Point Cloud Geometry Compression via Density-Constrained Adaptive Graph Convolution

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Background

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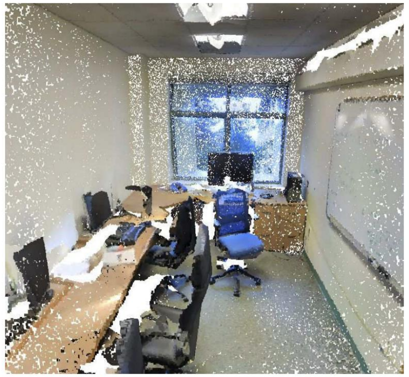
- **Point Cloud (PC)**
  - An effective representation of 3D objects or scenes
  - Consists of 3D coordinates and attributes information

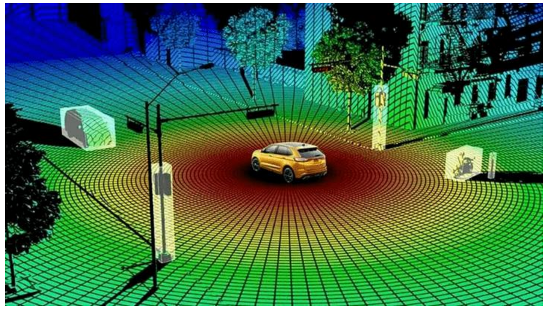
- **Wide Application Scenarios**
  - Autonomous driving
  - Augmented/virtual reality (AR/VR)

- **Challenges for Point Cloud Compression**
  - A huge amount of data
  - Irregular, unstructured and unordered

