Optimized Dynamic Point Cloud Compression OPT-PCC

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Deliverable D1
Coder Source Code

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Executive Summary

Point clouds are representations of three-dimensional (3D) objects in the form of a sample of points on their surface. Point clouds are receiving increased attention from academia and industry due to their potential for many important applications, such as real-time 3D immersive telepresence, automotive and robotic navigation, as well as medical imaging. Compared to traditional video technology, point cloud systems allow free viewpoint rendering, as well as mixing of natural and synthetic objects. However, this improved user experience comes at the cost of increased storage and bandwidth requirements as point clouds are typically represented by the geometry and colour (texture) of millions up to billions of 3D points. For this reason, major efforts are being made to develop efficient point cloud compression schemes. However, the task is very challenging, especially for dynamic point clouds (sequences of point clouds), due to the irregular structure of point clouds (the number of 3D points may change from frame to frame, and the points within each frame are not uniformly distributed in 3D space). To standardize point cloud compression (PCC) technologies, the Moving Picture Experts Group (MPEG) launched a call for proposals in 2017. As a result, three point cloud compression technologies were developed: surface point cloud compression (S-PCC) for static point cloud data, video-based point cloud compression (V-PCC) for dynamic content, and LIDAR point cloud compression (L-PCC) for dynamically acquired point clouds. Later, L-PCC and S-PCC were merged under the name geometry-based point cloud compression (G-PCC). The aim of the OPT-PCC project is to develop algorithms that optimise the rate-distortion performance [i.e., minimize the reconstruction error (distortion) for a given bit budget] of V-PCC. The objectives of the project are to:

1. O1: build analytical models that accurately describe the effect of the geometry and colour quantization of a point cloud on the bit rate and distortion;
2. O2: use O1 to develop fast search algorithms that optimise the allocation of the available bit budget between the geometry information and colour information;
3. O3: implement a compression scheme for dynamic point clouds that exploits O2 to outperform the state-of-the-art in terms of rate-distortion performance. The target is to reduce the bit rate by at least 20% for the same reconstruction quality;
4. O4: provide multi-disciplinary training to the researcher in algorithm design, metaheuristic optimisation, computer graphics, media production, and leadership and management skills.

As part of O3, this deliverable gives the source code of the algorithms used in the project to optimize the rate-distortion performance of V-PCC.

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1 Introduction

A static point cloud is a representation of a three-dimensional (3D) object, where in addition to the spatial coordinates of a sample of points on the surface of the object, attributes such as color, reflectance, transparency, and normal direction may be used (Fig. 1). A dynamic point cloud consists of several successive static point clouds. Each point cloud in the sequence is called a frame. Point clouds are receiving increased attention due to their potential for immersive video experience applications such as virtual reality, augmented reality, and immersive telepresence.

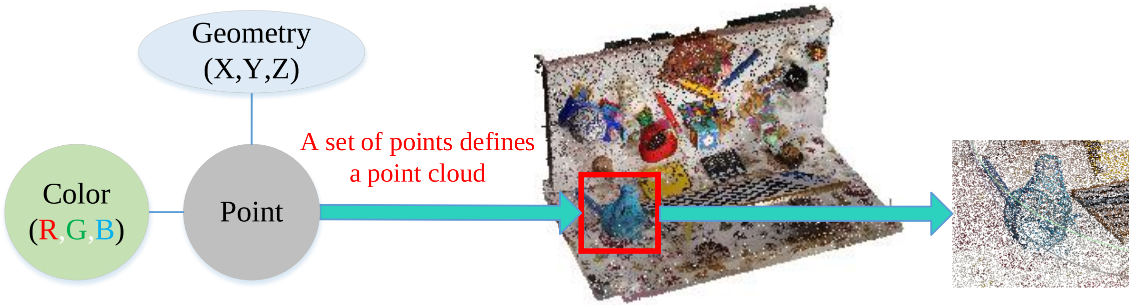

Fig. 1. Point cloud representation with color used as an attribute.

