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PointDSC: Robust Point Cloud Registration using Deep Spatial Consistency

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PointDSC: Robust Point Cloud Registration using Deep Spatial Consistency

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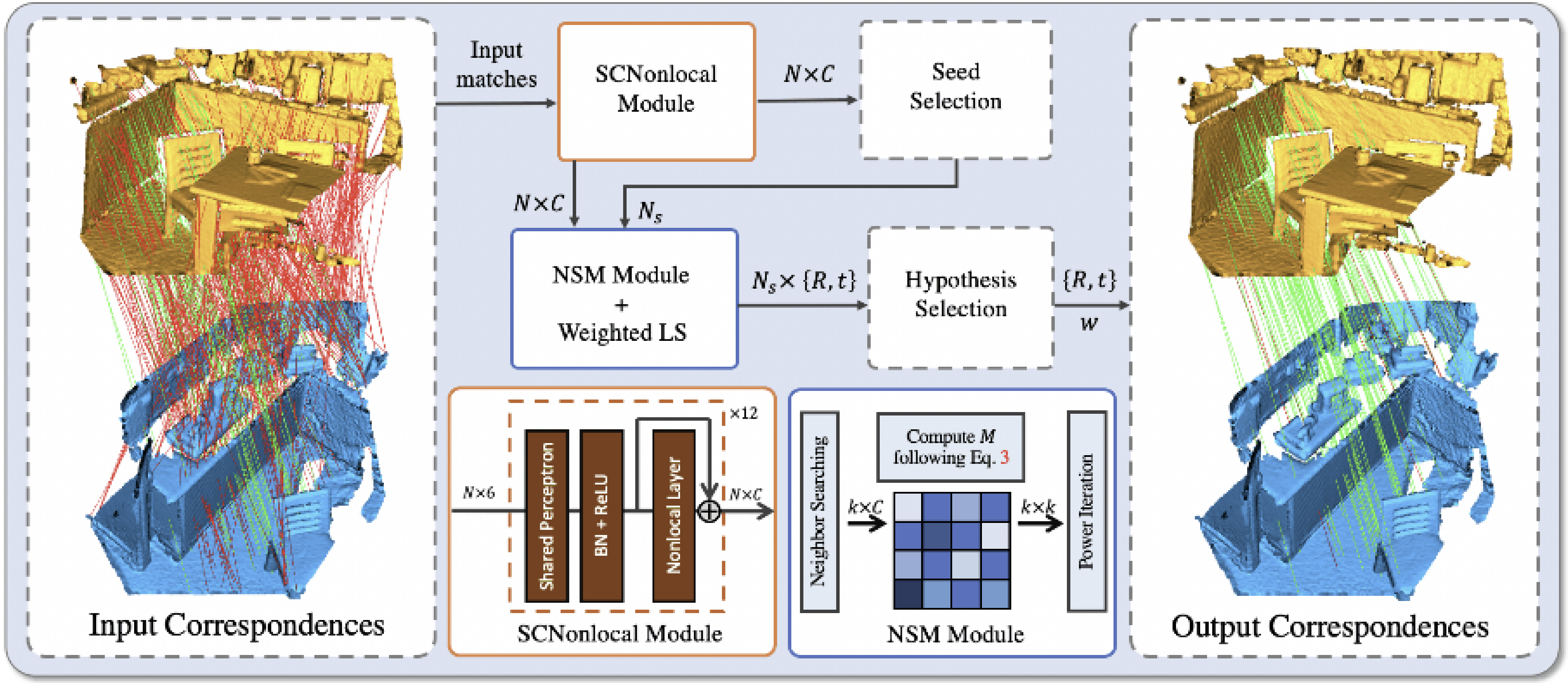
Abstract:

