th ACM international conference on Multimedia* (New York, NY, USA: Association for Computing Machinery), MM ’22), 3094–3103. doi:10.1145/3503161.3548220
- Subramanyam, S., Viola, I., Jansen, J., Alexiou, E., Hanjalic, A., and Cesar, P. (2022b). “Subjective QoE evaluation of user-centered adaptive streaming of dynamic point clouds,” in *2022 14th international conference on quality of Multimedia experience (QoMEX)*, 1–6. doi:10.1109/QoMEX55416.2022.9900879
- Themistocleous, K. (2018). Digitization issues in documenting cultural heritage with drones: case study of foinikas, Cyprus. *Earth Resour. Environ. Remote Sensing/GIS Appl. IX* 13, 13. doi:10.1117/12.2325459
- Tian, D., Ochimizu, H., Feng, C., Cohen, R., and Vetro, A. (2017). “Geometric distortion metrics for point cloud compression,” in *2017 IEEE international conference on image processing (ICIP)*, 3460–3464. doi:10.1109/ICIP.2017.8296925
- Tious, A., Vigier, T., and Ricordel, V. (2023). “Physically-based lighting of 3d point clouds for quality assessment,” in *Proceedings of the 2023 ACM international conference on interactive media experiences*, 423–426.
- Tious, A., Vigier, T., and Ricordel, V. (2024). Impact of point cloud normals compression on objective quality assessment, *32nd European Signal Processing Conference, EUSIPCO*, 531–535.
- Tliba, M., Chetouani, A., Valenzise, G., and Dufaux, F. (2022a). “Point cloud quality assessment using cross-correlation of deep features,” in *Proceedings of the 2nd workshop on quality of experience in visual Multimedia applications* (New York, NY, USA: Association for Computing Machinery, QoEVMMA ’22), 63–68. doi:10.1145/3552469.3555710
- Tliba, M., Chetouani, A., Valenzise, G., and Dufaux, F. (2022b). “Representation learning optimization for 3D point cloud quality assessment without reference,” in *2022 IEEE international conference on image processing (ICIP)*, 3702–3706. doi:10.1109/ICIP46576.2022.9897689
- Tliba, M., Chetouani, A., Valenzise, G., and Dufaux, F. (2023a). “Multi-Modal evaluation of 3D point clouds images: a novel No-reference approach using a multi-stream attentive architecture,” in *2023 31st European signal processing conference (EUSIPCO)*, 680–684. doi:10.23919/EUSIPCO58844.2023.10290034
- Tliba, M., Chetouani, A., Valenzise, G., and Dufaux, F. (2023b). “PCQA-graphpoint: efficient deep-based Graph metric for point cloud quality assessment,” in *Icassp 2023 - 2023 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, 1–5. doi:10.1109/ICASSP49357.2023.10096610
- Torlig, E. M., Alexiou, E., Fonseca, T. A., Queiroz, R. L. d., and Ebrahimi, T. (2018). A novel methodology for quality assessment of voxelized point clouds. *Appl. Digital Image Process. XLI (SPIE)* 10752, 18–190. doi:10.1117/12.2322741
- Tu, R., Jiang, G., Yu, M., Luo, T., Peng, Z., and Chen, F. (2023a). V-PCC projection based blind point cloud quality assessment for compression distortion. *IEEE Trans. Emerg. Top. Comput. Intell.* 7, 462–473. doi:10.1109/TETCI.2022.3201619
- Tu, R., Jiang, G., Yu, M., Zhang, Y., Luo, T., and Zhu, Z. (2023b). Pseudo-reference point cloud quality measurement based on joint 2-D and 3-D distortion description. *IEEE Trans. Instrum. Meas.* 72, 1–14. doi:10.1109/TIM.2023.3290291
- Van Damme, S., Mahdi, I., Ravuri, H. K., van der Hooft, J., De Turck, F., and Vega, M. T. (2023). “Immersive and interactive subjective quality assessment of dynamic volumetric meshes,” in *2023 15th international conference on quality of Multimedia experience (QoMEX)*, 141–146. doi:10.1109/QoMEX58391.2023.10178610
