

PDE-based Progressive Prediction Framework for Attribute Compression of 3D Point Clouds



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Introduction

- The existing attribute prediction methods are based on weighting the reconstructed attribute values with reference to their geometric distances.
- However, new theory is needed to guide point cloud attribute prediction task instead of simply approximate attribute correlation with geometric correlation.
- Diffusion-based image compression scheme inspires us to use diffusion theory to employ the diffusion model for point cloud attribute compression.
- We propose a PDE-based prediction model, which gets predictive values by optimizing attribute gradients.
- We propose a low-complexity method for calculating gradients and partial derivative operators on point clouds solving the occupancy uncertainty.
- We design a PDE-based attribute compression framework, including 2-layer LOD structure, diffusion-based point cloud interpolation, and texture-wised prediction strategy, which can fully explore LOD information and attain texture maintenance.

PDE-based model for attribute prediction

• The prediction value of point u can be gotten by optimizing the formula:

$$\min_{f(u)} \nabla f(u)^{\mathrm{T}} * D * \nabla f(u)$$

• It's worth stating that when D is an identity matrix, and $\nabla f(u)$ is calculated on a K-nearest neighbor graph:

$$\nabla f(u) = (\partial_v f(u) : v \sim u)^{\mathsf{T}} = (\partial_{v_1} f(u), \dots, \partial_{v_k} f(u))^{\mathsf{T}}, \forall (u, v_i) \in E$$

• The result is equal to G-PCC's method:

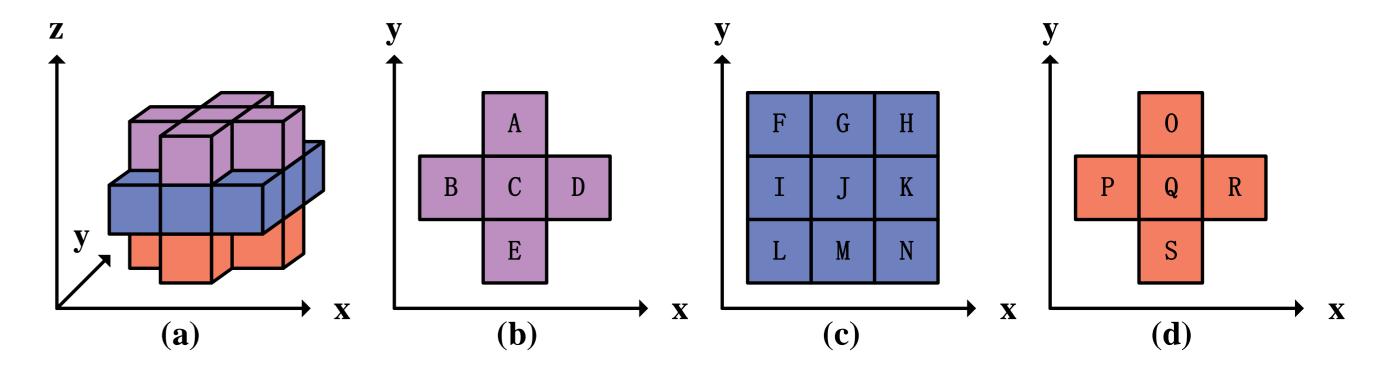
$$f(u) = \frac{\sum_{v \sim u} w(u, v) f(v)}{\sum_{v \sim u} w(u, v)}$$

• It shows that G-PCC's strategy can be a special case of ours.

PDE operators on point clouds

$$\nabla f(x, y, z) = [G_x, G_y, G_z]^{\mathrm{T}} = \left[\frac{\vartheta f(x, y, z)}{\vartheta x}, \frac{\vartheta f(x, y, z)}{\vartheta y}, \frac{\vartheta f(x, y, z)}{\vartheta z}, \frac{\vartheta f(x, y, z)}{\vartheta z}\right]^{\mathrm{T}}$$

• The gradient is a vector of 3×1 vector representing the speed at which the property changes along the x, y, and z directions.