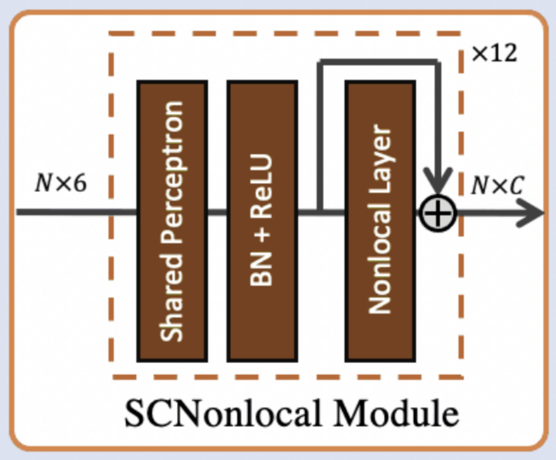
Removing outlier correspondences is one of the critical steps for successful feature-based point cloud registration. Despite the increasing popularity of introducing deep learning techniques in this field, spatial consistency, which is essentially established by a Euclidean transformation between point clouds, has received almost no individual attention in existing learning frameworks. In this paper, we present PointDSC, a novel deep neural network that explicitly incorporates spatial consistency for pruning outlier correspondences. First, we propose a nonlocal feature aggregation module, weighted by both feature and spatial coherence, for feature embedding of the input correspondences. Second, we formulate a differentiable spectral matching module, supervised by pairwise spatial compatibility, to estimate the inlier confidence of each correspondence from the embedded features. With modest computation cost, our method outperforms the state-of-the-art hand- crafted and learning-based outlier rejection approaches on several real-world datasets by a significant margin. We also show its wide applicability by combining PointDSC with different 3D local descriptors. [code release]

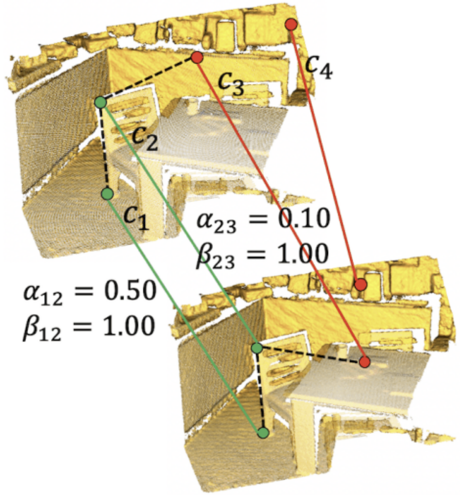
introduction



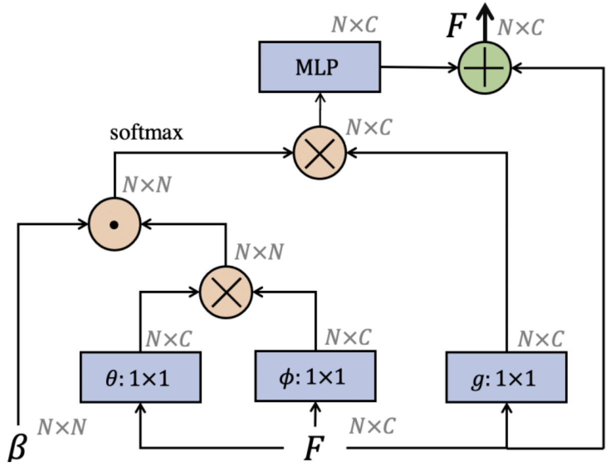
- Proposing a spatial-consistency guided nonlocal (SCNonlocal) module
- Proposing a differentiable neural spectral matching (NSM) module based on traditional SM