- Van Damme, S., Torres Vega, M., van der Hooft, J., and De Turck, F. (2022). “Clustering-based psychometric No-reference quality model for point cloud video,” in *2022 IEEE international conference on image processing (ICIP)*, 1866–1870. doi:10.1109/ICIP46576.2022.9897602
- van der Hooft, J., Vega, M. T., Timmerer, C., Begen, A. C., De Turck, F., and Schatz, R. (2020). “Objective and subjective QoE evaluation for adaptive point cloud streaming,” in *2020 twelfth international conference on quality of Multimedia experience (QoMEX)*, 1–6. doi:10.1109/QoMEX48832.2020.9123081
- Vanhoeve, K., Sauvage, B., Kraemer, P., and Lavoué, G. (2017). Visual quality assessment of 3D models: on the influence of light-material interaction. *ACM Trans. Appl. Percept.* 15 (5), 1–18. doi:10.1145/3129505
- Vats, S., Nguyen, M., Van Damme, S., van der Hooft, J., Vega, M. T., Wauters, T., et al. (2023). “A platform for subjective quality assessment in mixed reality environments,” in *2023 15th international conference on quality of Multimedia experience (QoMEX)*, 131–134. doi:10.1109/QoMEX58391.2023.10178443
- Viola, I., and Cesar, P. (2020). A reduced reference metric for visual quality evaluation of point cloud contents. *IEEE Signal Process. Lett.* 27, 1660–1664. doi:10.1109/LSP.2020.3024065
- Viola, I., Subramanyam, S., and Cesar, P. (2020). “A color-based objective quality metric for point cloud contents,” in *2020 twelfth international conference on quality of Multimedia experience (QoMEX)*, 1–6. doi:10.1109/QoMEX48832.2020.9123089
- Viola, I., Subramanyam, S., Li, J., and Cesar, P. (2022). On the impact of VR assessment on the quality of experience of highly realistic digital humans. *Qual. User Exp.* 7, 3. doi:10.1007/s41233-022-00050-3
- Wang, J., Gao, W., and Li, G. (2023a). Applying collaborative adversarial learning to blind point cloud quality measurement. *IEEE Trans. Instrum. Meas.* 72, 1–15. doi:10.1109/TIM.2023.3322475
- Wang, J., Gao, W., and Li, G. (2024). Zoom to perceive better: No-reference point cloud quality assessment via exploring effective multiscale feature. *IEEE Trans. Circuits Syst. Video Technol.* 34, 6334–6346. doi:10.1109/TCSVT.2024.3362369
- Wang, J., Zhu, H., Ma, Z., Chen, T., Liu, H., and Shen, Q. (2021). Lossy point cloud geometry compression via end-to-end learning. *IEEE Trans. Circuits Syst. Video Technol.* 31, 4909–4923. doi:10.1109/TCSVT.2021.3051377
- Wang, S., Wang, X., Gao, H., and Xiong, J. (2023b). “Non-local geometry and color gradient aggregation Graph model for No-reference point cloud quality assessment,” in *Proceedings of the 31st ACM international Conference on Multimedia (ottawa on Canada: ACM)* (Ottawa, Canada: MM ’23), 6803–6810. doi:10.1145/3581783.3612169
- Wang, Z., and Li, Q. (2010). Information content weighting for perceptual image quality assessment. *IEEE Trans. Image Process.* 20, 1185–1198. doi:10.1109/TIP.2010.2092435
- Wang, Z., Zhang, Y., Yang, Q., Xu, Y., Sun, J., and Liu, S. (2023c). “Point cloud quality assessment using 3D saliency maps,” in *2023 IEEE international conference on visual communications and image processing (VCIP)*, 1–5. doi:10.1109/VCIP59821.2023.10402711
- Wang, Z., Zhang, Y., Yang, Q., Xu, Y., Zhou, Y., Sun, J., et al. (2023d). “Improving point cloud quality metrics with noticeable possibility maps,” in *2023 IEEE international conference on Multimedia and expo (ICME)*, 360–365. doi:10.1109/ICME55011.2023.00069
