3D Point-Cloud Quality Assessment Using Color and Geometry Texture Descriptors

Rafael Diniz (Author)†
Department of Computer Science
University of Brasília
Brasília, Brazil
rafael@riseup.net

Pedro Garcia Freitas (Co-advisor)
Department of Computer Science
University of Brasília
Brasília, Brazil
pedrogarcia@ieee.org

Mylène C.Q. Farias (Advisor)
Department of Electrical Engineering
University of Brasília
Brasília, Brazil
mylene@ieee.org

***Abstract*—Since the mid-20th century, the use of digital formats for visual content allowed a great evolution in how society communicates. The Internet and digital broadcast systems introduced in the decade 90 to the wider public allowed an incredible expansion of multimedia consumption by the people, while the telecommunication networks and providers were pushed to their limits to address the growing multimedia content demand. Older electronic imaging systems, notably TV broadcasting systems, were designed after long subjective quality analysis for the definition of parameters like the number of lines of the video. But recent digital visual content services need faster and more affordable ways of evaluating the human perceived quality of the always-evolving multimedia systems. To address the need for automatic quality assessment, in the past decades many visual quality models based on algorithms that run on digital computers have been proposed. While the existing models are remarkably advanced for 2D digital imagery, a new set of immersive media is dawning, with different data structures, to which the 2D methods are not applicable, and need novel quality assessment metrics. These novel dawning immersive media formats provide a 3D visual representation of real objects and scenes. In this new visual format, objects can be captured, compressed, transmitted, and visualized in real-time not anymore as a flat 2D image, but as 3D content, allowing free-viewpoint selection by a consumer of such media. One of the most popular formats for immersive media is Point Cloud (PC), which is composed of points with 3 geometry coordinates plus color information, and sometimes, other information like reflectance and transparency. This work presents a research on the quality assessment of 3D PC based on novel color and geometric texture statistics. Considering that distortions to both color and geometry attributes of 3D visual content affect the perceived visual quality, it is proposed in this work to use both color-based and geometry-based texture descriptors for PC to obtain the visual degradation through their statistics. This work introduces 4 novels PC texture descriptors, 3 of them color-based, while 1 is geometry-based. Also, a new voxelization method is proposed, which converts points to voxels (volume elements), and improves the performance of the color-based texture descriptors. The performance of the proposed PC quality assessment method is among the best of the state-of-the-art PC quality assessment methods while being flexible and extensible to adapt to different types of distortions.**

†This work relates to the **Ph.D. thesis** defended by Rafael Diniz. The official publication of this thesis is available at https://repositorio.unb.br/handle/10482/42224

I. Introduction

Visual quality assessment is an essential problem in computer vision. With the emergent interest in 3D visual media allowing more immersive experiences compared to the classical bidimensional (2D) media, novel methods are urgently demanded to assess the visual quality of 3D media since the well-established methods for 2D media are usually unsuccessful to evaluate these novel types of media. In this context, PCs are becoming an eminent tridimensional (3D) format of the real world due to the availability of various acquisition sensors as well as efficient rendering, processing, and compression techniques. PCs are sets of 3D points represented by their $\{x, y, z\}$ coordinates and associated attributes. These attributes can be color, normals, material reflectance, and more. Moreover, a PC the points and its attributes can vary on time or not. Static PCs correspond to a single time instant, i.e., points not varying in time. Dynamic PC contain points evolving along time, thus corresponding to a series of static PC frames.

PCs can contain several billions of points to represent a scene of the real world with high visual fidelity. This enormous quantity of points results in huge data amounts that must be efficiently compressed to be transmitted and stored. Therefore, to enable real PC applications, compression solutions are fundamental to deal with the data amount produced by the PC acquisition devices [1]. Thus, to attend to the demands by the industry for PC compression solutions, the Joint Photographics Experts Group (JPEG) and Moving Picture Experts Group (MPEG) committees developed a set of standards targeting the efficient representation of static and dynamic PCs [2]–[6]. These standards enable several applications that deliver PCs to the end-user in different ways, such as head-mounted displays (HMDs), stereoscopic or multi-stereoscopic displays, and augmented reality devices. However, independently of the type of display, a PC cannot be directly visualized but requires a rendering process to produce the visual data to be displayed in a screen for human viewers [7]–[9]. This rendering process may significantly influence the perceived PC quality in different ways.