SCNonlocal





(a) Spatial Consistency Illustration



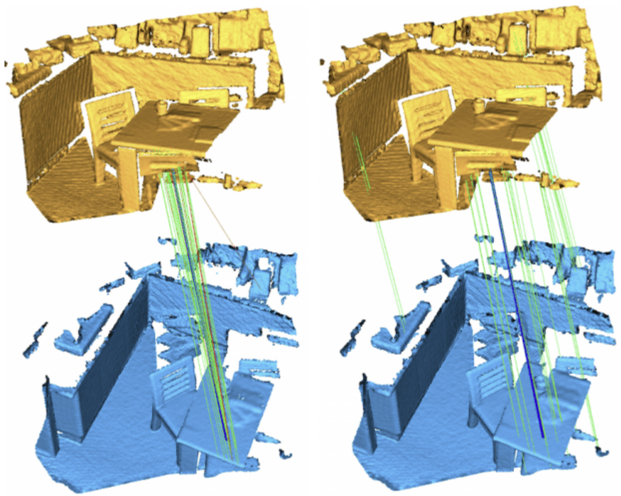
The features $$\boldsymbol{f_i} = \boldsymbol{f_i} + \mathrm{MLP}\left(\sum_j^{|C|} \mathrm{softmax}_j(\boldsymbol{\alpha\beta})g(\boldsymbol{f_j})\right)$$

$$\beta_{ij} = [1 - \frac{d_{ij}^2}{\sigma_d^2}]_+, \quad d_{ij} = \big| \|\boldsymbol{x_i} - \boldsymbol{x_j}\| - \|\boldsymbol{y_i} - \boldsymbol{y_j}\| \big|, \quad (2)$$

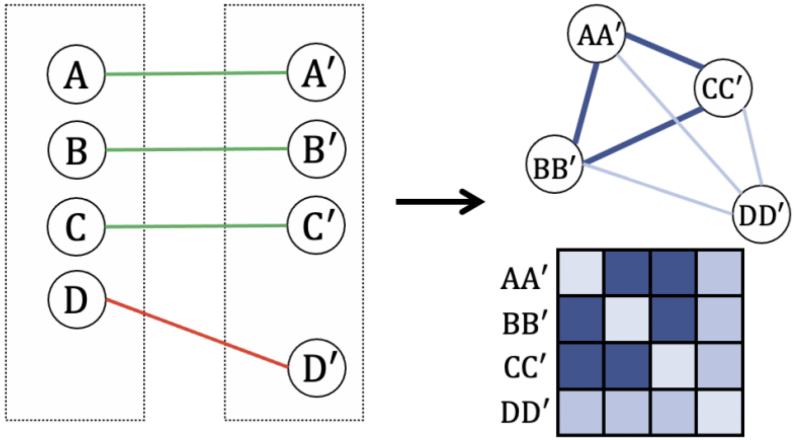
α:embedded dot-product similarity
β:length constraint
g:linear projection function

SCNonlocal module produces for each correspondence ci a feature representation fi, which will be used in both seed selection and neural spectral matching module.

Neural Spectral Matching



(b) Spatial kNN and Feature-space kNN



We set the matrix diagonal to zero following The weight of each graph edge represents the pairwise compatibility between two associated correspondences.

Given the correspondence subset $C' \subset C(|C'| = k)$of each seed constructed by kNN search

Construct a matrix M:

$$M_{ij} = \beta_{ij} * \gamma_{ij},$$

$$\gamma_{ij} = [1 - \frac{1}{\sigma_f^2} \left\| \bar{\boldsymbol{f}}_i - \bar{\boldsymbol{f}}_j \right\|^2]_+$$

$\bar{f}$i and $\bar{f}$j : L2- normalized feature vectors

σf : a parameter to control sensitivity to feature difference

$$\hat{\mathbf{R}}, \hat{\mathbf{t}} = \arg\max_{\mathbf{R}', \mathbf{t}'} \sum_{i}^{|C|} [\![||\mathbf{R}' \boldsymbol{x}_i + \mathbf{t}' - \boldsymbol{y}_i|| < \tau]\!]$$

