CF-Net: Complementary Fusion Network for Rotation-Invariant Point Cloud Completion

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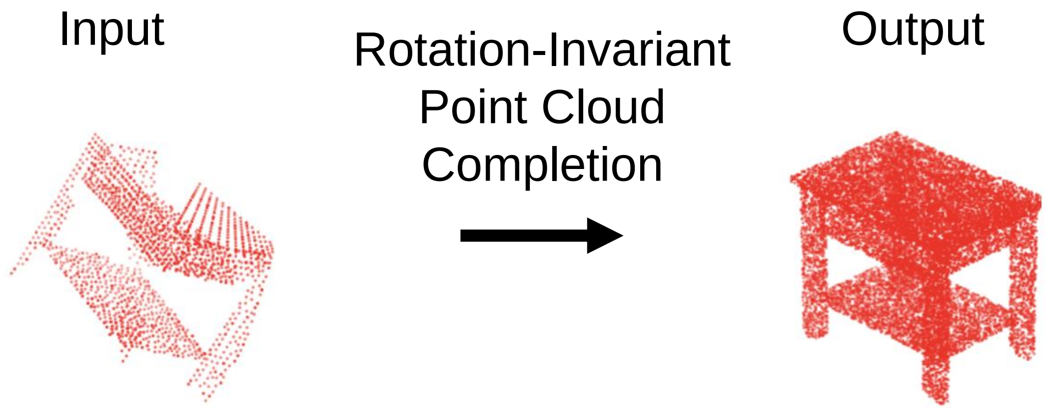
Outline

- Introduction
- Method
- Experiments
- Design Analyses
- Conclusion
- References

Rotation-Invariant Point Cloud Completion

- Point clouds without a fixed orientation, even though they are complete, can still undermine the performance of the downstream tasks.