From the capture to the display, the whole PC processing pipeline that includes denoising, coding, and rendering produces visual results that need to be accurately assessed

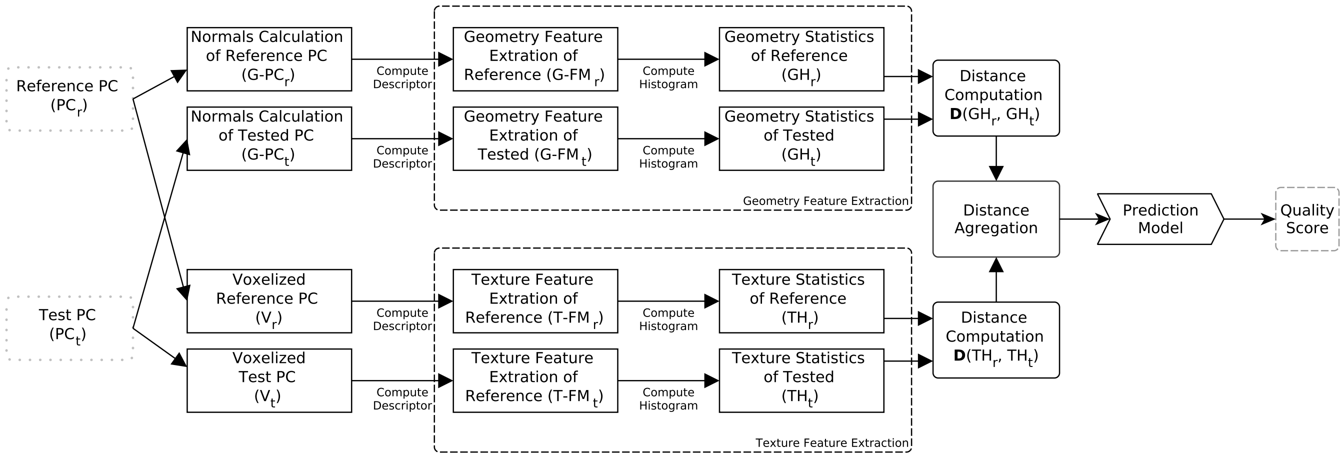


Fig. 1. Block diagram of the proposed framework for designing point cloud full-reference metrics.

in terms of the perceived quality. In other words, Point Cloud Quality Assessment (PCQA) is crucial to evaluate the performance of the various processing steps to improve the final Quality of Experience (QoE) offered to the end-users. Moreover, PCQA metrics are fundamental not only to monitor the quality of the experiences but also to allow the design and optimization of new PC applications. Based on this cruciality, pertinent works on objective and subjective quality assessment were proposed in the literature [1], [10]–[18]. Despite the efforts of the authors, these works bring insights and punctual understandings about specific aspects of PC quality. From the current literature, we can conclude that PCQA remains an open problem.

In order to contribute to the advancement of the PCQA area, this work addresses the problem of the PC quality assessment, through the development of a method that provides an objective Full-Reference (FR) PC quality assessment method with a good performance to any kind of content distortion. An objective metric should predict the quality of a given content automatically, without human intervention, while being a full-reference metric means the proposed metric considers the information of the original content and the distorted content to predict the quality, as close as possible to the human visual system perception. More specifically, we investigate the use of texture measures (or descriptors) in point cloud quality assessment methodologies. We chose to adopt a feature-based approach because this type of approach does not require assumptions about which types of artifacts (degradations) are present in the assessed stimuli or neither its semantic content. For this reason, the chosen approach is more general and can be more widely used in PC applications. Additionally, since PCs have two major components – geometry and texture –, we developed a set of geometry-based texture descriptors to better describe the quality properties.

This document summarizes the main contents of the Ph.D. thesis entitled "3D Point-Cloud Quality Assessment Using Color and Geometry Texture Descriptors", which was developed in the Department of Computer Science of the University of Brasília. In Section II, we describe the 3D quality assessment contributions of the thesis, containing all the proposed texture descriptors and PC quality assessment methods. Section III contains the experimental setup, simulation results, and comparisons of the proposed PCQA metrics and other state-of-the-art methods. The conclusions are presented in Section IV. Finally, we outline the accomplishments of this research in Section V.