- When calculating the gradient at point *J*, we choose its 18 neighbors that share a face or edge with the central point *J*.
- To address the problem of occupancy uncertainty, we use m_i to represent whether position i is occupied.

$$G_{x} = \frac{1}{10} * \left(\frac{1}{2} * \sum_{i=D,H,N,R} m_{i} * (f(i) - f(J)) - \frac{1}{2} * \sum_{i=B,F,L,P} m_{i} * (f(i) - f(J)) + m_{K} * (f(K) - f(J)) - m_{I} * (f(I) - f(J))\right)$$

Proposed framework Edge-enhancing diffusion Reference high-level LOD Voxelized Interpolated LOD generation Point Cloud The current Point Cloud point being Texture strength in directions EED-based Prediction Reference neighbor in lowlevel LOD Quatization & Entropy Coding Dequatization & Inverse Prediction Y direction X direction Z direction Recontructed Colors Iteration 1 state **Iteration 2 state**

Experiments

BD-BR and time comparisons under attribute near-lossless condition

PLT(v14) PLT(v19) Proposed **Point Clouds** BD-BR(%) Times (s) Times (s) BD-BR(%)Times (s) Enc. Dec. Dec. Enc. Dec. Enc. Basketball -16.36 -23.14 -11.23 -18.07 139.4 4.7 143.4 6.1 -19.60 -14.88 -21.89 122.4 121.0 5.1 8.6 Dancer Façade 00064 202.1 -14.91 -14.08 13.3 7.4 201.4 -14.57 Longdress 1.8 -15.79 -12.88 2.9 39.1 38.5 -34.37 -30.83 -27.03 -20.80 1.6 38.5 -16.46 Loot -23.25-20.39 3.4 53.7 Queen 2.0 -19.36 54.4 Readandblack -20.71 -17.08 34.9 34.5 -19.93 Soldier -33.47 2.3 -32.32 -36.25 3.7 49.8 Thaidancer -20.74 6.3 -13.66 119.8 117.1 -19.12 -10.26 58.7 58.5 -16.99 -4.66 3.3 Ricardo 85.3 -12.74 -17.38 -6.16 Sarah -10.23 -10.64 5.0 3.4 81.6 -12.64 -11.04 -12.48 4.6 78.4 Andrew 3.5 77.6 David -22.30-15.28 -17.38 5.5 91.0 -21.69 91.9 Phil -18.52 -19.08 3.8 -16.71 98.7 6.1 4.6

-16.14

5.3

86.6

86.0

-20.52

Average

-21.94

3.8

3.1

-12.00

Bitrate and time comparisons under attribute lossless condition

	PLT(v14)				PLT(v19)				Proposed		
Point Clouds	Bitrate	Bitrate gain	Times (s)		Bitrate	Bitrate gain	Times (s)		Bitrate	Times (s)	
	(bpp)	(%)	Enc.	Dec.	(bpp)	(%)	Enc.	Dec.	(bpp)	Enc.	Dec.
Basketball	7.72	1.43	5.38	4.44	7.68	0.93	7.34	6.27	7.61	97.50	96.7
Dancer	7.80	1.58	4.59	3.59	7.76	1.06	6.02	5.33	7.67	84.73	84.17
Façade_00064	10.16	0.52	7.36	6.02	10.12	0.13	9.64	8.58	10.11	146.6	147.1
Longdress	11.75	3.73	1.59	1.33	11.59	2.37	2.00	1.83	11.32	28.03	28.05
Loot	6.19	4.24	1.48	1.20	6.08	2.58	1.88	1.67	5.93	26.08	25.92
Queen	7.73	1.32	1.84	1.50	7.68	0.65	2.34	2.08	7.63	37.86	37.67
Readandblack	9.39	4.01	1.47	1.20	9.24	2.41	1.81	1.66	9.02	25.11	24.88
Soldier	7.08	4.59	1.98	1.75	6.96	2.94	2.52	2.36	6.75	36.78	35.56
Thaidancer	7.63	5.38	6.09	5.06	7.46	3.20	8.11	6.95	7.22	84.34	82.84
Ricardo	5.93	1.59	1.88	1.55	5.88	0.86	3.53	3.25	5.83	47.02	46.91
Sarah	4.70	2.09	2.48	2.11	4.68	1.61	5.17	4.75	4.60	59.92	59.39
Andrew	11.14	1.76	2.36	2.02	11.00	0.91	3.19	2.80	10.94	74.58	82.53
David	7.29	1.45	3.00	2.41	7.26	1.00	3.83	3.36	7.18	78.98	77.63
Phil	10.25	1.53	3.31	2.66	10.25	1.61	5.45	5.34	10.09	81.34	81.19
Average	8.20	2.52	3.20	2.63	8.12	1.59	4.49	4.02	7.99	64.92	65.04