Supplementary Material:

DCReg: Decoupled Characterization for Efficient Degenerate LiDAR Registration

Xiangcheng Hu, Xieyuanli Chen, Mingkai Jia, Jin Wu,
Ping Tan, and Steven L. Waslander

I. Overview

This supplementary material provides additional details to support the findings in the main manuscript "DCReg: Decoupled Characterization for Efficient Degenerate LiDAR Registration". The contents include:

- Additional baseline details and experimental setups.
- Extended quantitative comparisons (tables).

II. Extended Experimental Setup and Baseline Analysis

To comprehensively evaluate the registration performance, we expanded our comparative analysis to include state-of-the-art global registration algorithms. Unlike the directly degeneracy-aware methods discussed in the manuscript, these global approaches typically adopt a "passive" strategy towards degeneracy [1], attempting to mitigate its effects indirectly through robust estimation and aggressive outlier rejection [2], [3].

A. Additional Baselines

We incorporated two representative global registration methods:

- **GeoTransformer [2] (GeoTrans)**: An end-to-end learning-based approach that leverages geometric transformers to extract superpoint correspondences for robust registration.
- **SC2-PCR [3]**: A robust correspondence-based method. It utilizes a second-order spatial compatibility (SC2) measure to distinguish inliers from outliers and employs a consensus set sampling strategy for rigid transformation estimation.

For SC2-PCR, we evaluated two variants following its official experiments: 1) **SC2-PCR-FPFH** (SC2-FH): Utilizes FPFH descriptors for initial correspondence generation. 2) **SC2-PCR** (SC2): A geometry-only variant that operates without descriptor guidance.

B. Evaluation Metrics

Following standard benchmarks in global registration literature [2], [3], we introduced three additional metrics: Relative Rotation Error (RRE), Relative Translation Error (RTE), and Registration Recall (RR). The RRE and RTE are defined as:

$$\mathrm{RRE} = \arccos\left(\frac{\mathrm{tr}(\boldsymbol{R}_{gt}^{\top}\boldsymbol{R}_{est}) - 1}{2}\right), \quad \mathrm{RTE} = \|\boldsymbol{t}_{gt} - \boldsymbol{t}_{est}\|_2. \tag{1}$$

A registration pair is considered successful if RRE $< 5.0^\circ$ and RTE $< 0.2\,\mathrm{m}$. The Registration Recall (RR) is calculated as the fraction of successful frame pairs over the total number of pairs.

C. Implementation and Configuration

Given that the baseline implementations utilize Python-based frameworks (e.g., PyTorch, Open3D) while our system is C++-based, we adopted an offline processing pipeline. Point clouds and initial poses were serialized frame-by-frame, processed via Python inference scripts to obtain estimated poses, and then evaluated.

Parameter Settings: To assess generalization capability, we utilized pre-trained models provided by the authors. Specifically, GeoTransformer uses the model pre-trained on KITTI, and SC2-PCR uses its standard pre-trained weights. For SC2-PCR-FPFH, feature extraction parameters were aligned with other baselines: normal estimation using 5 nearest neighbors, search radius of $1.0\,\mathrm{m}$, and 30 matcher iterations. All experiments were conducted on a workstation equipped with an NVIDIA GTX 1080Ti GPU (11GB VRAM). The inference scripts are available at *https://github.com/JokerJohn/DCReg*.

TABLE I
PERFORMANCE COMPARISON OF REGISTRATION ALGORITHMS ON SIMULATED ILL-CONDITIONED CYLINDER

Methods	Error Metrics			ICP Metrics				Degeneracy Mask	
	Trans. (cm) ↓	Rot. (deg) ↓	CD (cm) ↓	RMSE (cm) ↓	Iter. (#) ↓	Fit. (%) ↑	Time (ms) ↓	Trans. (#)	Rot. (#)
O3D	–	–	–	–	30	–	46.49	–	–
SC2-FH	96.37	2.00	1.91	0.97	30	100	407.97	–	–
GeoTrans	95.91	1.99	18.73	1.00	–	100	355.53	–	–
ME-SR	96.19	3.66	92.30	19.73	30	2.25	19.40	111	000
ME-TSVD	2.91	0.97	34.81	14.57	30	24.85	19.81	111	000
ME-TReg	22.18	0.11	21.96	4.18	30	34.96	20.05	111	000
FCN-SR	96.24	3.76	93.12	19.58	12	2.43	29.74	111	100
SuperLoc	23.82	2.81	71.37	43.94	–	2.29	16.98	001	000
X-ICP	0.42	2.86	55.88	18.27	9	10.08	43.06	001	000
Ours	2.71	0.05	3.29	3.16	10	100	7.79	001	000

Note: Trans. = Translation Error, Rot. = Rotation Error, RMSE = ICP Residuals, Iter. = Iteration Count, Fit. = ICP Fitness. Degeneracy Mask: Binary indicators where 1/0 represent for degenerate/well-constrained direction. Best/second-best results: blue / light blue. Unavailable data shown in –.