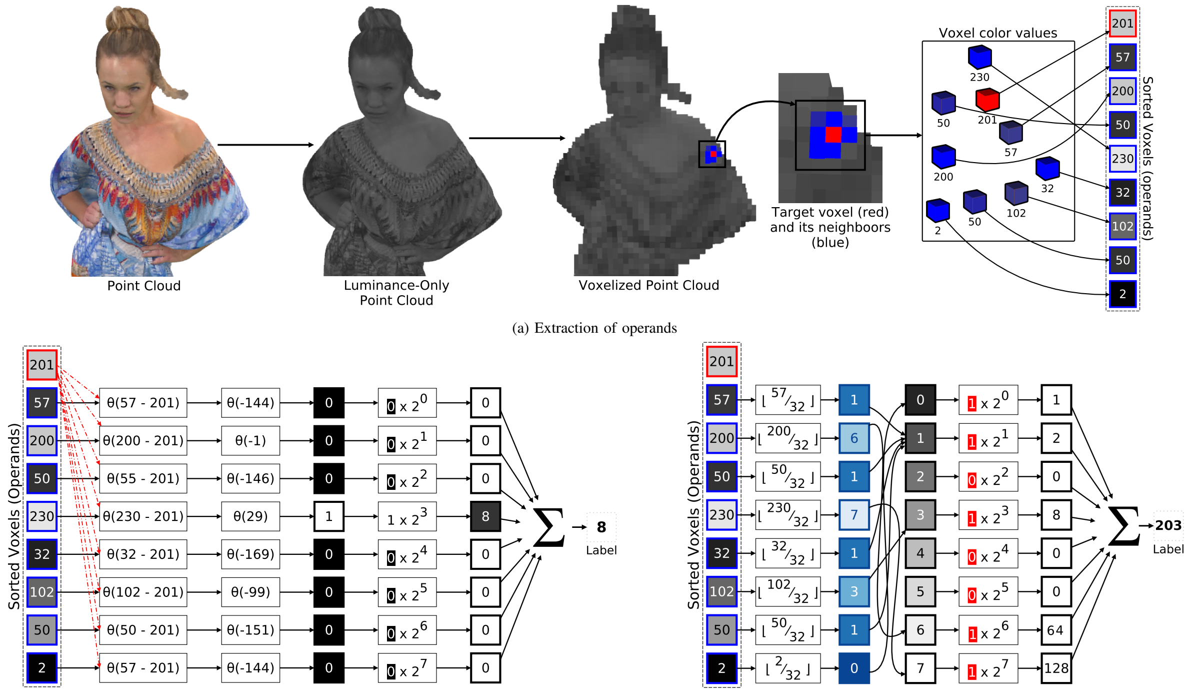
Fig. 2. Voxelization effect for very small (left), proper (middle), and oversized (right) voxel sizes.

II. Proposed Framework

In this thesis, we developed a general framework to create FR PCQA metrics based on local neighborhood feature extractors. Since PCs consist of texture and geometry per point, the main idea behind the proposed framework is to use color and geometry descriptors to independently extract PC features from the reference and test PCs. Figure 1 shows the block diagram of the proposed framework, which is divided into the following stages: (1) texture feature extraction, (2) geometry feature extraction, (3) computation of descriptors statistics and its distances, and (4) prediction model.

A. *Texture Feature Extraction*

The first step of texture feature extraction consists of PC voxelization. Voxelization is the process of converting data



(a) Extraction of operands

(b) Local Binary Pattern

(c) Local Color Pattern

Fig. 3. Feature descriptors computation steps: (a) extract of operands, (b) their use for computing LBP and (c) LCP.

structures that store geometric information into a rasterized representation (a discrete grid). Just like 2D images typically use square-shaped pixels, in PCs, the volumetric elements (voxels) typically adopt a cube shape. The voxels can be considered as discrete elements in a discrete 3D grid, but while in 2D images the discrete 2D space is dense, in PCs the 3D space is sparsely filled with voxels, which (typically) represent just the surface of objects. Figure 2 shows examples of a PC with 3 different voxel sizes for each of the three PC rendering examples. Important to note that, when the voxelization is applied for a given voxel size, more than one PC point might be present inside a single voxel. In this case, typically, the colors corresponding to these points are averaged to provide the final color value for the voxel. An algorithm to determine the best voxel size was developed in this work.

After voxelelizing the input point cloud, a proposed modification of the LBP descriptor is used to characterize the texture information. The LBP descriptor was designed for 2D images and operates considering the target pixel and a set of neighboring pixels, which are determined by a distance R. In 2D images, these neighbors can be sampled according to a geometric distribution in a 2D plane (e.g., circular, elliptical, etc). This sampling approach works because pixels in 2D images are equally distributed in a dense 2D grid. However, in PCs, the points are sparsely distributed in the 3D space, which makes the problem of determining the neighborhood for a LBP descriptor more complex. The challenge of dealing with point sparsity of PCs is dealt with the voxelization procedure, which optimally creates a neighborhood of discrete elements which are close enough to provide visually solid objects. Another challenge is the selection of the traversal order of neighbors, as the 2D equations for determining the traversal order do not apply in a 3D domain. To solve this challenge, a different approach is adopted, in which the distances between each neighbor and the central element are used to determine the traversal order, for example, from closest to farthest.