3D Object



3D Scene



Autonomous Driving

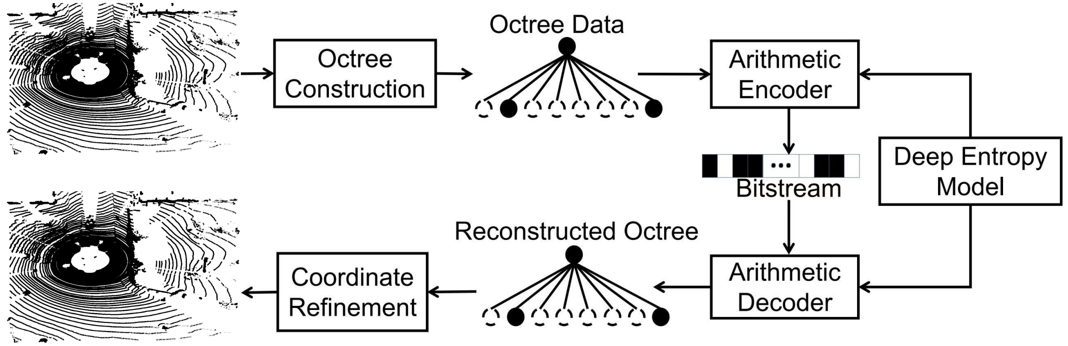
AR/VR

Related Work

Learned Point Cloud Geometry Compression (PCGC) Methods

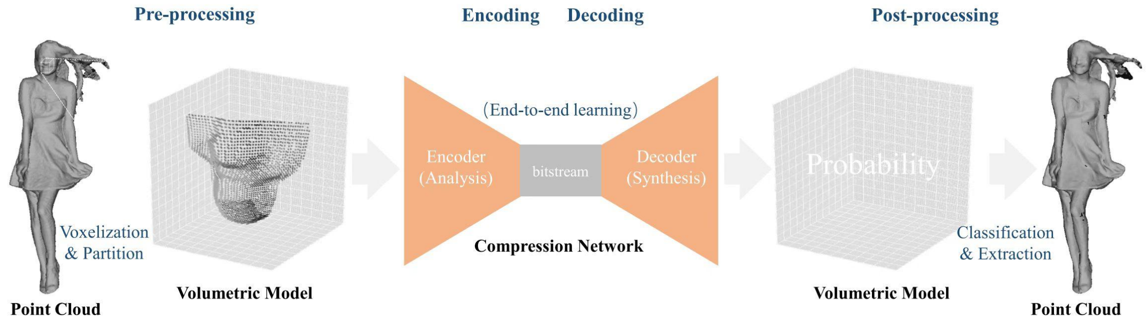
◆ **Octree-based Methods**

- ➢ Represent Point cloud with octree
- ➢ Applicable to large-scale LiDAR



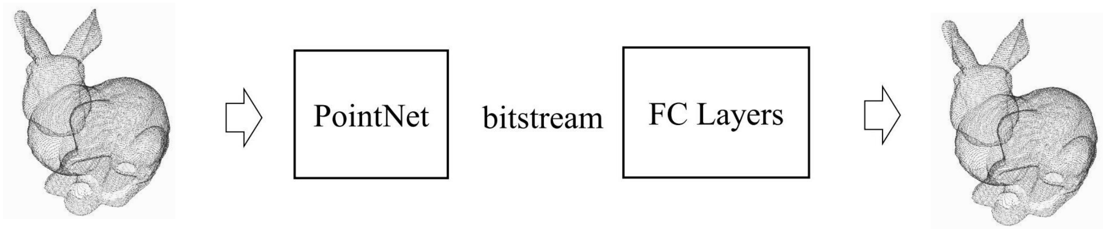
◆ **Voxel-based Methods**

- ➢ Voxelized Point cloud
- ➢ 3D CNN based Transform
- ➢ Binary Cross Entropy (BCE) Loss
- ➢ Suitable for dense Point cloud



◆ **Point-based Methods**

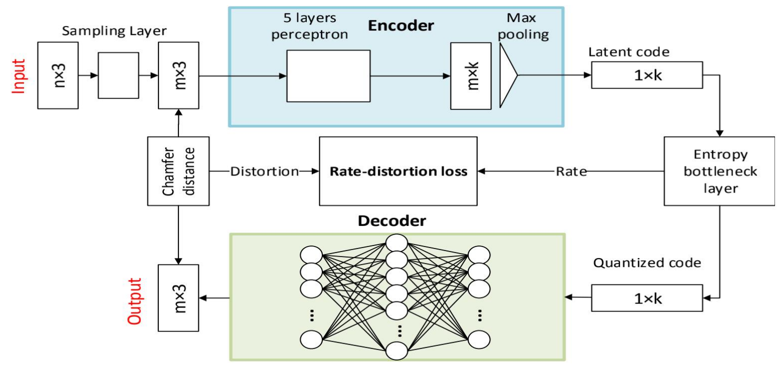
- ➢ Input Raw Points
- ➢ PointNet based Transform
- ➢ Chamfer Distance (CD) Loss
- ➢ Suitable for sparse Point cloud

