Cross-Regional Attention Network for Point Cloud Completion

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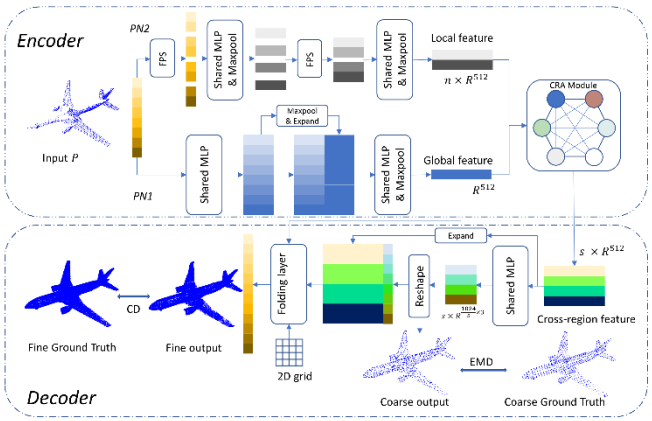
Introduction

Point clouds obtained from LiDARs or depth cameras are always incomplete, which will cause structural losses in 3D shape representations. In this paper, we propose a method to repair partial point clouds and restore complete object shapes.

Network Structure



The overall architecture of our network

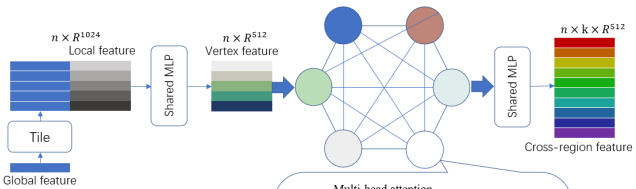
Compared with existing methods, the main contribution of our network is the usage of local features, they are conditioned by global features and fused with each other.

Three main parts in our network:

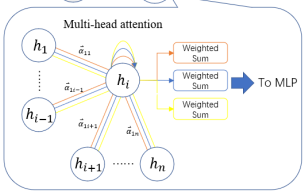
(1) **Multiscale Feature Extraction module (MFE)**: Independently extract local and global features from inputs.

(2) **Cross-Regional Attention module (CRA)**: Learn relationships of local features and make them fuse with each other.

(3) **Two-step Decoder**: Decode cross-regionally fused local features to generate complete point cloud from coarse to fine.

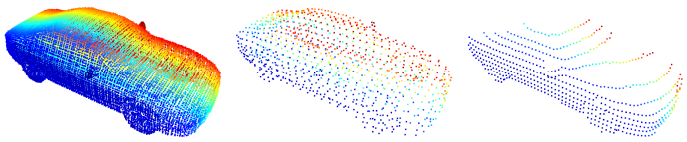


The architecture of CRA



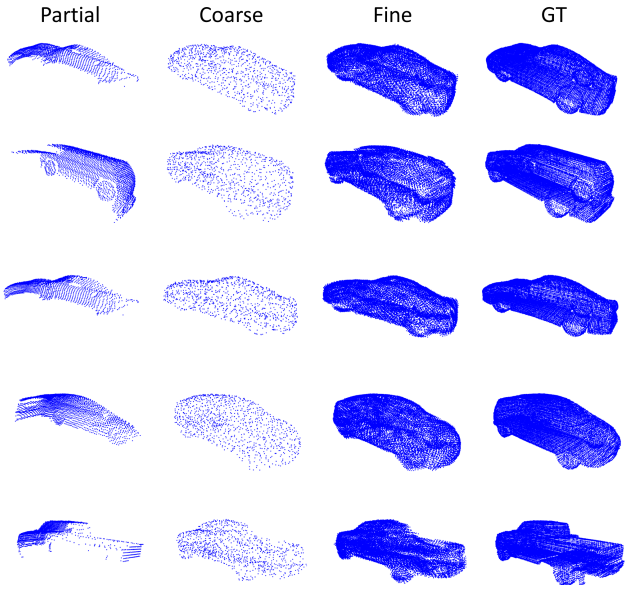
Experiments

We test our data on six categories of objects, partial point clouds are generated by the virtually scanning process of a multi-channel LiDAR.

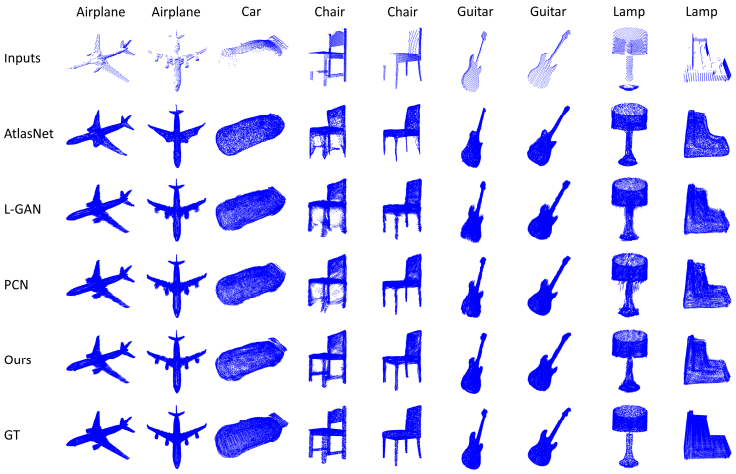


An example of point clouds in our dataset, the left two point clouds are ground truths with 16384 and 1024 points, respectively. The right point cloud is generated by a virtual 64-channel LiDAR

Intuitive Results



Some completion results on different types of cars



Comparison results on six categories of objects

Quantitative Results

Methods	*Average*	*Airplane*	*Car*	*Chair*	*Guitar*	*Lamp*	*Sofa*
L-GAN	13.49	8.52	8.09	16.79	11.01	25.88	10.65
AtlasNet	15.20	10.16	10.80	19.00	11.43	26.38	13.45
PCN	12.84	8.20	**7.82**	16.22	10.37	24.40	10.03
Ours	**11.70**	**7.58**	7.94	**15.12**	**9.15**	**20.53**	**9.89**

Similarity comparison in turns of EMD×100 (Lower is better)

Methods	*Average*	*Airplane*	*Car*	*Chair*	*Guitar*	*Lamp*	*Sofa*
L-GAN-Folding	3.06	1.68	2.01	3.93	1.80	6.04	2.92
AtlasNet	5.24	3.30	4.19	6.74	2.88	8.90	5.43
PCN	2.89	1.58	1.91	3.73	1.68	5.72	2.89
Ours	**2.70**	**1.56**	**1.85**	**3.62**	**1.54**	**5.06**	**2.61**

Similarity comparison in turns of CD×100 (Lower is better)

Conclusion

In this paper, we propose a new point cloud completion network based on local features. Both intuitive and quantitative results show that our network performs well. We hope that our method is able to contribute to future 3D visions.