Figure 3-(a) shows the application of the LBP for a target voxel P(n) in the 3D space, showing the sampling of the nearest voxels to create the LBP neighborhood. The neighborhood is visited from closer to farther points, which results in a performance that is slightly better than the reverse order (as shown later in the text). This figure illustrates the case where the neighborhood of the target voxel has 8 voxels. Figure 3-(b) illustrates how the LBP label is obtained for a given PC element, considering example luminance values for the target element and neighbors. Similarly, Figure 3-(c) an additional texture descriptor called Local Luminance Pattern (LLP) that was proposed by us. The idea behind this descriptor is to obtain luminance patterns that are representative of intrinsic PC texture characteristics and that can be useful for quality estimation. Further to the LBP and LLP descriptors, we developed a number of descriptors that can be used in the proposed framework and are detailed in [19]–[24].

B. Geometry Feature Extraction

After testing the texture descriptors described in the last section, it became clear that the geometric information of a PC also plays a role in the perceived PC quality, as already evaluated by Alexiou et al. [11]. While the proposed texture-based descriptors can, to some extent, identify some geometric

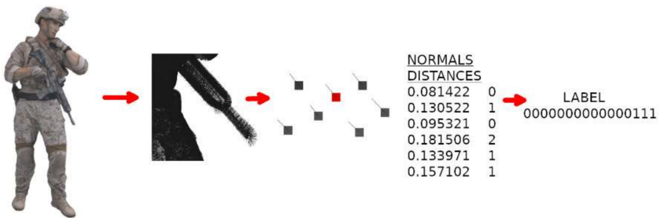


Fig. 4. Geometry-based descriptor with normal vectors as black lines.

distortions, they usually miss representing most geometric distortions. To deal with this limitation, we developed a geometry-based descriptor that considers the geometric information of the surface tangent to each PC point and its neighbors. In order to establish a relationship between each point and its neighborhood, the normal vector information is used. The normal vector of a PC point is the vector orthogonal to the point's local surface. Since typical PC capture devices do not capture normal vectors, only depth-plus-color information being generally available, the normal vectors need to be computed prior to the descriptor application.

The normal vectors are computed through the Eigenvectors from the covariance matrix of the local neighborhood 3D coordinates. For each PC point, this local neighborhood can have at most 16 points, which are located inside a maximum radius of 6 times the average distance of the 8 nearest neighbors. To overcome the fact that each PC point has 2 normal vectors that correctly represent the tangent plane, we orient the normals to an arbitrary direction, in order to remove ambiguities. In our case, we oriented all PC normals to the direction (0, 0, 1) and normalized the magnitude normal values to 1. A diagram of the geometry-based descriptor is shown in Figure 4. More details about this descriptor can be found in [23].

The proposed geometry-based texture descriptor complements the color-based descriptors in describing intrinsic features of PC, which can be used for PC Quality Assessment. The geometry-based texture descriptor has similarities to the color-based LLP and LCP descriptors, especially for the label construction, as all of them use an iterative algorithm that sets bits in a label according to each neighbor, but is independent of any order among the neighbors, providing rotation invariant descriptors. The main difference is that in the geometry-based descriptor, the voxelization step does not improve its performance, as it compromises and alters the geometry properties of a PC. The different behavior between color-based and geometry-based texture descriptors is expected and shows it is capturing different characteristics of a PC.

C. Computation of Descriptors Statistics and Its Distances

A full-reference PCQA metric compares reference and degraded PC characteristics. In the case of the PCQA method proposed in this thesis, the metric is based on the distance between histograms of the labels extracted from reference and test PC. This metric design based on the comparison of histograms presents some advantages. First, the divergence between the pristine (reference) and the assessed (distorted/processed) can be modeled using statistical distances. Second, the histograms of the proposed descriptors are very compact representations of visual information. This compactness enables reduced reference metric usage (for instance, the histogram associated with the reference can be sent in a transmission and the impaired content can still be assessed using only this histogram).