- Watanabe, R., Sridhara, S. N., Hong, H., Pavez, E., and Ortega, A. (2023). “ICIP 2023 challenge: full-reference and non-reference point cloud quality assessment methods with support vector regression,” in *2023 IEEE international conference on image processing challenges and workshops (ICIPCW)*, 3654–3658. doi:10.1109/ICIPCW59416.2023.10328379
- Weil, J., Alkhalili, Y., Tahir, A., Gruczyk, T., Meuser, T., Mu, M., et al. (2023). “Modeling quality of experience for compressed point cloud sequences based on a subjective study,” in *2023 15th international conference on quality of Multimedia experience (QoMEX)*, 135–140. doi:10.1109/QoMEX58391.2023.10178579
- Wu, C.-H., Hsu, C.-F., Hung, T.-K., Griwodz, C., Ooi, W. T., and Hsu, C.-H. (2023). Quantitative comparison of point cloud compression algorithms with PCC arena. *IEEE Trans. Multimedia* 25, 3073–3088. doi:10.1109/TMM.2022.3154927
- Wu, X., Zhang, Y., Fan, C., Hou, J., and Kwong, S. (2021). Subjective quality database and objective study of compressed point clouds with 6DoF head-mounted display. *IEEE Trans. Circuits Syst. Video Technol.* 31, 4630–4644. doi:10.1109/TCSVT.2021.3101484
- Xie, W., Wang, K., Ju, Y., and Wang, M. (2023). “pmbQA: projection-based blind point cloud quality assessment via multimodal learning,” in *Proceedings of the 31st ACM international conference on Multimedia* (New York, NY, USA: Association for Computing Machinery), MM ’23), 3250–3258. doi:10.1145/3581783.3611998
- Xiong, J., Wu, S., Luo, W., Suo, J., and Gao, H. (2023). “ψ-Net: point structural information network for No-reference point cloud quality assessment,” in *Icassp 2023 - 2023 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, 1–5. doi:10.1109/ICASSP49357.2023.10096258
- Xu, Y., Lu, Y., and Wen, Z. (2017). OwlII dynamic human mesh sequence dataset

- Xu, Y., Yang, Q., Yang, L., and Hwang, J.-N. (2022). EPES: point cloud quality modeling using elastic potential energy similarity. *IEEE Trans. Broadcast.* 68, 33–42. doi:10.1109/TBC.2021.3114510
- Yang, Q., Chen, H., Ma, Z., Xu, Y., Tang, R., and Sun, J. (2021). Predicting the perceptual quality of point cloud: a 3D-to-2D projection-based exploration. *IEEE Trans. Multimedia* 23, 3877–3891. doi:10.1109/TMM.2020.3033117
- Yang, Q., Liu, Y., Chen, S., Xu, Y., and Sun, J. (2022a). “No-reference point cloud quality assessment via domain adaptation,” in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 21179–21188.
- Yang, Q., Ma, Z., Xu, Y., Li, Z., and Sun, J. (2022b). Inferring point cloud quality via Graph similarity. *IEEE Trans. Pattern Analysis Mach. Intell.* 44, 3015–3029. doi:10.1109/TPAMI.2020.3047083
- Yang, Q., Zhang, Y., Chen, S., Xu, Y., Sun, J., and Ma, Z. (2022c). MPED: quantifying point cloud distortion based on multiscale potential energy discrepancy. *IEEE Trans. Pattern Analysis Mach. Intell.* 45, 6037–6054. doi:10.1109/TPAMI.2022.3213831
- Yingjie, Z., Zicheng, Z., Wei, S., Xiongkuo, M., and Guangtao, Z. (2023). Perceptual quality assessment for point clouds: a survey. *ZTE Commun.* 21. doi:10.12142/ZTECOM.202304002
- Zerman, E., Gao, P., Ozcinar, C., Smolic, A., Gao, P., Ozcinar, C., et al. (2019). Subjective and objective quality assessment for volumetric video compression. *Electron. Imaging* 31, 323-1–323-7. doi:10.2352/ISSN.2470-1173.2019.10.IQSP-323
