Learning SO(3)-Invariant Semantic Correspondence via Local Shape Transform

Chunghyun Park[1]*, Seungwook Kim[1]*, Jaesik Park[2], and Minsu Cho[1] (*equal contribution)
CVPR 2024 · [1]POSTECH · [2]Seoul National University

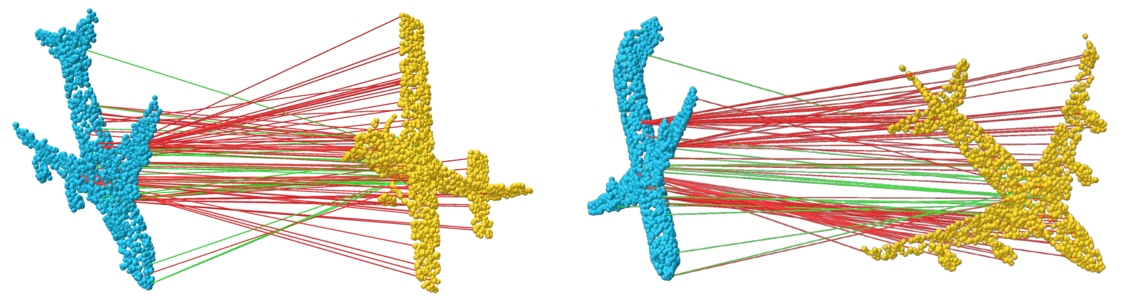
Website

3D Semantic Correspondence

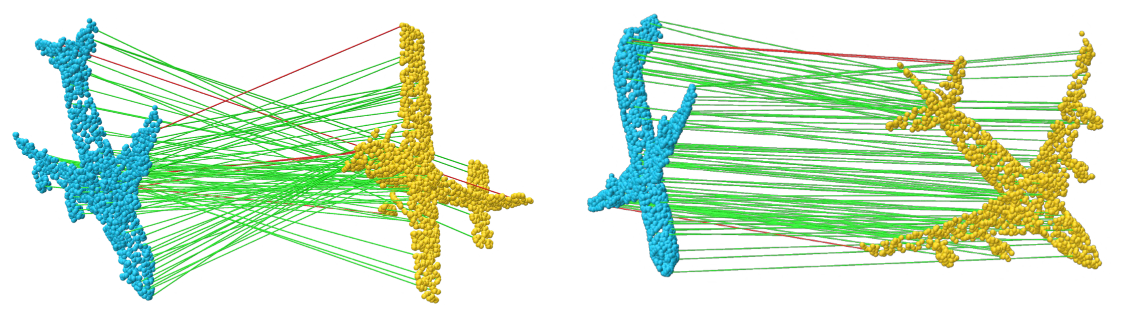
- **Problem Definition**
  Given two different shapes $\mathbf{P}_1 \in \mathbb{R}^{N\times 3}$ and $\mathbf{P}_2 \in \mathbb{R}^{N\times 3}$ of the same semantic category, find all semantically matching point pairs $\{\mathbf{p}_i, \mathbf{q}_i\}_{i=1}^{N'}$ such that $\mathbf{p}_i \in \mathbf{P}_1$ and $\mathbf{q}_i \in \mathbf{P}_2$.

  *$N' \leq N$; there could be points with no pairs.

- **Limitations of Previous Approaches**
  - Impractical assumption of aligned shapes
  - Fail to match rotated shapes even with rotation augmentation during training