- Rotation-invariant point cloud completion

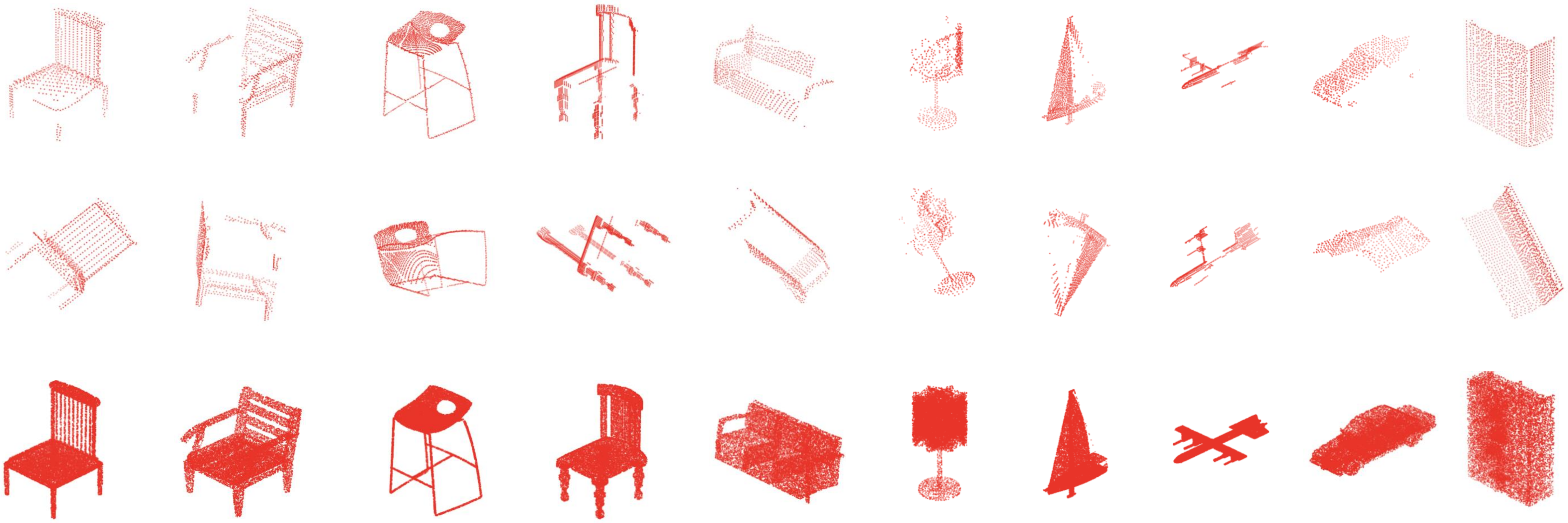


ShapeNet Dataset

Original Input

Rotated Input

Ground Truth



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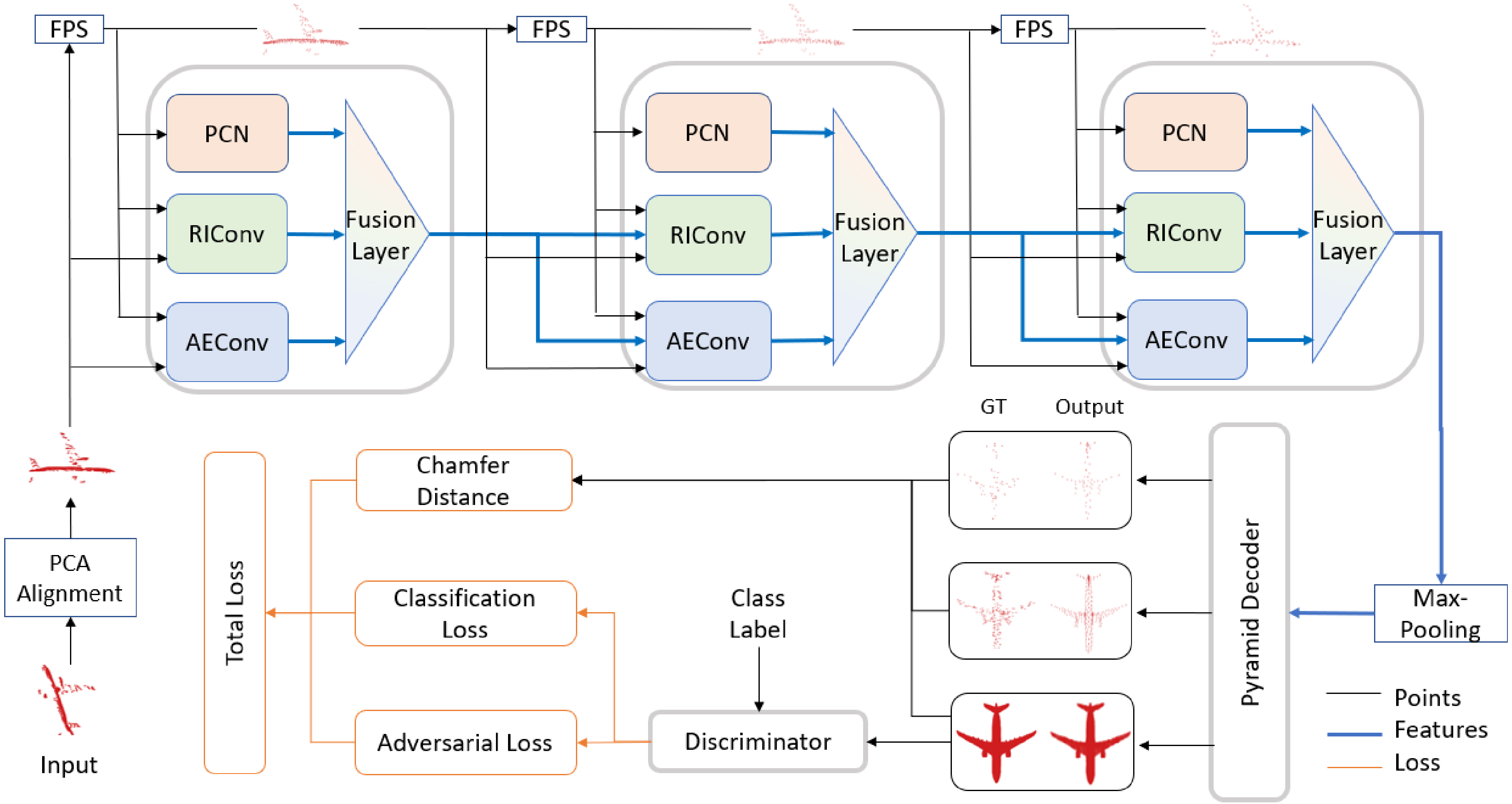
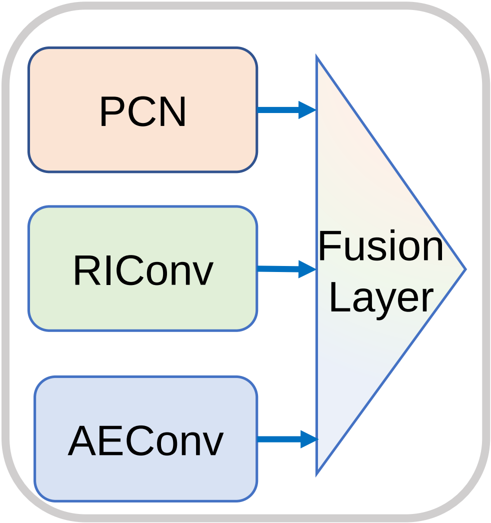
CF-Net – Overall Architecture