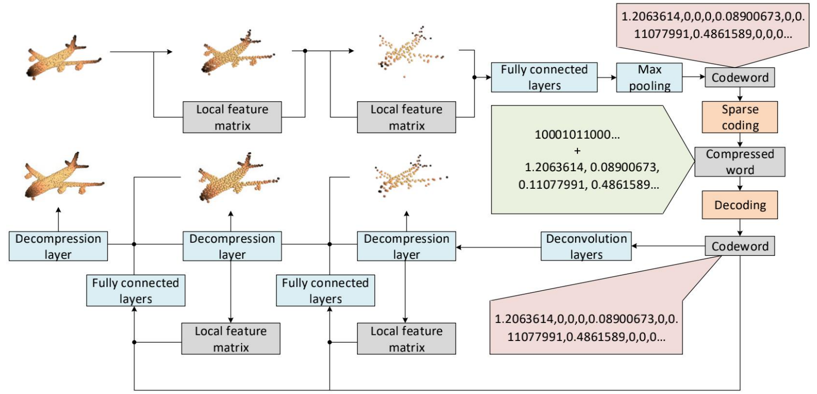


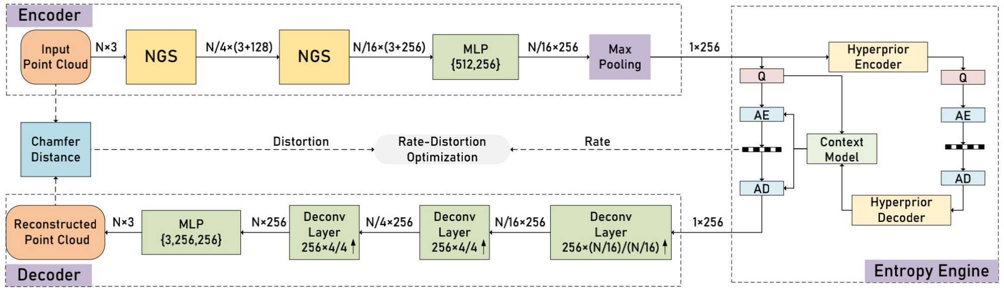
Related Work

Point-based PCGC Methods

- **Yan's Method** [1]
  - PointNet based Autoencoder structure
  - Chamfer Distance (CD) Loss
- **Huang's Method** [2]
  - PointNet++ based Autoencoder structure
  - Hierarchical reconstruction
  - Chamfer Distance (CD) Loss
- **Gao's Method** [3]
  - Variational Autoencoder (VAE) structure
  - Neural Graph Sampling (NGS) for feature extraction
  - Layered deconvolutions for reconstruction
  - Chamfer Distance (CD) Loss







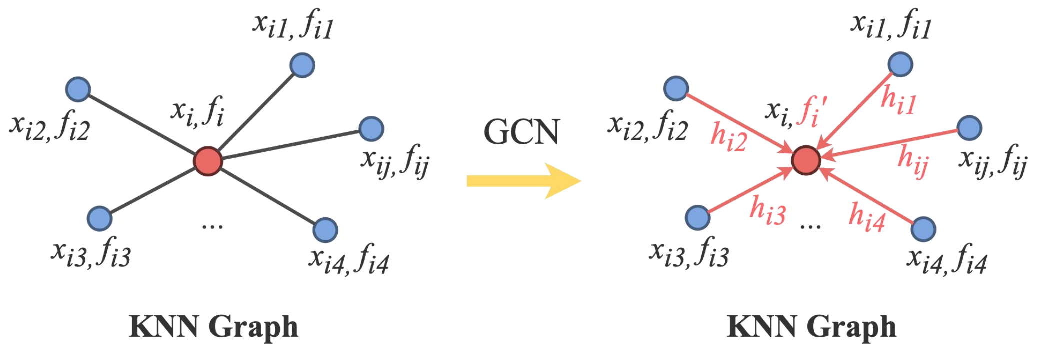
[1] Wei Yan, Yiting Shao, Shan Liu, Thomas H. Li, Zhu Li, and Ge Li, “Deep autoencoder-based lossy geometry compression for point clouds,”ArXiv, vol. abs/1905.03691, 2019.
[2] Tianxin Huang and Yong Liu, “3d point cloud geometry compression on deep learning,” in Proceedings of the 27th ACM International Conference on Multimedia. 2019, MM’19, p. 890–898.
[3] Linyao Gao, Tingyu Fan, Jianqiang Wan, et al., “Point cloud geometry compression via neural graph sampling,” in 2021 IEEE International Conference on Image Processing (ICIP), 2021, pp. 3373–3377.

Proposed Method

Drawbacks of Existing Point-based PCGC Methods

- ➢ MLPs and 1D convolution result in weight sharing
- ➢ Poor representation of local geometric features

How to Improve?