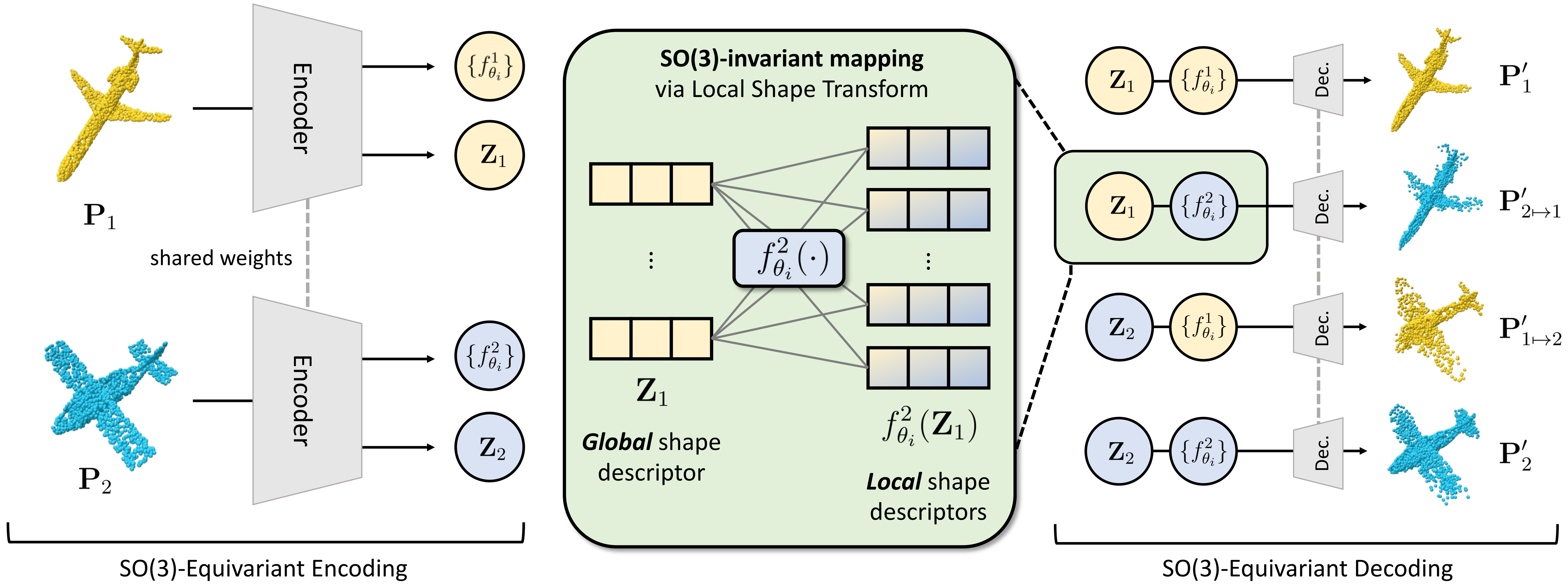


Our Contributions



- **Local Shape Transform**
  We formulate local shape information of each point as a novel function called ***local shape transform*** with dynamic input-dependent parameters.
- **Self-Supervised Learning for SO(3)-Invariant Semantic Correspondence**
  The proposed SO(3)-Invariant local shape transform enables a self-supervised approach for matching two rotated shapes.