After computing the histograms of the reference and assessed PCs, these histograms are compared using a distance metric such as Euclidean, f-divergences (Kullback-Leibler, Hellinger, Total Variation, Jensen-Shannon, etc), Lévy–Prokhorov metric, Bray-Curtis, Canberra, Cityblock, Chebyshev, Cosine, Euclidean, Wasserstein, and Energy. The distance measure between PC histograms created by the proposed descriptors provide the value which is used to estimate the quality of a degraded PC. In this thesis we conducted a comprehensive experimental test to analyze the suitability of different distances to model PC quality.

D. Prediction Model

To predict the quality of a given visual content, it is typical to use a regression model to estimate the perceived quality. In quality assessment methodologies, the regression model is often used to adjust the subjective quality scores provided by the different quality datasets. In the case of the PCQA methodologies proposed in this thesis, the coefficients of the regression function obtained with data from subjective experiments are used to map the distances of the PC texture descriptor histograms (described in section 3.2). The mapping can also be applied to a combination of two or more histogram distances, providing a way to jointly use different PC texture descriptors for quality estimation.

The regression algorithm takes as input the distance of the histograms and maps it into an objective (predicted) quality score, using the available subjective Mean Opinion Scores (MOS) values as ground-truth values. Different regression models exist to map the distances D into objective quality scores. Some examples include the Random Forest Regressor, Extra Trees Regressor, Gradient Boosting Regressor, Bayesian Ridge, Elastic Net, Lasso, RANSAC Regressor, KNeighbors Regressor, MLP Regressor and the Logistic function, which is recommended by the International Telecommunication Union (ITU) tutorial about objective quality assessment. Regression maps the distance metrics into predicted quality scores and, therefore, simulates how human subjects perceive the different levels and types of distortions. To identify the best regression algorithm, we conducted a vast number of experiments that are detailed in the thesis and produced papers.

III. Experimental Results

During the conduction of the research that culminated in this thesis, we performed a series of experiments and much data amount was collected analyzed. Ours published papers [19]–[24] present several analyses of these experiments. In short, the proposed PC quality assessment metrics developed in

TABLE I
PERFORMANCE OF OUR METRIC PROPOSAL AND OTHER METRICS THE DIFFERENT DATASETS.

Metrics	Data Sets														
	D1			D2			D3			D4			Average		
	PCC	SROCC	RMSE	PCC	SROCC	RMSE	PCC	SROCC	RMSE	PCC	SROCC	RMSE	PCC	SROCC	RMSE
po2point_MSE	0.270	0.250	1.122	0.808	0.835	1.095	*0.941*	0.920	*0.534*	0.418	0.350	3.857	0.609	0.589	1.652
PSNR-po2point_MSE	0.518	0.484	*0.953*	0.494	0.430	1.352	0.538	0.549	1.025	0.470	0.376	3.832	0.505	0.460	1.791
po2point_Haus	0.270	0.215	1.122	0.627	0.421	1.282	0.496	0.446	1.024	0.261	0.224	3.900	0.414	0.327	1.832
PSNR-po2point_Haus	0.512	0.469	0.968	0.454	0.396	1.379	0.549	0.527	1.008	0.481	0.455	3.833	0.500	0.462	1.797
Color-YCbCr_MSE	0.383	0.367	1.039	0.553	0.571	1.333	0.755	0.682	0.921	0.500	0.512	3.822	0.548	0.533	1.779
PSNR-Color-YCbCr_MSE	0.368	0.337	1.097	0.536	0.565	1.351	0.793	0.801	0.797	0.504	0.503	*3.805*	0.550	0.552	1.763
Color-YCbCr_Haus	0.147	0.172	1.131	0.413	0.375	1.380	0.377	0.306	1.122	0.191	0.095	3.955	0.282	0.237	1.897
PSNR-Color-YCbCr_Haus	0.386	0.320	1.059	0.435	0.391	1.417	0.445	0.449	1.100	0.344	0.270	3.875	0.403	0.358	1.863
po2plane_MSE	0.270	0.275	1.122	*0.845*	0.858	**1.031**	**0.958**	*0.945*	**0.492**	0.432	0.370	3.859	0.626	0.612	*1.626*
PSNR-po2plane_MSE	0.484	0.421	0.984	0.499	0.495	1.361	0.542	0.579	1.021	0.380	0.390	3.893	0.476	0.471	1.815
po2plane_Hausdorff	0.270	0.247	1.122	0.604	0.427	1.267	0.586	0.418	0.981	0.223	0.188	3.990	0.421	0.320	1.840
PSNR-po2plane_Haus	0.440	0.408	1.016	0.428	0.367	1.394	0.497	0.463	1.034	0.464	0.451	3.836	0.457	0.422	1.820
PCQM	0.797	**0.898**	2.656	0.607	*0.915*	2.899	0.738	**0.970**	3.123	0.271	0.708	5.786	0.603	**0.873**	3.616
PointSSIM-Color	*0.842*	0.823	2.234	**0.910**	**0.918**	2.436	0.869	0.865	2.697	*0.676*	*0.682*	5.354	*0.824*	0.822	3.180
PointSSIM-Geometry	0.804	0.820	2.102	0.784	0.834	2.321	0.849	0.905	2.534	0.527	0.560	5.323	0.741	0.780	3.070
LCP + GEO (proposed)	**0.876**	*0.896*	**0.572**	0.819	0.839	1.068	0.936	0.932	0.544	**0.730**	**0.714**	**3.663**	**0.840**	*0.845*	**1.462**
LBP + GEO (proposed)	*0.845*	0.837	*0.620*	*0.845*	0.850	*1.037*	0.863	0.869	0.672	0.579	0.543	3.764	0.783	0.775	1.523
LLP + GEO (proposed)	0.790	0.795	0.702	0.812	0.822	1.077	0.873	0.877	0.651	0.672	0.660	3.705	0.787	0.789	1.534