Experiments

	FCGF (learned descriptor)							FPFH (traditional descriptor)						
	RR(%↑)	RE(°↓)	TE(cm↓)	IP(%↑)	IR(%↑)	F1(%↑)	Time(s)	RR(%↑)	RE(°↓)	TE(cm↓)	IP(%↑)	IR(%↑)	F1(%↑)	Time(s)
FGR [82]	78.56	2.82	8.36	-	-	-	0.76	40.67	3.99	9.83	-	-	-	0.28
SM [38]	86.57	2.29	7.07	81.44	38.36	48.21	0.03	55.88	2.94	8.15	47.96	70.69	50.70	0.03
TEASER [71]	85.77	2.73	8.66	**82.43**	68.08	73.96	0.11	75.48	2.48	7.31	**73.01**	62.63	66.93	0.03
GC-RANSAC-100k [5]	92.05	2.33	7.11	64.46	**93.39**	75.69	0.47	67.65	2.33	6.87	48.55	69.38	56.78	0.62
RANSAC-1k [24]	86.57	3.16	9.67	76.86	77.45	76.62	0.08	40.05	5.16	13.65	51.52	34.31	39.23	0.08
RANSAC-10k	90.70	2.69	8.25	78.54	83.72	80.76	0.58	60.63	4.35	11.79	62.43	54.12	57.07	0.55
RANSAC-100k	91.50	2.49	7.54	78.38	85.30	81.43	5.50	73.57	3.55	10.04	68.18	67.40	67.47	5.24
RANSAC-100k refine	92.30	2.17	6.76	78.38	85.30	81.43	5.51	77.20	2.62	7.42	68.18	67.40	67.47	5.25
3DRegNet [51]	77.76	2.74	8.13	67.34	56.28	58.33	0.05	26.31	3.75	9.60	28.21	8.90	11.63	0.05
DGR w/o s.g. [16]	86.50	2.33	7.36	67.47	78.94	72.76	0.56	27.04	2.61	7.76	28.80	12.42	17.35	0.56
DGR [16]	91.30	2.40	7.48	67.47	78.94	72.76	1.36	69.13	3.78	10.80	28.80	12.42	17.35	2.49
PointDSC	**93.28**	**2.06**	**6.55**	79.10	86.54	**82.35**	0.09	**78.50**	**2.07**	**6.57**	68.57	**71.61**	**69.85**	0.09

Table 1: Registration results on

	RR(↑)	RE(↓)	TE(↓)	F1(↑)	Time
SM [38]	79.64	0.47	12.15	56.37	0.18
RANSAC-1k [24]	11.89	2.51	38.23	14.13	0.20
RANSAC-10k	48.65	1.90	37.17	42.35	1.23
RANSAC-100k	89.37	1.22	25.88	73.13	13.7
DGR [16]	73.69	1.67	34.74	4.51	0.86
PointDSC	90.27	**0.35**	**7.83**	70.89	0.31
DGR re-trained	77.12	1.64	33.10	27.96	0.86
PointDSC re-trained	**98.20**	**0.35**	8.13	**85.54**	0.31

Table 2: Registration results on KITTI under FPFH setting.

	Living1	Living2	Office1	Office2	AVG
ElasticFusion [69]	66.61	24.33	**13.04**	35.02	34.75
InfiniTAM [35]	46.07	73.64	113.8	105.2	84.68
BAD-SLAM[63]	fail	40.41	18.53	26.34	-
Multiway + FGR [82]	78.97	24.91	14.96	21.05	34.98
Multiway + RANSAC [24]	110.9	19.33	14.42	17.31	40.49
Multiway + DGR [16]	21.06	21.88	15.76	11.56	17.57
Multiway + PointDSC	**20.25**	**15.58**	13.56	**11.30**	**15.18**

Table 3: ATE(cm) on Augmented ICL-NUIM. The last column is the average ATE over all scenes. Since BAD-SLAM fails on one scene, we do not report its average ATE.

PointDSC achieves the best Registration Recall as well as the lowest average TE and RE in both settings.

