Correspondence-Free Point Cloud Registration with SO(3)-Equivariant Implicit Shape Representations (Supplementary Material)

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1 Experiment on ModelNet40 dataset

1.1 Ablation study on the sampling strategy of the feature initialization layer

A possible reason for the increased error when the input point clouds have different densities is that the DGCNN layer for feature initialization at the beginning of the encoder is sensitive to the point cloud density since it takes the relative coordinate of neighboring points as inputs.

Therefore, we experimented with replacing the k-nearest neighbor with random sampling in a ball centered at each point when collecting neighboring points for the edge-convolution of that point. In practice, we sample 20 neighboring points for both strategies, and the radius for ball sampling is 0.2.

The result is shown in Table 1. One can see that the ball sampling strategy can improve the registration performance for point clouds of different densities. However, the error is slightly higher than k-NN when the input condition is more benign, i.e., when the point clouds are rotated copies or with Gaussian noise with the same number of points. It is understandable since the ball sampling introduces randomness in the feature initialization and can slightly worsen the registration when the inputs are near ideal.

Table 1: Ablation study on the point sampling strategy in feature initialization layer on ModelNet40. Since our method is invariant to the initial rotation angle, in this table, we only report results with random and unrestricted initial rotation angles (up to 180 degrees). The three columns of input conditions correspond to Tables 1, 2, and 3 in the paper.

Condition of input point clouds	noise-free	with noise	of different density
Samping strategy	Rotation error after registration		
k-nearest neighbors	**0.02**	**3.26**	16.50
random sampling in a ball	3.35	4.84	**13.23**

2 Experiment on 7Scenes dataset

2.1 Registration with point clouds that are partially overlapping

This part reports the registration results of point clouds coming from adjacent frames in the sequence. Because of camera movement, the pair of point clouds only overlap partially. Since our method only estimates rotations, we first align the adjacent frames using the ground truth pose, then randomly rotate two point clouds separately in a common frame so that the input point clouds are related by a rotation. To our knowledge, we are also one of the first to show quantitative results on partially overlapping point clouds in correspondence-free methods [1, 2, 3].

The results are in Table 2. Both our method and the baseline deteriorate in this setting. For FMR, the system completely fails when taking partially-overlapping inputs. Our method consistently gives better rotation estimation under all initial conditions. Still, the accuracy has a lot of room for im-

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Table 2: Rotational registration error of partially overlapping point clouds on 7Scenes.

Max initial rotation angle	0	30	60	90	120	150	180
Methods	Rotation error after registration						
FMR[2]	38.81	42.42	48.59	62.43	80.90	80.28	101.60
Ours	**25.12**	**24.04**	**23.67**	**24.25**	**25.31**	**24.32**	**24.50**

provement, indicating that there is still a long way to go for correspondence-free registration methods. For example, recent work by Huang et al. [4] predicting the overlapping part of point cloud pairs may inspire correspondence-free methods to better handle partial overlapping inputs by predicting features focused on the overlapping parts.

References

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