RIST: Rotation-Invariant Local Shape Transform



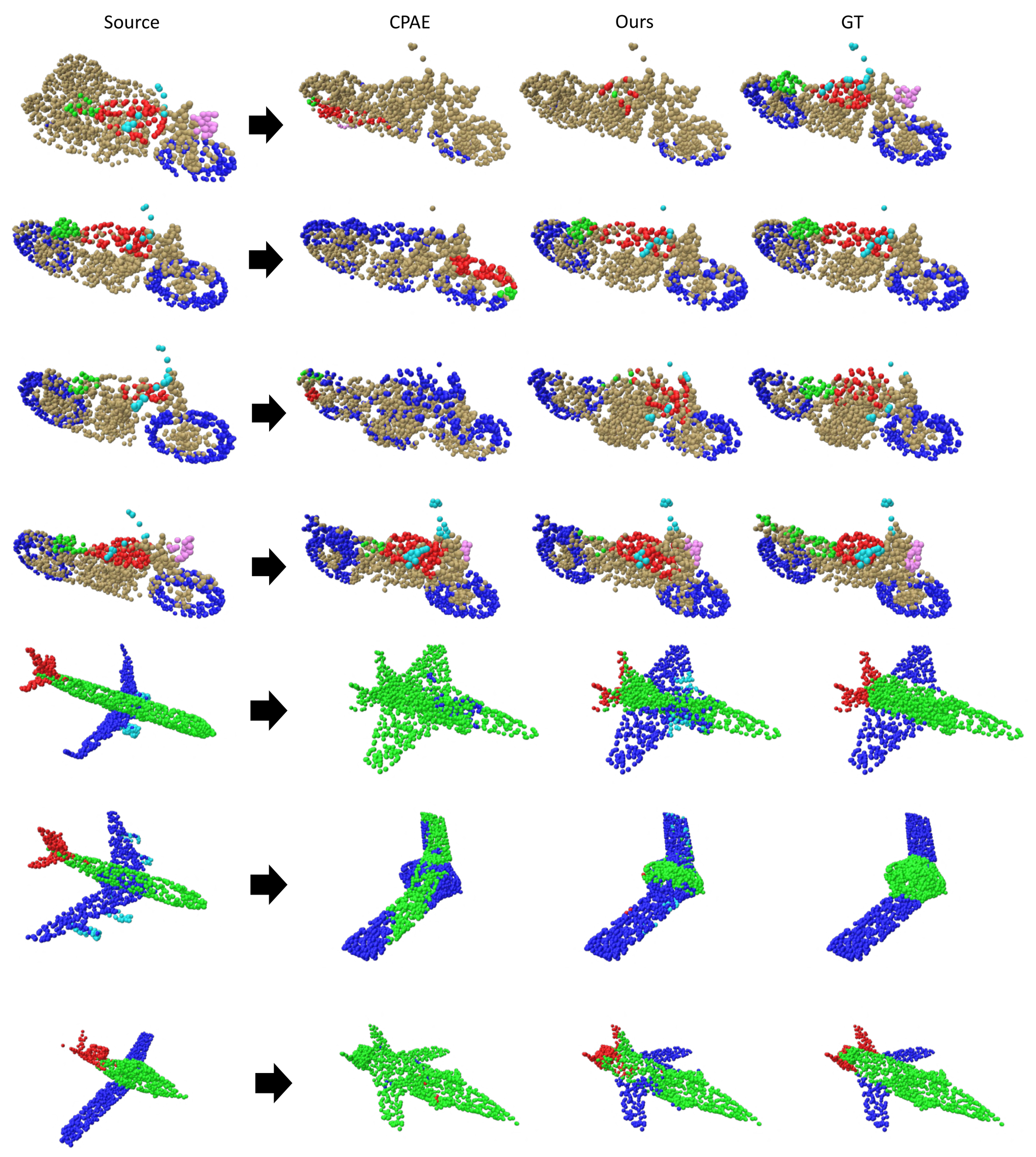
- Self-reconstruction Loss: $\mathcal{L}_{\mathrm{SR}} = \lambda_{\mathrm{MSE}}\,\mathrm{MSE}(\mathbf{P},\mathbf{P}') + \lambda_{\mathrm{EMD}}\,\mathrm{EMD}(\mathbf{P},\mathbf{P}')$
- Cross-reconstruction Loss: $\mathcal{L}_{\mathrm{CR}} = \lambda_{\mathrm{CD}}\,\mathrm{CD}(\mathbf{P}_1,\mathbf{P}'_{2\mapsto 1})$

Self-supervised training of **RIST** for 3D semantic correspondence!