Experiments

		RR(↑)	IP(↑)	IR(↑)	F1(↑)	Time
PointCN	**+ classifier**	78.19	58.05	39.59	42.65	0.04
Nonlocal	**+ classifier**	83.30	65.49	67.13	64.28	0.07
SCNonlocal	**+ classifier**	88.17	74.74	77.86	75.04	0.07
PointCN	**+ NSM**	92.48	78.48	82.10	79.98	0.06
Nonlocal	**+ NSM**	92.54	78.68	83.13	80.58	0.09
SCNonlocal	**+ NSM**	**93.28**	**79.10**	**86.54**	**82.35**	0.09

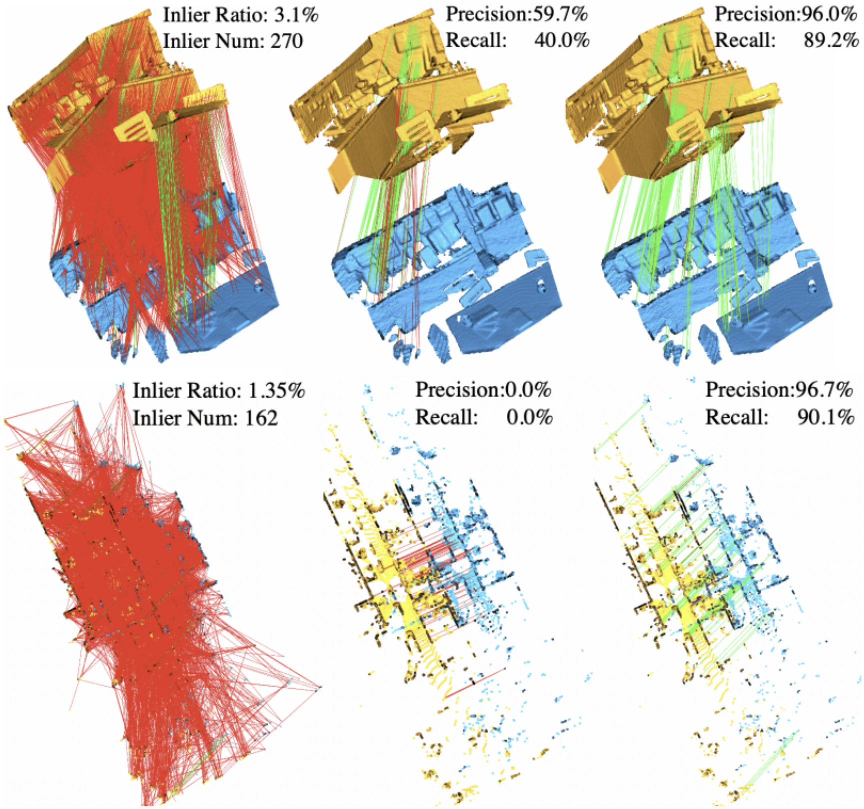
Table 4: Ablation experiments of SCNonlocal module. Rows 1-3 and Rows 4-6 show the registration results of different feature extractors combined with a classification layer and the neural spectral matching module, respectively.

	RR(↑)	RE(↓)	TE(↓)	F1(↑)	Time
Traditional SM	86.57	2.29	7.07	48.21	0.03
+ neural	88.43	2.21	6.91	48.88	0.06
+ seeding	92.91	2.15	6.72	82.35	0.08
+ refine	**93.28**	**2.06**	**6.55**	**82.35**	0.09
w/o L_{sm}	92.61	2.07	6.75	81.58	0.09

Table 5: Ablation experiments of NSM module. Note that every row with '+' represents the previous row equipped with the new component. **+refine** is our full model. The last row is the full model trained without L_{sm}.

- The proposed SCNonlocal module consistently improves the registration results across all the settings and metrics.
- For +seeding, we adopt the neural spectral matching over multiple correspondence subsets found by the featurespace kNN search from highly confident seeds, and determine the best transformation that maximizes the geometric consensus. This significantly boosts the performance.

Experiments



Visualization of outlier rejection results on examples with high outlier ratios from 3DMatch (first row) and KITTI (second row). From left to right: input correspondences, results of RANSAC-100k, and results of PointDSC

Conclusion

- Proposed a spatialconsistency guided nonlocal module (SCNonlocal) and a neural spectral matching module (NSM) for feature embedding and outlier pruning, respectively.
- Designed a novel 3D outlier rejection network that explicitly incorporates spatial consistency established by Euclidean transformations.
- The extensive experiments on diverse datasets showed that our method brings remarkable improvement over the state-of-the-arts.

Thank You!

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