To compress point clouds efficiently, the Moving Picture Experts Group (MPEG) launched in January 2017 a call for proposals for point cloud compression technology. As a result, two point cloud compression standards were developed: video-based point cloud compression (V-PCC) [1] for point sets with a relatively uniform distribution of points and geometry-based point cloud compression (G-PCC) [2] for more sparse distributions.

In this project, we focus on V-PCC for dynamic point clouds. In V-PCC, the input point cloud is first decomposed into a set of patches, which are independently mapped to a two-dimensional grid of uniform blocks. This mapping is then used to store the geometry and color information as one geometry video and one color video. Next, the generated geometry video and color video are compressed separately with a video coder, e.g., H.265/HEVC [3]. Finally, the geometry and color videos, together with metadata (occupancy map for the two-dimensional grid, auxiliary patch, and block information) are multiplexed to generate the bit stream (Fig. 2). In the video coding step, compression is achieved with quantization, which is determined by a quantization step or, equivalently, a quantization parameter (QP), see Appendix A.

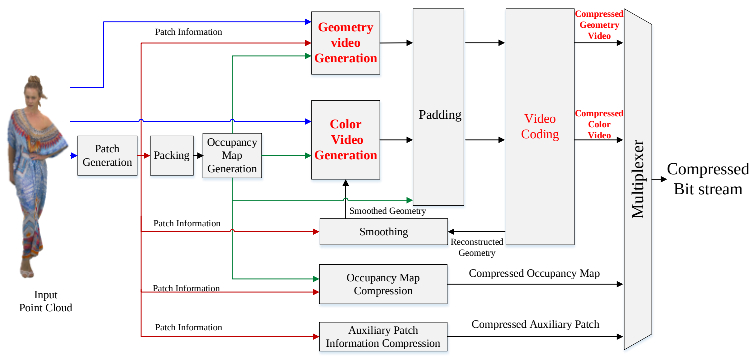

Fig. 2. V-PCC encoder test model [1].

Given a dynamic point cloud consisting of a group of N frames, an optimal encoding can be obtained by determining for each frame i ($i = 1, \ldots, N$) the geometry quantization step $Q_{g,i} \in \{q_0, \ldots, q_{M-1}\}$ and colour quantization step $Q_{c,i} \in \{q_0, \ldots, q_{M-1}\}$ that minimize the distortion subject to a constraint R_T on the bit budget. This can be formulated as the multi-objective optimization problem

$$\min_{\boldsymbol{Q}_g, \boldsymbol{Q}_c} \left[D_g(\boldsymbol{Q}_g, \boldsymbol{Q}_c), D_c(\boldsymbol{Q}_g, \boldsymbol{Q}_c)\right] \quad (1)$$
$$s.t. \quad R(\boldsymbol{Q}_g, \boldsymbol{Q}_c) \leq R_T,$$