Encoder

- PCN [1]
  - Robust against local defects
  - Rotation-variant
- RIConv [10]、AEConv [11]
  - Sensitive to local defects
  - Rotation-invariant
  - Different perceptive fields
- Attention-based fusion layer similar to that proposed in LGR-Net [12]



Decoder/Discriminator

- Pyramid Decoder [4]
  - Proposed in PFNet
  - Coarse-to-fine completion results

- ACGAN Discriminator [14]
  - With classification loss is added
  - Prevents generating an object in a wrong category but with high visual authenticity

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Evaluation Metric - Geometric

- Chamfer Distance (CD)
- F-score

- Geometric metrics have limitations.

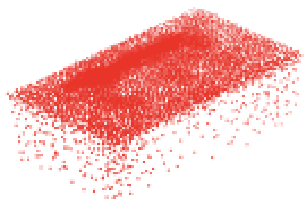
Input

Output

???

CD=0.0183
F =0.1923

Table / Cabinet



CD=0.0351
F =0.0682

Ground Truth

Cabinet

Evaluation Metric – Semantic

- Train a separate classification network on the ground truths
  - PointNet-like [2]
  - DGCNN-like [15]
- Feed the completion results to the classification network.
  - Classification accuracy is the semantic metric
- High classification accuracy means
  - Completion results perceived as the correct object
  - Benefits downstream modules

Results

Table 1: Completion results on the rotated (SO3) ShapeNet dataset.

Methods	CD	F-score	Acc. (%) PointNet	Acc. (%) DGCNN
PCN [1]	18.48	0.4175	67.78	68.72
TopNet [3]	30.55	0.2261	29.53	33.00
PFNet [4]	30.42	0.1840	20.11	21.92
RFA [5]	21.20	0.3754	61.17	63.28
GLFA [5]	22.78	0.3415	57.11	57.83
GRNet [16]	29.63	0.2810	50.25	52.17
Ours	**16.30**	**0.5190**	**90.47**	**88.72**
Ground Truth	-	-	95.83	96.92