D. Rationale for Dataset Selection

We deliberately excluded standard global registration benchmarks (e.g., 3DMatch [4], 3DLoMatch [5], KITTI [6]) from our evaluation for three primary reasons:

1) **Modality Discrepancy**: 3DMatch and 3DLoMatch are primarily RGB-D datasets. Our research focuses specifically on LiDAR point cloud registration, which exhibits distinct sparsity and noise characteristics.
2) **Scenario Relevance**: The KITTI dataset, collected with a 64-beam LiDAR in structured urban environments, lacks significant geometric degeneracy. In contrast, our study targets challenging degenerate scenarios. We selected popular datasets published in top journels and conferences (FusionPortable [7], [8]), the degeneracy-specific GEODE dataset [9], and the SubT-MRS Cave dataset [10], [11]. Besides, these datset can provide a ground thruth map or prior map for our long-duration localization experiments. These datasets also cover a wide range of sensor configurations (16 to 128 beams) and provide more rigorous testing grounds for degeneracy handling.
3) **Task Objectives**: Global registration tasks on benchmarks typically focus on robust matching of point cloud pairs with large displacements (10-20 m) without initial pose. Conversely, our application

targets sequential SLAM scenarios where a reasonable initial pose is available, but high precision and explicit degeneracy detection are paramount.

Therefore, we applied these global baselines directly to the simulation and real-world sequences described in Section 7 of the manuscript to evaluate their performance in the specific context of degenerate tracking.

TABLE II
COMPREHENSIVE PERFORMANCE EVALUATION ON REAL-WORLD SCENARIOS

Method	**Stairs** 3-5k pts/frame, 128M pts/map							**Corridor** 1-2k pts/frame, 67M pts/map							**Building** 5-10k pts/frame, 241M pts/map						
	DR (%)	RR (%)	ATE (cm)	RRE (°)	RTE (cm)	AC (cm)	Time (ms)	DR (%)	RR (%)	ATE (cm)	RRE (°)	RTE (cm)	AC (cm)	Time (ms)	DR (%)	RR (%)	ATE (cm)	RRE (°)	RTE (cm)	AC (cm)	Time (ms)
Odom	–	0	25.18	4.60	231.46	–	16.79	–	10.76	26.34	1.22	60.74	–	49.10	–	0	16.47	3.38	265.57	–	58.30
O3D	–	78.67	80.51	2.05	35.23	7.23	889.69	–	13.85	1418.37	22.48	1381.90	7.09	15.02	–	89.33	15.15	0.30	10.83	**5.04**	377.91
SC2-FH	–	0	3431.36	124.73	3339.14	–	282.73	–	0	5029.13	125.35	4529.33	–	226.14	–	0.02	5254.55	126.44	4622.15	–	362.65
GeoTrans	–	0	3320.69	103.17	4566.50	–	1911.32	–	4.00	4841.94	83.68	3856.34	–	626.87	–	5.59	2907.36	75.62	2166.00	–	2032.53
ME-SR	18.91	19.94	160.75	2.58	259.29	7.90	129.19	39.27	73.92	173.82	1.00	87.81	4.55	13.31	0	80.75	13.83	0.30	14.11	5.72	39.37
ME-TSVD	9.26	99.09	6.44	0.44	5.37	6.09	56.16	34.84	76.12	94.32	0.64	48.05	4.36	11.60	0	80.73	13.86	0.30	14.08	5.74	39.16
ME-TReg	9.20	98.97	7.16	0.43	5.64	6.06	59.41	33.21	92.26	26.24	0.52	9.67	3.62	8.22	0	80.28	13.79	0.30	14.14	5.70	39.28
FCN-SR	94.77	0.30	280.07	14.00	584.06	7.80	207.13	85.28	11.69	231.40	4.35	238.96	6.64	38.17	17.19	12.08	337.13	4.18	529.18	6.73	685.99
Ours	50.71	**99.85**	**3.96**	**0.40**	**2.90**	**5.55**	**6.47**	58.04	**96.28**	**7.44**	**0.49**	**4.56**	**3.45**	**1.24**	15.03	**82.15**	**13.64**	**0.29**	**14.00**	5.69	**4.58**

Note: Best and second-best results are highlighted in blue and light blue. **DR**: Degeneracy Ratio (%). **RR**: Recall Rate (%). **ATE**: Absolute Trajectory Error (cm). **RRE**: Relative Rotation Error (°). **RTE**: Relative Translation Error (cm). **AC**: Accuracy (cm).