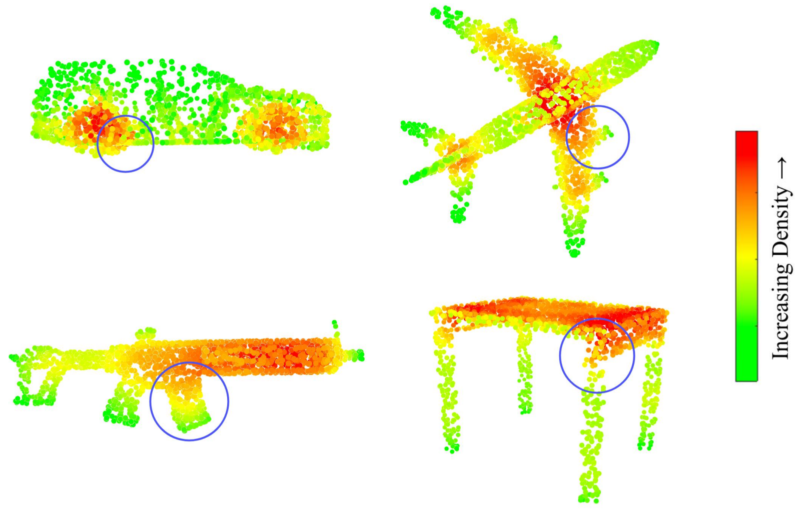


◆ **Graph Convolution Networks (GCN)**

- ➢ Search for KNN to construct local graph of each point
- ➢ Extract and aggregate edge features of center point

◆ **Spatial Geometry Information: Density**

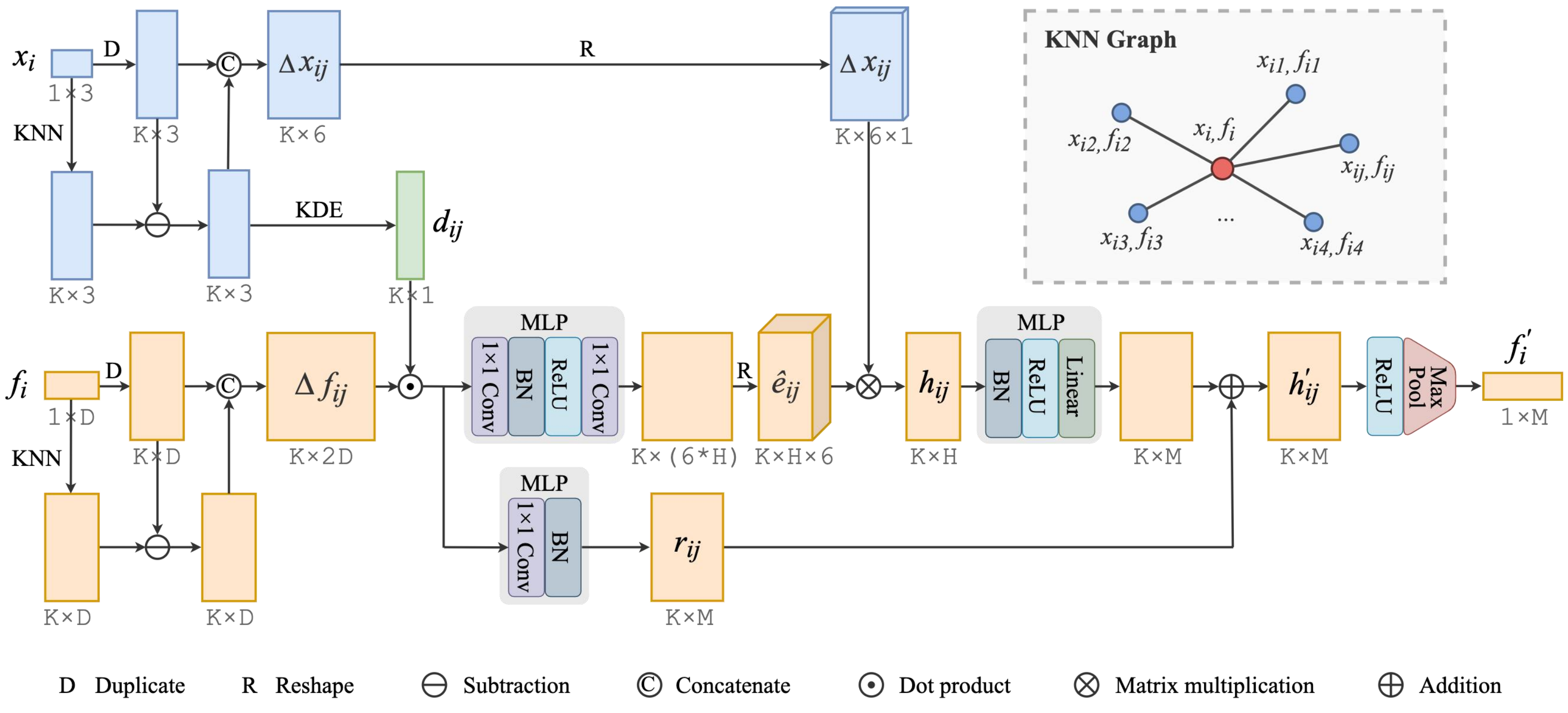
- ➢ Involve interaction between neighbors in the local graph
- ➢ Use Kernel Density Estimation (KDE) to calculate density
- ➢ Density varies greatly in key areas (such as edges, corners and the areaswith rapid shape changes)
- ➢ For the dense points in the local graph, each point contributes less, on thecontrary, sparse points contribute more