- Zerman, E., Ozcinar, C., Gao, P., and Smolic, A. (2020). “Textured mesh vs coloured point cloud: a subjective study for volumetric video compression,” in *2020 twelfth international conference on quality of Multimedia experience (QoMEX)*, 1–6. doi:10.1109/QoMEX48832.2020.9123137
- Zhang, J., Huang, W., Zhu, X., and Hwang, J.-N. (2014). “A subjective quality evaluation for 3D point cloud models,” in *2014 international conference on audio, language and image processing*, 827–831. doi:10.1109/ICALIP.2014.7009910
- Zhang, Y., Yang, Q., and Xu, Y. (2021). “MS-GraphSIM: inferring point cloud quality via multiscale Graph similarity,” in *Proceedings of the 29th ACM international conference on Multimedia (virtual event China: ACM) (China: MM '21)*, 1230–1238. doi:10.1145/3474085.3475294
- Zhang, Y., Yang, Q., Zhou, Y., Xu, X., Yang, L., and Xu, Y. (2023a). TCDM: transformational complexity based distortion metric for perceptual point cloud quality assessment. *IEEE Trans. Vis. Comput. Graph.* 30, 6707–6724. doi:10.1109/TVCG.2023.3338359
- Zhang, Z., Sun, W., Min, X., Wang, Q., He, J., Zhou, Q., et al. (2023b). “MM-PCQA: multi-modal learning for no-reference point cloud quality assessment,” in *Proceedings of the thirty-second international joint conference on artificial intelligence (<conf-loc>, <city>Macao</city>, <country>P.R.China</country>, </conf-loc>)* (Macao, China: IJCAI '23), 1759–1767. doi:10.24963/ijcai.2023/195
- Zhang, Z., Sun, W., Min, X., Wang, T., Lu, W., and Zhai, G. (2022). No-reference quality assessment for 3D colored point cloud and mesh models. *IEEE Trans. Circuits Syst. Video Technol.* 32, 7618–7631. doi:10.1109/TCSVT.2022.3186894
- Zhang, Z., Sun, W., Wu, H., Zhou, Y., Li, C., Chen, Z., et al. (2024). GMS-3DQA: projection-based grid mini-patch sampling for 3D model quality assessment. *ACM Trans. Multimedia Comput. Commun. Appl.* 20 (178), 1–19. doi:10.1145/3643817
- Zhang, Z., Sun, W., Zhou, Y., Lu, W., Zhu, Y., Min, X., et al. (2023c). “EEP-3DQA: efficient and effective projection-based 3D model quality assessment,” in *2023 IEEE international conference on Multimedia and expo (ICME)*, 2483–2488. doi:10.1109/ICME55011.2023.00423
- Zhang, Z., Sun, W., Zhu, Y., Min, X., Wu, W., Chen, Y., et al. (2023d). Evaluating point cloud from moving camera videos: a No-reference metric. *IEEE Trans. Multimedia*, 1–13doi. doi:10.1109/TMM.2023.3340894
- Zhou, Q., Feng, A., Yang, T.-S., Liu, S., and Kuo, C.-C. J. (2023a). “BPQA: a blind point cloud quality assessment method,” in *2023 IEEE international conference on image processing challenges and workshops (ICIPCW)*, 1–5. doi:10.1109/ICIPCW59416.2023.10328342
- Zhou, W., Yue, G., Zhang, R., Qin, Y., and Liu, H. (2023b). Reduced-reference quality assessment of point clouds via content-oriented saliency projection. *IEEE Signal Process. Lett.* 30, 354–358. doi:10.1109/LSP.2023.3264105
- Zhou, X., Alexiou, E., Viola, I., and Cesar, P. (2023c). “PointPCA+: extending PointPCA objective quality assessment metric,” in *2023 IEEE international conference on image processing challenges and workshops (ICIPCW)*, 1–5. doi:10.1109/ICIPCW59416.2023.10328338
- Zhou, X., Viola, I., Alexiou, E., Jansen, J., and Cesar, P. (2023d). “QAVA-DPC: eye-tracking based quality assessment and visual attention dataset for dynamic point cloud in 6 DoF,” in *2023 IEEE international symposium on mixed and augmented reality (ISMAR)*, 69–78. doi:10.1109/ISMAR59233.2023.00021