

Institute of Geodesy and Photogrammetry

2D-Informed Point Cloud Registration: Leveraging RGB Image Priors

PhD Student: Zhaoyi Wang; Supervisor: Prof. Dr. Andreas Wieser

Geosensors and Engineering Geodesy, IGP, ETH Zürich

Motivation

Problem: Common geometry-based point cloud registration methods may fail to align two point clouds when the overlap is geometrically smooth.

Solution: Use a 2D pretrained model (e.g., ResNet-50) to extract highlevel image features from multi-view RGB images. Then, either unproject these features to 3D features or jointly train 3D features constrained by

these features.









$\mathcal{F}^{\mathsf{pcd}}$ **2D Image-3D Point Cloud Feature Fusion** Helport. Feature Extraction Late fusion ${\mathcal T}$ fused $\mathcal{F}^{\mathsf{fused}}$ Feature Contraction of the Extraction Early fusion Timg Feature Extraction Feature Extraction Fime : projection : concatenation Source $\mathcal{F}^{\mathsf{pcd}}$ tout ! Feature Feed $S_{1}; S_{2}$ Joint learning Extraction : loss functions (\mathcal{L}) Target $\mathcal{F}^{\mathsf{img}}$ Fred $S_1; S_2$ Feature Extraction : does not work





Quantitative Results

Table 1. Results on 3DMatch and 3DLoMatch Dataset

	3DMatch			3DLoMatch			
# Samples	1000	500	250	1000	500	250	
Methods	$ Registration Recall(\%) \uparrow$						
FCGF	83.3	81.6	71.4	38.2	35.4	26.8	
D3Feat	83.4	82.4	77.9	46.9	43.8	39.1	
SpinNet	84.5	79.0	69.2	49.8	41.0	26.7	
Predator	90.6	88.5	86.6	62.4	60.8	58.1	
PCR-CG(early fusion)	90.0	88.7	86.8	69.0	68.5	65.0	
PCR-CG(early fusion, retrain)	90.0	89.5	87.8	65.6	64.0	60.7	
Joint learning	88.3	88.4	86.1	59.0	57.9	55.2	
Late fusion	92.7	91.1	89.0	66.3	65.5	61.6	

Table 2. Results on 3DMatch_Smooth and 3DLoMatch_Smooth Dataset

# Samples = 1k pts	$3DMatch_Smooth$	3DLoMatch_Smooth
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Visual Resuls on 3DMatch Dataset



Methods	$ \operatorname{RRE}(^{\circ}) \downarrow$	$\operatorname{RTE}(m){\downarrow}$	$\mathrm{RR}(\%)\uparrow$	$RRE(^{\circ})\downarrow$	$\operatorname{RTE}(m){\downarrow}$	$\mathrm{RR}(\%)\uparrow$
Predator	3.003	0.065	58.4	3.845	0.093	48.2
PCR-CG (early fusion)	2.682	0.069	65.2	3.791	0.101	53.6
Joint learning	3.338	0.086	59.0	4.803	0.120	34.5
Late fusion	2.849	0.074	62.6	3.607	0.094	51.0

Table 3. Generalizing to IndoorLRS_Smooth Dataset

Indoor LRS_Smooth w. 1k pts Indoor LRS_Smooth w. 250 pts							
Methods	$ RRE(^{\circ}) \downarrow$	$\operatorname{RTE}(m){\downarrow}$	$\mathrm{RR}(\%)\uparrow$	$RRE(^{\circ})\downarrow$	$\operatorname{RTE}(m){\downarrow}$	$\mathrm{RR}(\%)\uparrow$	
Predator	2.159	0.100	78.7	2.875	0.130	76.5	
LCD64 (only Img.)	2.933	0.139	69.2	5.100	0.226	64.8	
Late fusion (Pred. $+$ LCD64)	1.749	0.084	82.2	3.034	0.125	78.8	
Late fusion (Pred. $+$ Img16)	1.610	0.073	84.1	2.603	0.124	78.6	

Conclusion & Outlook

Conclusion:

□ Instead of emphasizing the high or low levels of overlapping ratios, I subsetted new datasets that contained cases of geometric smoothness. □ I investigated different 2D image and 3D point cloud feature fusion strategies for point cloud registration task.

□ Early fusion and late fusion perform better on these datasets w.r.t. selected pure geometry method, while joint learning method does not perform as effective as expected.

Outlook:

□ Further investigate the joint learning method.

Conduct experiments on end-to-end methods (i.e., plus matching and estimation).

• Extend the method to large-scale TLS datasets, which may contain different color format and LiDAR intensity.