Proposed Method

Density-Constrained Adaptive Graph Convolution (DCAGC)

- ➢ Use inverse density scale to constrain neighbor features
- ➢ Fuse the global feature and local feature
- ➢ Learn neighbor features dynamically to generate unique adaptive kernel of each point

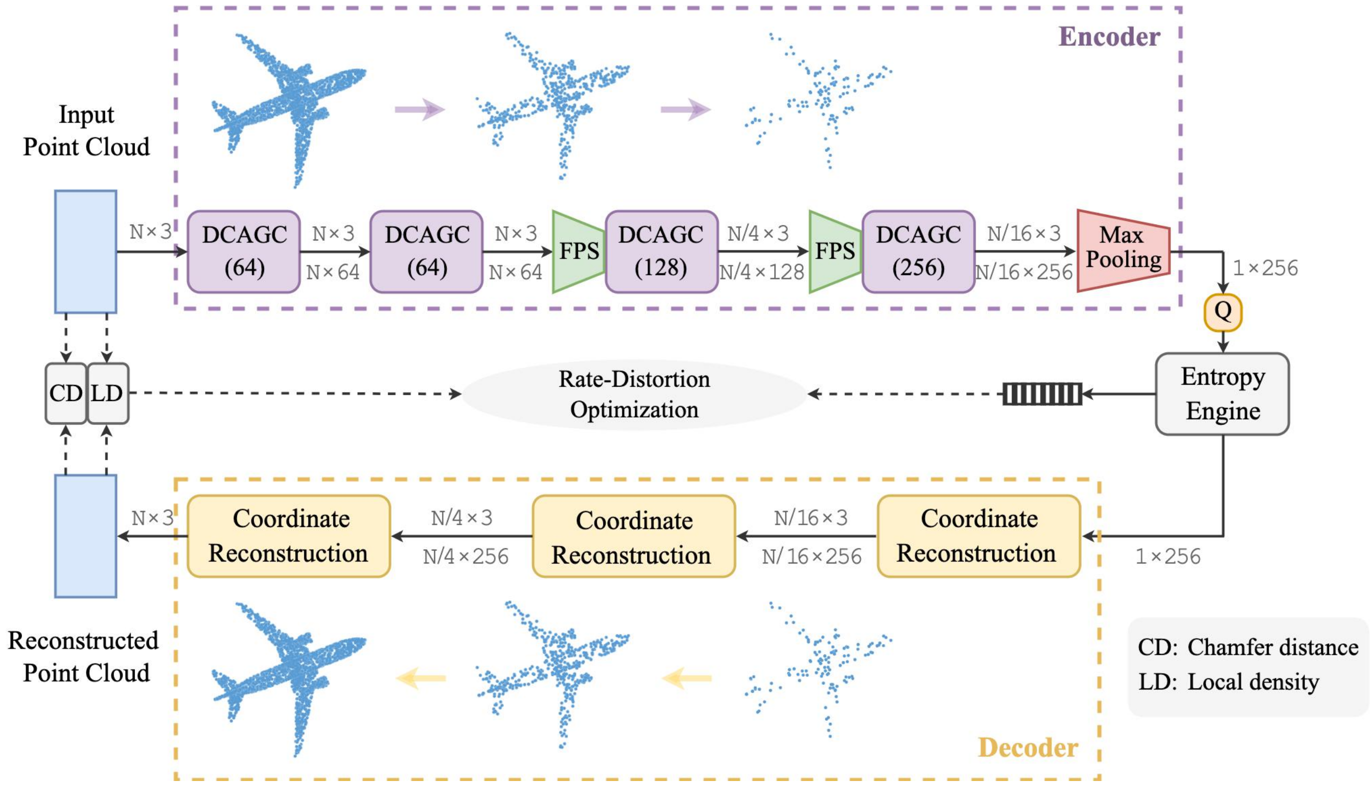


Density-Constrained Adaptive Graph Convolution (DCAGC)