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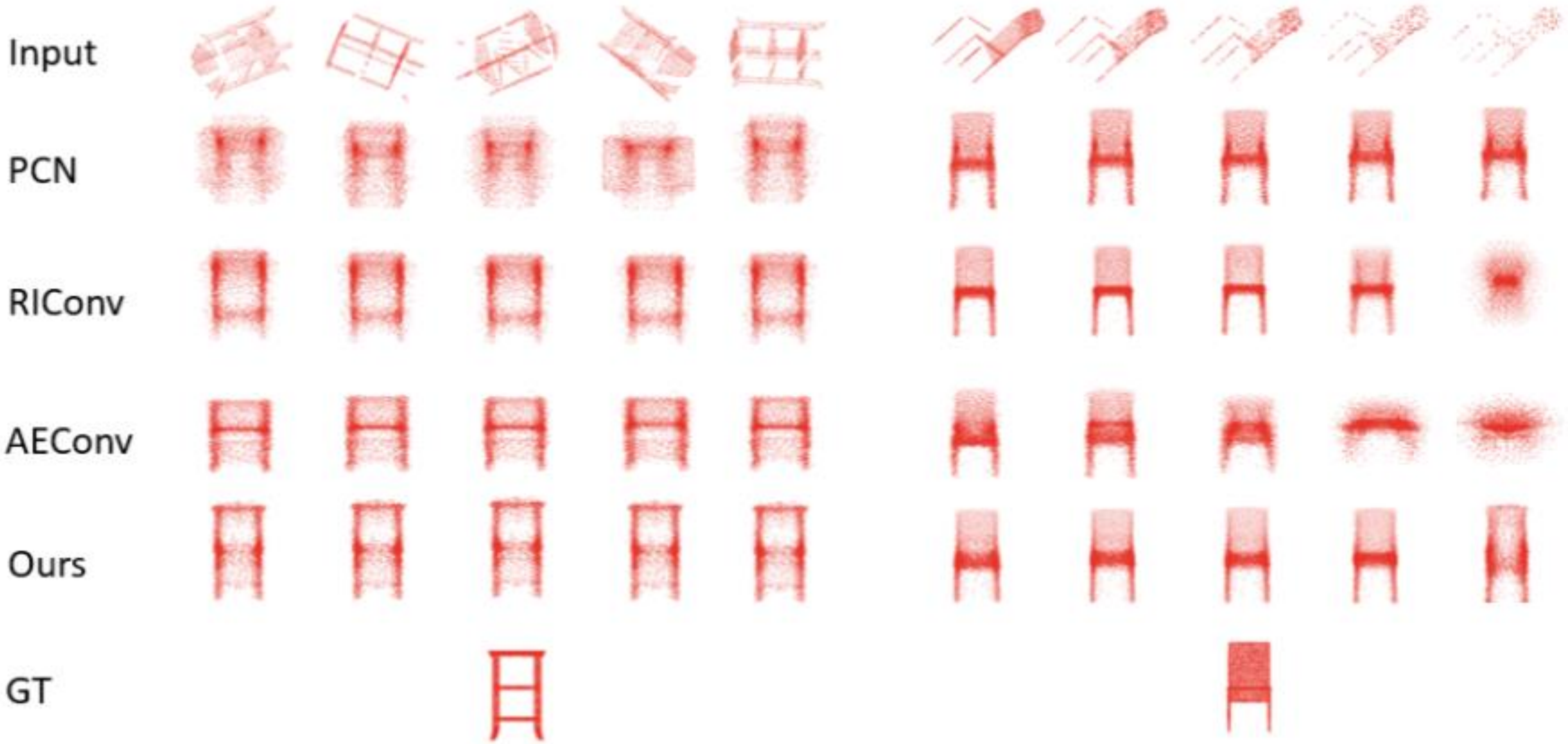
Operator Analysis

- We compare the operators included in our design
  - For a fair comparison, we use a fully connected decoder for each operator

Methods	CD	F-score	Acc. PointNet	Acc. DGCNN
PCN*	18.85	0.3440	49.70	52.61
RIConv*	19.13	0.3563	60.78	61.33
AEConv*	18.57	0.3590	61.61	63.78
Ours*	**15.81**	**0.4651**	**82.47**	**79.25**

*: with fully connected decoder

Operator Analysis



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Conclusion

- A good completion method should be able to handle input data taken from different viewpoints, and generate complete point clouds of a unified orientation.

- In this work, a neural network is designed for rotation invariant point cloud completion. The proposed CF-Net, with an encoder-decoder structure, can generate quality results semantically and geometrically.

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Thank You