Experiments – I. Part Label Transfer

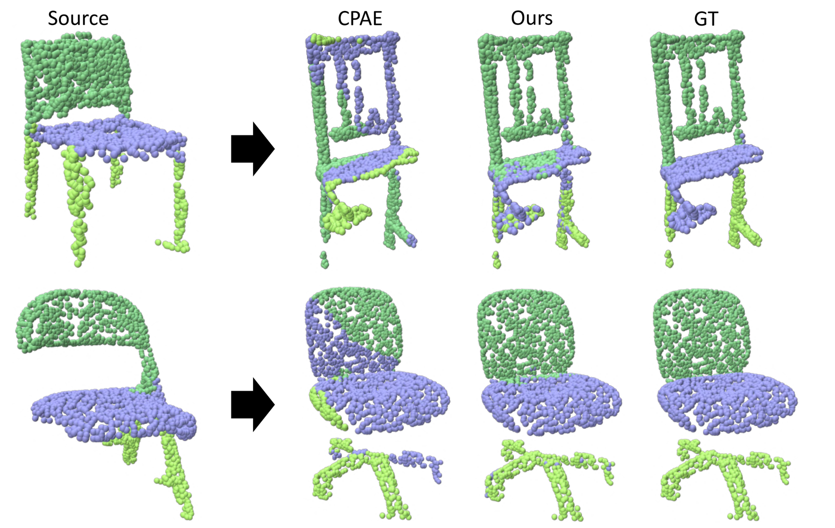
- ShapeNet

Training	Method	Airplane	Cap	Chair	Guitar	Laptop	Motorcycle	Mug	Table	Average
w/o Rotations	FoldingNet	17.8	34.7	22.5	22.1	<u>36.2</u>	12.6	50.0	34.6	28.8
	AtlasNetV2	19.7	31.4	23.6	22.7	36.0	13.1	49.7	35.2	28.9
	DPC	<u>22.7</u>	37.1	25.6	<u>31.9</u>	35.0	<u>17.5</u>	51.3	<u>36.8</u>	<u>32.2</u>
	CPAE	21.0	<u>38.0</u>	<u>26.0</u>	22.7	34.9	14.7	<u>51.4</u>	35.5	30.5
	RIST (ours)	**52.1**	**54.5**	**58.3**	**74.1**	**56.5**	**48.6**	**75.0**	**41.3**	**57.6**
w/ Rotations	FoldingNet	22.5	33.2	24.0	31.0	35.9	13.5	49.9	37.0	30.9
	AtlasNetV2	21.1	32.7	25.2	28.8	35.5	14.5	49.9	<u>41.0</u>	31.1
	DPC	<u>24.6</u>	<u>38.5</u>	<u>25.6</u>	<u>40.2</u>	34.9	<u>19.3</u>	51.8	37.3	<u>34.0</u>
	CPAE	17.0	36.6	24.5	39.4	<u>37.4</u>	15.8	<u>51.9</u>	36.7	32.4
	RIST (ours)	**51.2**	**57.0**	**55.0**	**73.5**	**60.6**	**48.5**	**72.2**	**44.4**	**57.8**