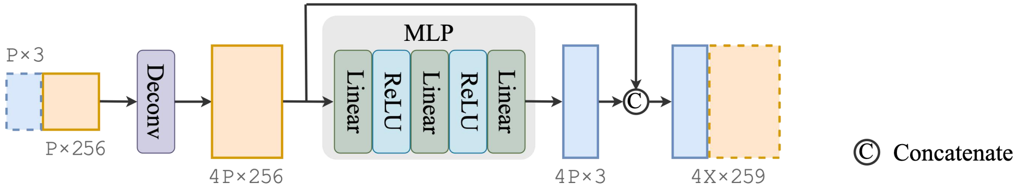
Proposed Method

Proposed PCGC Framework

- **Encoder**
  - DCAGC
  - Farthest Point Sampling (FPS)
  - Max pooling
- **Entropy Engine**
  - Variational Autoencoder (VAE)
  - Hyperpriors for Entropy Modeling [1]
- **Decoder**
  - Coordinate Reconstruction (CR)
  - Hierarchical reconstruction
- **Loss Function**
  - Chamfer Distance (CD) Loss
  - Local density (LD) Loss



Network Architecture



Coordinate Reconstruction (CR)

[1] Johannes Ball´e, David C. Minnen, Saurabh Singh, et al., "Variational image compression with a scale hyperprior,"ArXiv, vol. abs/1802.01436, 2018.

Proposed Method

◆ Loss Function

➢ Rate-distortion optimization (RDO)

$$L = \lambda \cdot D + R$$

$$D = (L_{CD} + \alpha L_{CD}^{1} + \beta L_{CD}^{2}) + \gamma L_{LD}$$

➢ Chamfer Distance (CD) Loss

$$L_{CD}(S_1, S_2) = \frac{1}{|S_1|} \sum_{p \in S_1} \min_{q \in S_2} \|p - q\|_2^2 + \frac{1}{|S_2|} \sum_{p \in S_2} \min_{q \in S_1} \|p - q\|_2^2$$

➢ Local density (LD) Loss

$$L_{LD} = \frac{1}{N} \sum_{i=1}^{N} | \overline{Y_1^i} - \overline{Y_2^i} |, \quad \overline{Y^i} = \frac{1}{k} \sum_{j=1}^{\mathcal{N}(i)} \|x_{ij} - x_i\|_2$$

Experiment settings

◆ Dataset

➢ ShapeNetCoreV2

◆ Evaluation Metrics

➢ Point-to-point PSNR (D1 PSNR)

➢ Point-to-plane PSNR (D2 PSNR)

➢ point-to-point Chamfer Distance (CD)

◆ Comparison Methods (SOTA)

➢ Yan's [1]

➢ Huang's [2]

➢ Gao's [3]

[1] Wei Yan, Yiting Shao, Shan Liu, Thomas H. Li, Zhu Li, and Ge Li, "Deep autoencoder-based lossy geometry compression for point clouds,"ArXiv, vol. abs/1905.03691, 2019.

[2] Tianxin Huang and Yong Liu, "3d point cloud geometry compression on deep learning," in Proceedings of the 27th ACM International Conference on Multimedia. 2019, MM'19, p. 890–898.