this thesis were tested with a variety of PC datasets and compared to the state-of-the-art. The selected datasets and their associated subjective scores represent the most up-to-date and diverse datasets available in the literature [25]–[28]. More specifically, in this thesis, the dataset referred to as 'D1' was produced by Torlig et al. [25], 'D2' by Alexiou et al. [26], 'D3' the dataset by Stuart el at. [27], and 'D4' the dataset by Yang et al. [28]. It is worth mentioning that 'D2' and 'D3' contain only distortions from MPEG codecs, while 'D1' and 'D4' have a more distortion set.

Table I summarizes the results of the proposed and the state-of-the-art methods on the investigated datasets. The summarized results are reported using the Spearman's Rank Correlation Coefficient (SROCC), Pearson's Correlation Coefficient (PCC), and Root-Mean-Square Error (RMSE) statistical measures. These measures were chosen because they are under ITU recommendations for visual quality assessment [29]. The LCP combined with the geometry-based descriptor (LCP+GEO in the table), LBP combined with the geometry-based descriptor (LCP+GEO), and LLP combined with the geometry-based descriptor (LLP+GEO). The conditions the other metrics were evaluated were the same which were applied to the proposed methods, including the same PC source content, same normal vectors (for the metrics which need normals), and the logistic regressor. In this table, the best values in the table are shown in bold, while the second-best are shown in italic. The three last columns show the average values, which indicate clearly that the "LCP+GEO" metric has arguably the best performance, with averaged PCC of 0.840, an average SROCC of 0.845, and an average RMSE of 1.462. Also, the RMSE of the proposed method is by far the smallest.

IV. CONCLUSION

In this thesis, our goal was to investigate how to estimate the quality of point cloud data. In the proposed approach, visual quality methods were generated using geometry and texture measurements. We first presented a general framework to predict point cloud quality using a proposed modification of the LBP descriptor and some of its variants.

In short, the thesis at hand contributes to the fields of Multimedia, Computer Graphics, and Computer Vision with the following novelties:

- A parameterized voxelization method.
- Development of a set of extensions of the LBP descriptor for 3D data, which are designed to produce quality-aware features that are useful to predict visual quality.
- Proposal of a framework to estimate point cloud quality using texture descriptors.
- Development of a set of point cloud quality assessment metrics using the proposed framework.

The proposed solutions are generic enough to be used in multimedia applications that require a quality estimate for point cloud data, such as video compression, network transmission, streaming services, etc. In future work, other types of descriptors that produce texture features that are sensitive to other types of distortions (such as brightness, contrast, etc) can be designed using the proposed framework. Saliency-aware descriptors are also under investigation for even improving the currently proposed metrics.

V. RESEARCH ACCOMPLISHMENTS

As a result of the work produced in this Ph.D. dissertation, **8 papers** were produced and published in top-tier venues:

◇ Published Conference Papers:

C1: *"Real-time 3D volumetric human body reconstruction from a single view RGB-D capture device."* – Electronic Imaging, 2019 – **Not Classified in Qualis**

C2: *"Local Luminance Patterns for Point Cloud Quality Assessment."* – MMSP, 2020 – **Qualis A4**

C3: *"Multi-Distance Point Cloud Quality Assessment."* – ICIP, 2020 – **Qualis A1**

C4: *"Towards a Point Cloud Quality Assessment Model using Local Binary Patterns."* – QoMEX, 2020 – **Qualis A3**