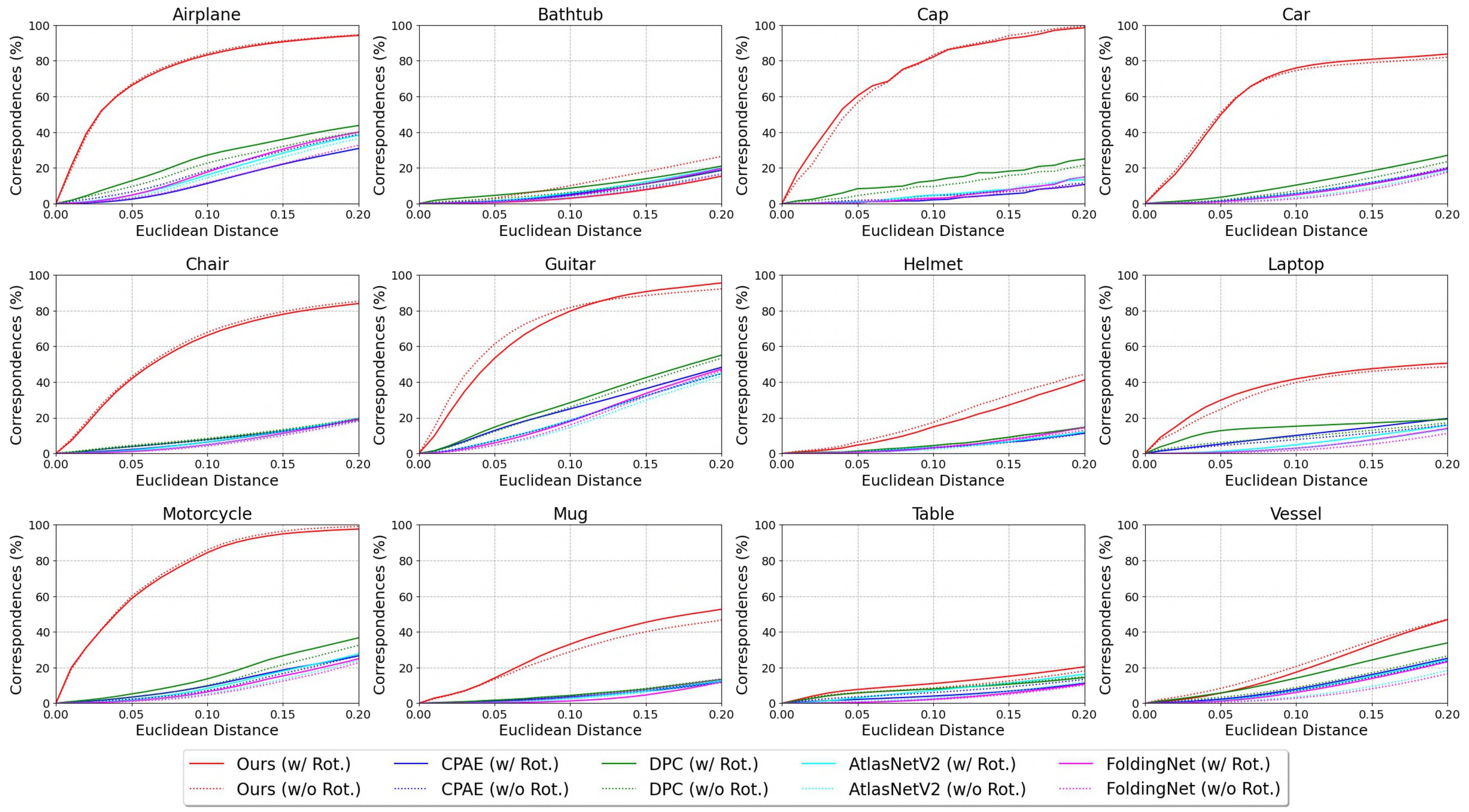
- ScanObjectNN

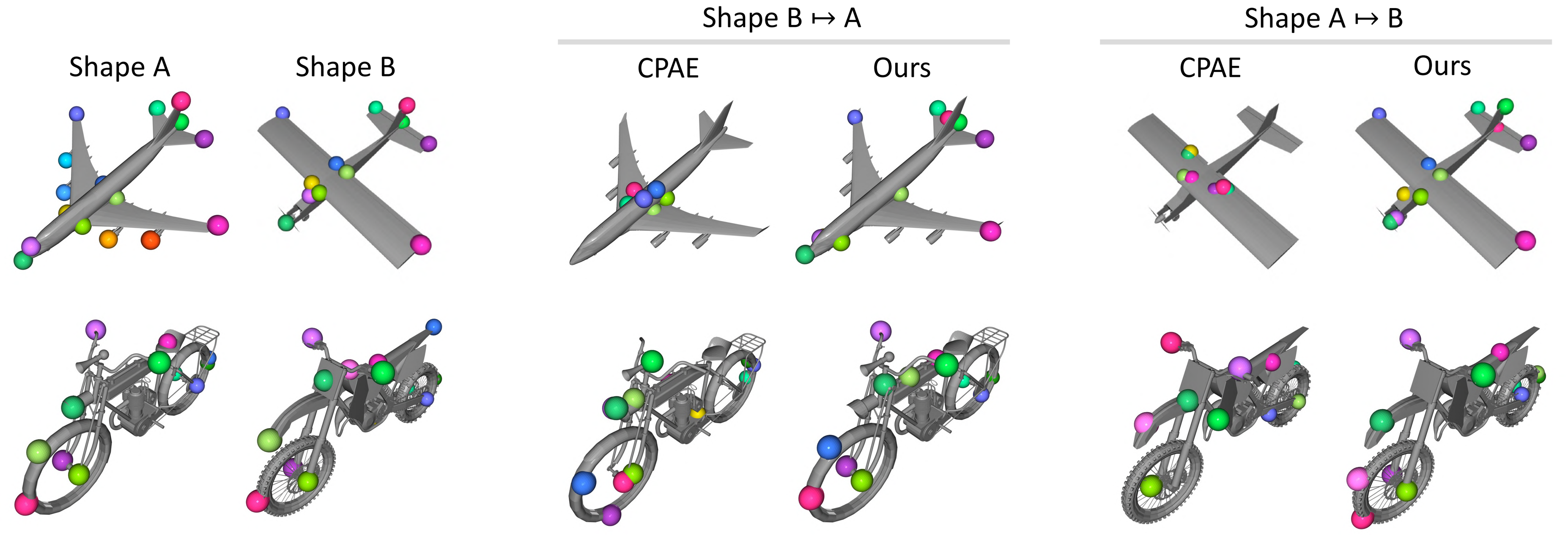
Method	w/o Rotations	w/ Rotations
FoldingNet	23.2	23.3
AtlasNetV2	23.6	<u>24.1</u>
DPC	23.9	23.9
CPAE	<u>24.4</u>	23.9
RIST (ours)	**39.6**	**37.9**