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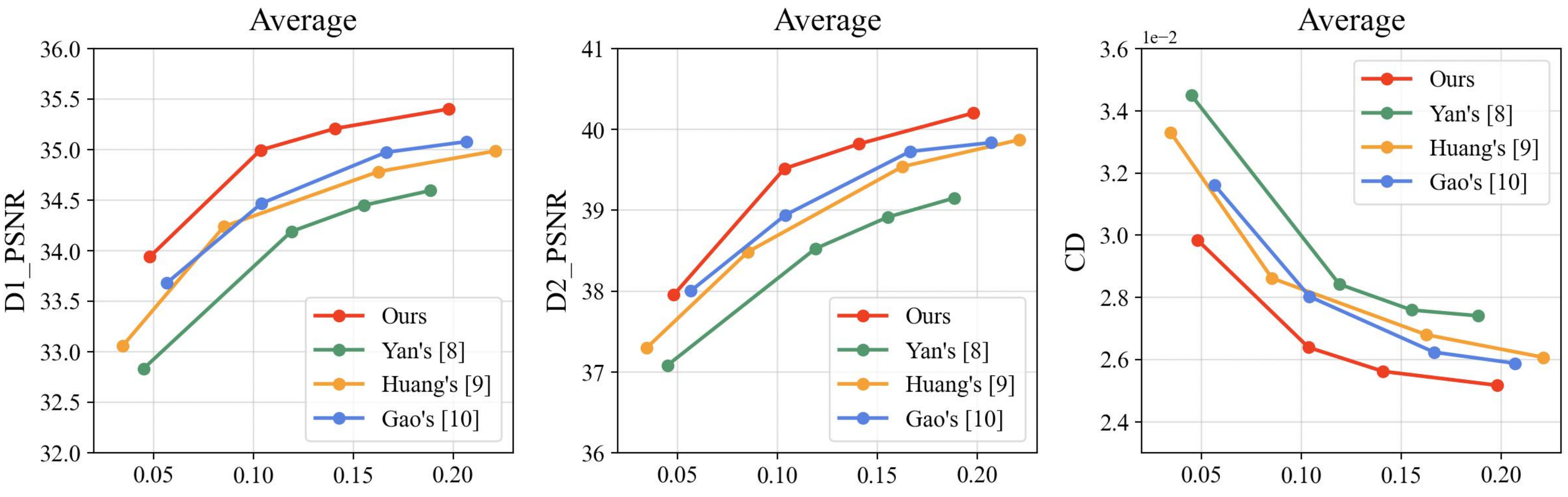
Experimental results and Analysis

