A. Supplementary Material

Firstly, we provide additional ablation results on ModelNet40 (we use the official train/test split for training and testing). Then, we provide the results of complete-to-complete and complete-to-partial point cloud registration. Lastly, we show qualitative results on 7Scenes.

A.1. Additional ablation study results

Different overlapping ratios. Because the overlap ratio may affect the performance of registration, we analyze the performance variation when the overlap ratio decreases gradually. We evaluate the performance of OGMM on noisy ModelNet40. We utilize the same crop setting as RPMNet to generate point clouds with approximate overlap ratios of 70%, 60%, 50%, 40%, and 30%, respectively. Based on [18, 10], we randomly draw a rigid transformation along each axis to generate the target points; the rotation along each axis is sampled in $[0, 45°]$ and translation is in $[-0.5, 0.5]$. We train OGMM on data with a 50% overlap ratio and test on different overlap ratios. Tab. 7 shows the registration results under different overlap ratios with Gaussian noise sampled from $\mathcal{N}(0, 0.01)$ and clipped to $[-0.05, 0.05]$. The lower the overlap ratio, the higher the registration error.

Different cluster numbers. We show the performances of OGMM under different cluster numbers (8, 16, 32, 48, and 64) with a 50% overlap ratio. Tab. 8 shows that when the number of clusters is small (e.g. 8, 16) we obtain a larger registration error. When we set the number of clusters between 32 to 64, the registration error is reduced and it varies slightly.

A.2. Additional registration results

Because OGMM is a GMM-based method, we compare it against GMM-based baselines.

Complete-to-complete setup. We first evaluate the complete-to-complete registration performance on ModelNet40 with Gaussian noise sampled from $\mathcal{N}(0, 0.01)$ and clipped to $[-0.05, 0.05]$ and follow the sampling and transformation settings in Sec. 4.3. Tab. 9 shows that our method can outperform the GMM-based baselines on this setup.

Table 7. The effects of the overlap ratio on ModelNet40.

Ratio	30%	40%	50%	60%	70%
MAE (R)	5.6462	3.5995	2.1000	1.2067	0.9111
MAE (t)	0.1220	0.0716	0.0178	0.0159	0.0071
CCD	0.1097	0.0957	0.0937	0.0664	0.0645

Table 8. The effects of the cluster numbers on ModelNet40 with 50% overlapping ratio and Gaussian noise.

Ratio	8	16	32	48	64
MAE (R)	5.6462	3.5995	2.1625	2.0834	2.1000
MAE (t)	0.1220	0.0716	0.0187	0.0181	0.0178
CCD	0.1097	0.0957	0.0942	0.0885	0.0937

Table 9. Registration results on ModelNet40.

Method	Complete-to-complete setup			Complete-to-partial setup		
	MAE(R)	MAE(t)	CCD	MAE(R)	MAE(t)	CCD
CPD [29]	0.8171	0.0050	0.0037	10.293	0.0767	0.1118
GMMReg [20]	7.7326	0.0508	0.0837	24.318	0.2578	0.1119
SVR [4]	7.8047	0.0592	0.0744	24.063	0.2480	0.0947
FilterReg [12]	3.4899	0.0247	0.0605	30.653	0.2676	0.1197
DeepGMR [49]	2.2736	0.0150	0.0503	12.612	0.1527	0.1266
OGMM (ours)	**0.1461**	**0.0021**	**0.4237**	**7.2820**	**0.0633**	**0.1142**

Complete-to-partial setup. We also evaluate the complete-to-partial registration performance on ModelNet40 with Gaussian noise. We crop the generated source point cloud in Sec. 4.3 to create a new source point cloud with approximate overlap ratios of 70%, which includes 717 points. We randomly draw a rigid transformation along each axis to transform the target point cloud, which contains 1024 points. Tab. 9 shows that our method can outperform the GMM-based baselines also on this setup.

Visualization of predicted overlap scores and registration results on 7scene. Fig. 4 shows successful and unsuccessful registration results, where the overlap between the two point clouds is 70%. For the unsuccessful case, pairs with repetitive local geometric structures lead to features of similar structures in different locations have a small distance in the feature space

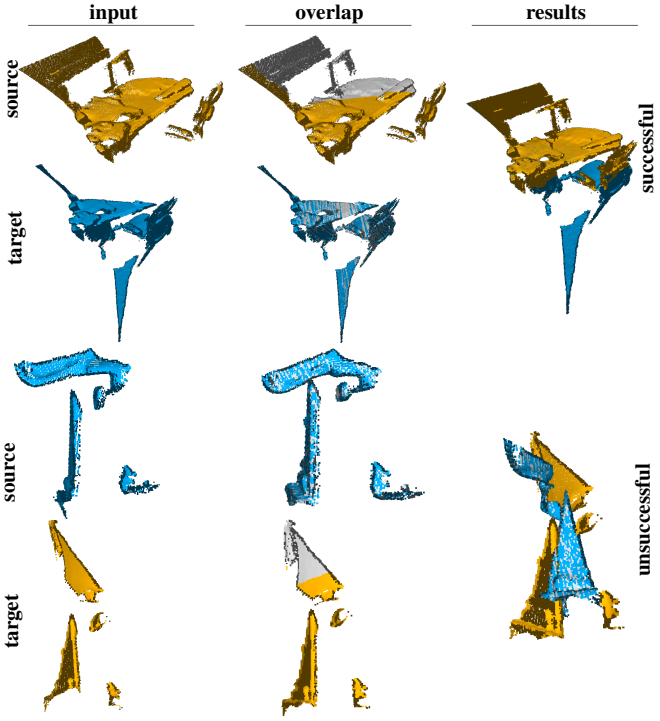

Figure 4. Qualitative results on the 7scenes dataset.