where $\boldsymbol{Q}_g = (Q_{g,1,}Q_{g,2,\ldots,}Q_{g,N})$, $\boldsymbol{Q}_c = (Q_{c,1,}Q_{c,2,\ldots,}Q_{c,N})$, $D_g(\boldsymbol{Q}_g, \boldsymbol{Q}_c)$ is the geometry distortion, $D_c(\boldsymbol{Q}_g, \boldsymbol{Q}_c)$ is the color distortion, and $R(\boldsymbol{Q}_g, \boldsymbol{Q}_c)$ is the total number of bits. Here $D_g(\boldsymbol{Q}_g, \boldsymbol{Q}_c) = \frac{1}{N}\sum_{i=1}^{N} D_{g,i}(\boldsymbol{Q}_g, \boldsymbol{Q}_c)$ and $D_c(\boldsymbol{Q}_g, \boldsymbol{Q}_c) = \frac{1}{N}\sum_{i=1}^{N} D_{c,i}(\boldsymbol{Q}_g, \boldsymbol{Q}_c)$,where $D_{g,i}(\boldsymbol{Q}_g, \boldsymbol{Q}_c)$ and $D_{c,i}(\boldsymbol{Q}_g, \boldsymbol{Q}_c)$ are the geometry and color distortions of the i th frame, respectively. Similarly, $R(\boldsymbol{Q}_g, \boldsymbol{Q}_c)$=$R_g(\boldsymbol{Q}_g, \boldsymbol{Q}_c) + R_c(\boldsymbol{Q}_g, \boldsymbol{Q}_c)$, where $R_g(\boldsymbol{Q}_g, \boldsymbol{Q}_c) = \sum_{i=1}^{N} R_{g,i}(\boldsymbol{Q}_g, \boldsymbol{Q}_c)$ is the number of bits for the geometry information, $R_{g,i}(\boldsymbol{Q}_g, \boldsymbol{Q}_c)$ is the number of bits for the geometry information in the ith frame, $R_c(\boldsymbol{Q}_g, \boldsymbol{Q}_c) = \sum_{i=1}^{N} R_{c,i}(\boldsymbol{Q}_g, \boldsymbol{Q}_c)$ is the number of bits for the color information, and $R_{c,i}(\boldsymbol{Q}_g, \boldsymbol{Q}_c)$ is the number of bits for the color information in the ith frame. In practice, problem (1) is scalarized as

$$\min_{\boldsymbol{Q}_g, \boldsymbol{Q}_c} \left[D(\boldsymbol{Q}_g, \boldsymbol{Q}_c) = \omega D_c(\boldsymbol{Q}_g, \boldsymbol{Q}_c) + (1-\omega) D_g(\boldsymbol{Q}_g, \boldsymbol{Q}_c)\right] \quad (2)$$
$$s.t. \quad R(\boldsymbol{Q}_g, \boldsymbol{Q}_c) \leq R_T,$$

where $\omega \in [0,1]$ is a weighting factor that sets the relative importance of the geometry and color distortions. As the number of possible solutions is M^{2N}, solving the problem with exhaustive search is not feasible when M or N is large as the computation of the distortion and the number of bits requires encoding and decoding the point cloud, which is very time consuming.

In this deliverable, we provide the source codes of two methods [4] used in this project to solve the constrained optimization problem (2). The first one uses rate and distortion models, while the second uses the actual rate and distortion. Both methods apply a variant of differential evolution (DE) [5] for optimization.

2 Source codes

This deliverable provides four source codes, which we have made publicly available in [6], [7], and [8].

- The source code in [6] generates analytical models for the rate and distortion and applies DE to (2), where the rate and distortion are replaced by the models. Only one group of four frames is considered.
- The source code in [7] applies DE to (2), where the actual rate and distortion are used. Only one group of four frames is considered.
- In [8], we provide two source codes. The first one extends the source code in [6] to two groups of frames. The second one extends the source code in [7] to two groups of frames. The aim is to show that the proposed methods can be generalized to an arbitrary number of groups of frames.

3 Appendix A: Quantization

Relationship between QP and quantization step (Q_{step})

QP	Q_{step}	QP	Q_{step}	QP	Q_{step}	QP	Q_{step}	QP	Q_{step}	QP	Q_{step}	QP	Q_{step}
0	0.625	**8**	1.625	**16**	4	**24**	10	**32**	26	**40**	64	**48**	160
1	0.6875	**9**	1.75	**17**	4.5	**25**	11	**33**	28	**41**	72	**49**	176
2	0.8125	**10**	2	**18**	5	**26**	13	**34**	32	**42**	80	**50**	208
3	0.875	**11**	2.25	**19**	5.5	**27**	14	**35**	36	**43**	88	**51**	224
4	1	**12**	2.5	**20**	6.5	**28**	16	**36**	40	**44**	104	NA	
5	1.125	**13**	2.75	**21**	7	**29**	18	**37**	44	**45**	112		
6	1.25	**14**	3.25	**22**	8	**30**	20	**38**	52	**46**	128		
7	1.375	**15**	3.5	**23**	9	**31**	22	**39**	56	**47**	144		

4 References

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