Quantitative Performance

Quantitative results (BDBR) comparison with SOTA

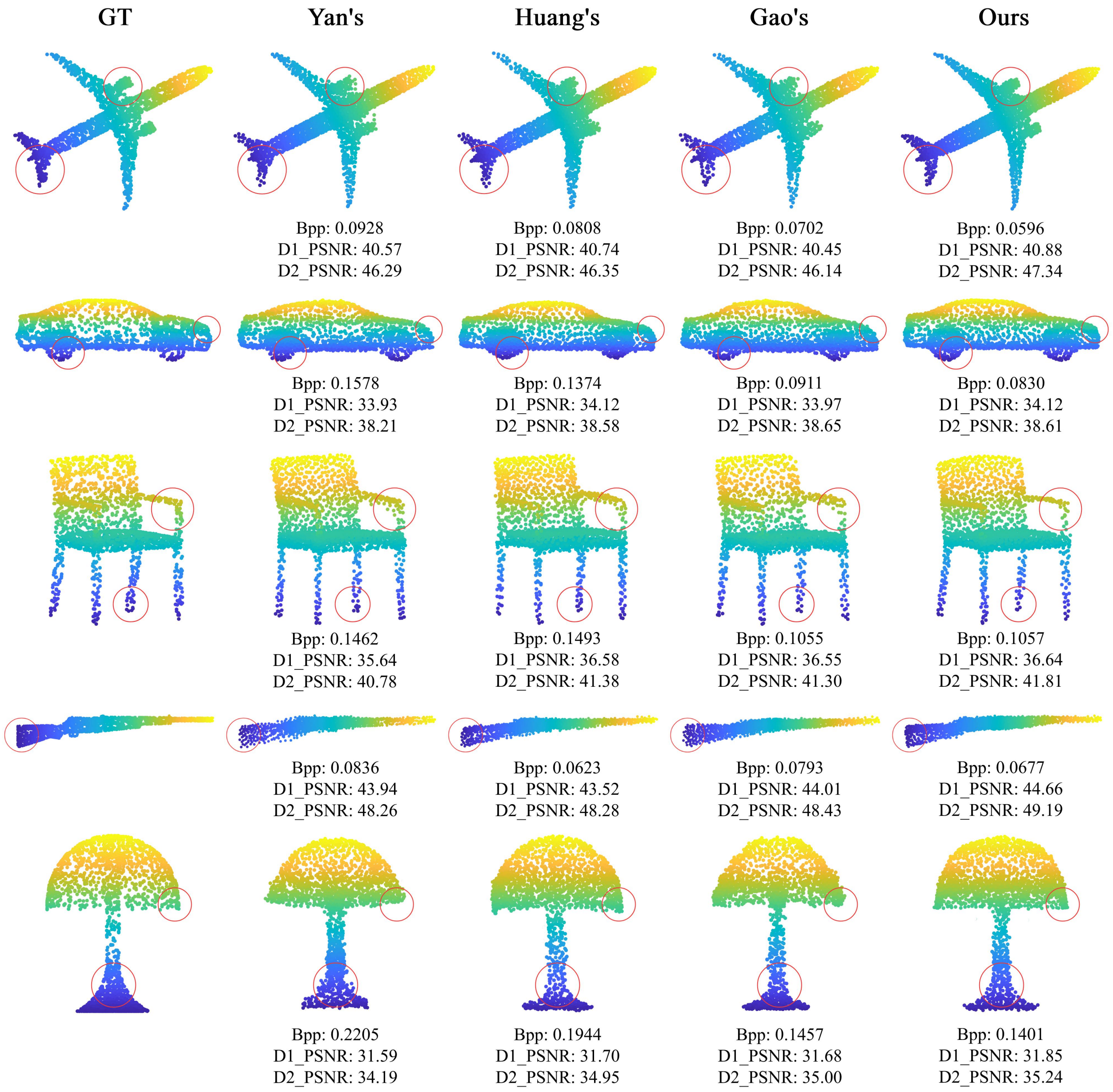
Category	Ours vs Yan's [8]		Ours vs Huang's [9]		Ours vs Gao's [10]	
	D1	D2	D1	D2	D1	D2
Airplane	-51.30%	-55.53%	-44.15%	-41.60%	-41.23%	-35.85%
Car	-56.21%	-54.94%	-46.90%	-42.06%	-34.25%	-35.77%
Rifle	-50.25%	-56.50%	-41.66%	-36.92%	-37.00%	-47.72%
Table	-53.05%	-66.25%	-39.44%	-47.92%	-41.04%	-40.31%
Average	**-57.40%**	**-58.38%**	**-42.51%**	**-39.70%**	**-40.61%**	**-37.21%**



Rate-distortion (RD) curves

Experimental results and Analysis

Qualitative Performance



Experimental results and Analysis

Computational Complexity

Method	Yan's [8]	Huang's [9]	Gao's [10]	Ours
Running time (s)	**0.091**	0.252	0.166	0.243
Model size (MB)	68.45	43.27	38.02	**32.16**

Ablation Study

Baseline	DCAGC	Deconv	CR	$L_{CD}s$	L_{LD}	Bpp	D1_PSNR (dB)	D2_PSNR (dB)
✓		✓				0.1530	35.0410	39.5989
	✓	✓				0.1491	35.1956	39.7708
	✓		✓	✓		0.1445	35.1793	39.8200
	✓		✓	✓	✓	**0.1409**	**35.2086**	**39.8212**

Baseline: without density constraint
Deconv: Deconvolution
L_{CD}s: multi-scale L_{CD}

Conclusion

Contributions

- We design a density-constrained adaptivegraph convolution (DCAGC) to efficiently represent point cloud local geometry.
- We propose a novel point-based point cloud compression method based on DCAGC.
- The proposed method outperforms the SOTA in terms of rate-distortion with average 47% D1 BD Bitrate (BDBR) and 45% D2 BDBR gain, and achieves more satisfactory reconstructions with clearer geometric details.

Future Works

- More effective down-sampling methods to reduce complexity.
- Migrate to a large-scale point cloud (LiDAR etc.)

Thank you for your attention!