III. ADDITIONAL RESULTS ANALYSIS

A. *Simulation Analysis (Cylinder Scenario)*

Table I (in the main text) presents the quantitative results for the symmetric cylinder simulation.

The results reveal a critical limitation of global registration methods in degenerate environments: **lack of degeneracy awareness**. Similar to standard Open3D ICP (O3D), SC2-PCR (and its variants) and GeoTransformer act as "black boxes" that cannot detect or characterize the specific dimensions of degeneracy.

1) Fitness vs. Accuracy Discrepancy: Observing the matching results, SC2-PCR-FPFH achieved the lowest Chamfer Distance (CD) and a perfect fitness score (100%). However, its translation error remained high at 96.37 cm. This phenomenon highlights that *high fitness scores or low point-to-point residuals do not guarantee successful registration in degenerate scenarios*. The algorithm converged to a local minimum that minimized geometric distance but failed to recover the correct pose. GeoTransformer exhibited similar behavior, achieving high fitness but large pose errors (95.91 cm translation error), indicating a failure to escape the local minimum induced by the symmetric geometry.

2) Comparison with DCReg: These global methods performed comparably to the failure cases of ME-SR and FCN-SR, struggling to resolve the ambiguity along the degenerate axis. In contrast, although DCReg did not achieve the absolute lowest CD, it successfully registered the point cloud with the minimum rotation error and significantly reduced translation error. Crucially, DCReg correctly identified and mitigated the translational degeneracy, a capability absent in the global baselines.

In terms of efficiency, DCReg is at least **45 times faster** than the evaluated global methods per frame, demonstrating superior suitability for real-time robotic applications.

B. *Real-world Long-duration Localization*

The performance on real-world datasets (Cave, Parking Lot, etc.) further corroborates the simulation findings (Table II and Table III).

Registration Failure: Lacking explicit degeneracy handling, SC2, SC2-FH, and GeoTransformer failed in nearly all degenerate sequences, even when provided with the same initial pose as other methods. The estimated trajectories exhibited large drifts (tens of meters) between consecutive frames. Successful registration was observed only in non-degenerate sequences (e.g., the Building dataset).

Computational Cost: In long-duration localization tasks, the computational overhead of global methods is prohibitive. Their average processing time exceeded that of DCReg by a factor of **30 to 1600**. This fundamental efficiency gap, combined with the lack of robustness in degenerate tracking, underscores that global registration and degenerate LiDAR tracking address fundamentally different problem domains. DCReg effectively bridges this gap by providing efficient, degeneracy-aware local tracking.

TABLE III
PERFORMANCE EVALUATION ON DEGENERATE SCENARIOS

	Cave02 3-5k pts/frame, 53M pts/map						**Parking Lot** 4-8k pts/frame, 218M pts/map					
Method	DR (%)	RR (%)	ATE (cm)	RRE (°)	RTE (cm)	Time (ms)	DR (%)	RR (%)	ATE (cm)	RRE (°)	RTE (cm)	Time (ms)
Odom	–		129.78	75.35	84.78	22.39	–	12.87	32.98	3.15	54.17	22.31
O3D	–	84.33	16.88	0.66	11.68	328.53	–	–	36.89	–	–	345.10
SC2-FH	–	0	5386.90	125.64	4655.22	262.86	–	0.38	6533.35	129.07	6096.82	473.39
GeoTrans	–	1.51	3523.82	103.19	4734.09	1942.73	–	3.71	2421.66	46.22	1623.44	1684.25
ME-SR	6.47	0	565.61	5.01	498.20	146.80	89.59	2.96	62.11	3.08	57.77	16.01
ME-TSVD	0.83	0	497.05	10.68	419.34	116.54	87.69	18.21	30.46	3.13	28.87	13.96
ME-TReg	19.03	0.78	209.53	3.94	184.79	115.87	87.24	1.28	47.07	3.06	44.81	11.40
FCN-SR	58.89	0	491.29	23.29	447.28	232.51	98.15	7.45	64.50	3.14	57.22	17.59
Ours	32.90	**99.16**	**4.57**	**0.73**	**2.89**	**3.71**	86.74	**25.42**	**29.56**	3.15	**27.75**	**2.11**

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