Experiments – II. Keypoint Transfer

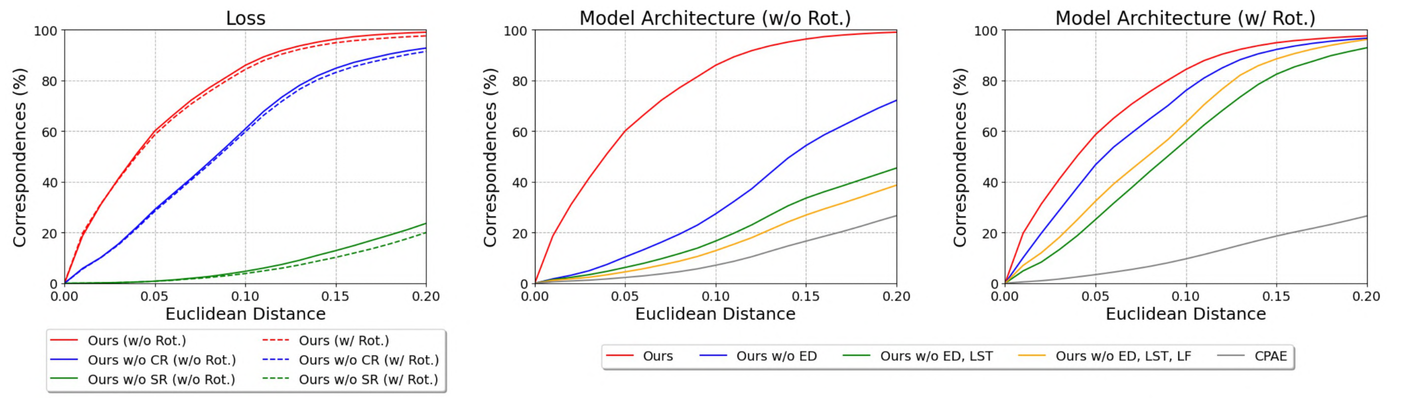
- Quantitative & Qualitative Results on KeypointNet





- Ablation Study on Losses and Model Components

SR: Self-reconstruction
CR: Cross-reconstruction
ED: Equivariant Decoder
LST: Local Shape Transform
LF: Local Feature



Acknowledgement

This work was supported by IITP grants (No.2021-0-02068: AI Innovation Hub (50%), No. 2022-0-00290: Visual Intelligence for Space-Time Understanding and Generation (40%), No.2019-0-01906: Artificial Intelligence Graduate School Program at POSTECH (5%), NO.2021-0-01343, Artificial Intelligence Graduate School Program at Seoul National University (5%)) funded by the Korea government (MSIT). Seungwook was supported by the Hyundai-Motor Chung Mong-koo Foundation.