C5: *"A Novel Point Cloud Quality Assessment Metric Based on Perceptual Color Distance Patterns."* – Electronic Imaging, 2021 – **Not Classified in Qualis**

C6: *"On the Performance of Temporal Pooling Methods for Quality Assessment of Dynamic Point Clouds."* – QoMEX, 2022 (accepted, not published) – **Qualis A3**

C7: *"Comparative Evaluation of Temporal Pooling Methods for No-Reference Quality Assessment of Dynamic Point Clouds."* – ACMMM/PIES-ME, 2022 (accepted, not published) – **Not Classified in Qualis**

◇ Published Journal Papers:

J1: *"Color and Geometry Texture Descriptors for Point-Cloud Quality Assessment"* – IEEE Signal Processing Letters (SPL), 2021 – **Qualis A1**.

J2: *"Point cloud quality assessment based on geometry-aware texture descriptors"* – Computer & Graphics (CAG), 2022 – **Qualis A2**.

J3: *"Point Cloud Quality Assessment: Unifying Projection, Geometry, and Texture Similarity"* – The Visual Computer, 2022 – **Qualis A3**.

ACKNOWLEDGMENTS

This work was supported in part by the Conselho Nacional de Desenvolvimento Cientfico e Tecnológico (CNPq), the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES), the Fundação de Apoio a Pesquisa do Distrito Federal (FAP-DF), and the University of Brasília (UnB).

REFERENCES

[1] A. Javaheri, C. Brites, F. Pereira, and J. Ascenso, "Point cloud rendering after coding: Impacts on subjective and objective quality," *IEEE Transactions on Multimedia*, vol. 23, pp. 4049–4064, 2020.

[2] P. Astola, L. A. da Silva Cruz, E. A. da Silva, T. Ebrahimi, P. G. Freitas, A. Gilles, K.-J. Oh, C. Pagliari, F. Pereira, C. Perra *et al.*, "Jpeg pleno: Standardizing a coding framework and tools for plenoptic imaging modalities," *ITU Journal: ICT Discoveries*, 2020.

[3] S. Schwarz, M. Preda, V. Baroncini, M. Budagavi, P. Cesar, P. A. Chou, R. A. Cohen, M. Krivokuća, S. Lasserre, Z. Li *et al.*, "Emerging mpeg standards for point cloud compression," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 9, no. 1, pp. 133–148, 2018.

[4] M. 3DG, "ISO/IEC JTC 1/SC29/WG11: ""call for proposals for point cloud compression v2" MPEG Meeting, Hobart, Australia," International Organization for Standardization, Tech. Rep., April, 2017.

[5] R. Mekuria, C. Tulvan, and Z. Li, "ISO/IEC JTC 1/SC29/WG11 input: "requirements for point cloud compression" MPEG Meeting, Geneva, Switzerland," International Organization for Standardization, Tech. Rep., June, 2016.

[6] D. Graziosi, O. Nakagami, S. Kuma, A. Zaghetto, T. Suzuki, and A. Tabatabai, "An overview of ongoing point cloud compression standardization activities: Video-based (v-pcc) and geometry-based (g-pcc)," *APSIPA Transactions on Signal and Information Processing*, vol. 9, 2020.

[7] M. Schütz and M. Wimmer, "High-quality point-based rendering using fast single-pass interpolation," in *2015 Digital Heritage*, vol. 1. IEEE, 2015, pp. 369–372.

[8] P. Rosenthal and L. Linsen, "Image-space point cloud rendering," in *Proceedings of Computer Graphics International*. Citeseer, 2008, pp. 136–143.

[9] M. Schütz, B. Kerbl, and M. Wimmer, "Rendering point clouds with compute shaders and vertex order optimization," in *Computer Graphics Forum*, vol. 40, no. 4. Wiley Online Library, 2021, pp. 115–126.

[10] E. Alexiou and T. Ebrahimi, "On the performance of metrics to predict quality in point cloud representations," in *Applications of Digital Image Processing XL*, vol. 10396. International Society for Optics and Photonics, 2017, p. 103961H.

[11] ——, "On subjective and objective quality evaluation of point cloud geometry," in *2017 Ninth International Conference on Quality of Multimedia Experience (QoMEX)*. IEEE, 2017, pp. 1–3.

[12] H. Su, Z. Duanmu, W. Liu, Q. Liu, and Z. Wang, "Perceptual quality assessment of 3d point clouds," in *2019 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2019, pp. 3182–3186.

[13] E. Alexiou and T. Ebrahimi, "Impact of visualisation strategy for subjective quality assessment of point clouds," in *2018 IEEE International Conference on Multimedia & Expo Workshops (ICMEW)*. IEEE, 2018, pp. 1–6.

[14] E. Alexious, A. M. Pinheiro, C. Duarte, D. Matković, E. Dumić, L. A. da Silva Cruz, L. G. Dmitrović, M. V. Bernardo, M. Pereira, and T. Ebrahimi, "Point cloud subjective evaluation methodology based on reconstructed surfaces," in *Applications of Digital Image Processing XLI*, vol. 10752. International Society for Optics and Photonics, 2018, p. 107520H.

[15] E. Alexiou and T. Ebrahimi, "Benchmarking of objective quality metrics for colorless point clouds," in *2018 Picture Coding Symposium (PCS)*. IEEE, 2018, pp. 51–55.

[16] L. A. da Silva Cruz, E. Dumić, E. Alexiou, J. Prazeres, R. Duarte, M. Pereira, A. Pinheiro, and T. Ebrahimi, "Point cloud quality evaluation: Towards a definition for test conditions," in *2019 Eleventh International Conference on Quality of Multimedia Experience (QoMEX)*. IEEE, 2019, pp. 1–6.

[17] A. Javaheri, C. Brites, F. Pereira, and J. Ascenso, "Subjective and objective quality evaluation of 3d point cloud denoising algorithms," in *2017 IEEE International Conference on Multimedia & Expo Workshops (ICMEW)*. IEEE, 2017, pp. 1–6.

[18] E. Alexiou, E. Upenik, and T. Ebrahimi, "Towards subjective quality assessment of point cloud imaging in augmented reality," in *2017 IEEE 19th International Workshop on Multimedia Signal Processing (MMSP)*, 2017, pp. 1–6.

[19] R. Diniz, P. G. Freitas, and M. C. Farias, "Towards a point cloud quality assessment model using local binary patterns," in *2020 Twelfth International Conference on Quality of Multimedia Experience (QoMEX)*. IEEE, 2020, pp. 1–6.

[20] ——, "Local luminance patterns for point cloud quality assessment," in *2020 IEEE 22nd International Workshop on Multimedia Signal Processing (MMSP)*. IEEE, 2020, pp. 1–6.

[21] ——, "Multi-distance point cloud quality assessment," in *2020 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2020, pp. 3443–3447.

[22] R. Diniz, P. G. Freitas, and M. Farias, "A novel point cloud quality assessment metric based on perceptual color distance patterns," *Electronic Imaging*, vol. 2021, no. 9, pp. 256–1, 2021.

[23] R. Diniz, P. G. Freitas, and M. C. Farias, "Color and geometry texture descriptors for point-cloud quality assessment," *IEEE Signal Processing Letters*, vol. 28, pp. 1150–1154, 2021.

[24] R. Diniz, P. Garcia Freitas, and M. C. Farias, "Point cloud quality assessment based on geometry-aware texture descriptors," *Computers & Graphics*, vol. 103, pp. 31–44, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0097849322000036

[25] E. M. Torlig, E. Alexiou, T. A. Fonseca, R. L. de Queiroz, and T. Ebrahimi, "A novel methodology for quality assessment of voxelized point clouds," in *Applications of Digital Image Processing XLI*, vol. 10752. International Society for Optics and Photonics, 2018, p. 107520I.

[26] E. Alexiou, I. Viola, T. M. Borges, T. A. Fonseca, R. L. De Queiroz, and T. Ebrahimi, "A comprehensive study of the rate-distortion performance in mpeg point cloud compression," *APSIPA Transactions on Signal and Information Processing*, vol. 8, 2019.

[27] S. Perry, H. P. Cong, L. A. da Silva Cruz, J. Prazeres, M. Pereira, A. Pinheiro, E. Dumic, E. Alexiou, and T. Ebrahimi, "Quality evaluation of static point clouds encoded using mpeg codecs," in *2020 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2020, pp. 3428–3432.

[28] Q. Yang, H. Chen, Z. Ma, Y. Xu, R. Tang, and J. Sun, "Predicting the perceptual quality of point cloud: A 3d-to-2d projection-based exploration," *IEEE Transactions on Multimedia*, vol. 23, pp. 3877–3891, 2020.

[29] K. Brunnstrom, D. Hands, F. Speranza, and A. Webster, "Vqeg validation and itu standardization of objective perceptual video quality metrics [standards in a nutshell]," *IEEE Signal processing magazine*, vol. 26, no. 3, pp. 96–101, 2009.