Generalized LOAM: LiDAR Odometry Estimation with Trainable Local Geometric Features – Supplementary Material –

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I. Compalison with Baseline Methods

We compared the proposed method with four lidar odometry estimation algorithms; LOAM [1], LeGO-LOAM [2], (plane-to-plane) GICP [3], and SuMa [4]. LOAM and GICP are implemented by ourselves, and share common processes (e.g., preprocessing and pose optimization) and parameters for a fair comparison. LeGO-LOAM and SuMa show the results with parameters tuned by Optuna [5] in [6]. Note that all algorithms are compared using only the front-end part (loop closure is disabled).

Table I and II show the translational and rotational RTEs compared with all baseline methods. Table III shows the result of ablation study. Table IV shows the results of the comparison with different scan matching schemes. Two types of scan matching methods were implemented: Frame-to-Frame (F-F) and Frame-to-Model (F-M) matching. F-F matches consecutive frames frame-by-frame and estimates the sensor trajectory by accumulating the matching results. F-M matches the current scan and a model that is created by accumulating past frames. Our proposed two MLPs were trained for F-F scan matching.

References

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TABLE I

AVERAGE TRANSLATIONAL RTES [%] FOR KITTI DATASET [7]

Seq. ID	Training dataset 01	03	05	07	09	Avg.	Test dataset 00	02	04	06	08	10	Avg.
LOAM	2.33	4.18	5.34	2.02	7.35	4.24	3.51	10.8	3.40	1.19	4.66	4.08	4.61
LeGO-LOAM	3.07	1.63	1.02	1.02	1.29	1.61	1.87	1.83	1.33	1.09	1.76	1.83	1.62
GICP	3.18	1.06	0.90	0.57	1.26	1.40	1.11	1.54	1.07	0.72	1.15	1.40	1.17
SuMa	5.59	1.14	0.87	0.66	0.86	1.82	0.84	1.27	0.56	0.60	1.43	1.73	1.07
Generalized LOAM (PN++)	3.16	1.04	0.82	0.53	1.15	1.34	1.04	1.45	1.01	0.68	1.10	1.24	1.09
Generalized LOAM (RN)	2.91	0.95	0.76	0.53	1.00	1.23	0.94	1.33	0.87	0.64	1.06	0.99	0.97

[1] Red and blue respectively indicate the first and second best results.
[2] PN++ and RN mean PointNet++ and RandLA-Net, respectively.
[3] LOAM and GICP are implemented by ourselves. LeGO-LOAM and SuMa show the results with parameters tuned by Optuna in [6].

TABLE II

AVERAGE ROTATIONAL RTES [°/ m] FOR KITTI DATASET [7]

Seq. ID	Training dataset 01	03	05	07	09	Avg.	Test dataset 00	02	04	06	08	10	Avg.
LOAM	0.50	1.87	2.30	1.24	2.33	1.65	1.48	3.41	1.50	0.41	1.89	2.06	1.79
LeGO-LOAM	0.95	1.03	0.59	0.75	0.71	0.81	0.92	0.81	0.95	0.65	0.80	0.85	0.83
GICP	0.55	0.58	0.45	0.45	0.55	0.52	0.52	0.55	0.67	0.36	0.47	0.61	0.53
SuMa	0.83	0.85	0.47	0.62	0.50	0.65	0.51	0.59	0.23	0.27	0.63	0.86	0.52
Generalized LOAM (PN++)	0.51	0.55	0.41	0.41	0.50	0.48	0.49	0.52	0.62	0.35	0.43	0.54	0.49
Generalized LOAM (RN)	0.45	0.51	0.37	0.34	0.43	0.42	0.43	0.46	0.53	0.33	0.40	0.45	0.44

[1] Red and blue respectively indicate the first and second best results.
[2] PN++ and RN mean PointNet++ and RandLA-Net, respectively.
[3] LOAM and GICP are implemented by ourselves. LeGO-LOAM and SuMa show the results with parameters tuned by Optuna in [6].

TABLE III

ABLATION STUDY ON KITTI DATASET [7]

Method/Seq.		00		02		04		06		08		10		mean	
		t_{RTE} [1]	r_{RTE} [1]	t_{RTE}	r_{RTE}	t_{RTE}	r_{RTE}	t_{RTE}	r_{RTE}	t_{RTE}	r_{RTE}	t_{RTE}	r_{RTE}	t_{RTE}	r_{RTE}
GICP (Baseline)		1.11	0.52	1.54	0.55	1.07	0.67	0.72	0.36	1.15	0.47	1.40	0.61	1.27	0.52
GICP+DA [2]	PN++ [3]	1.06	0.50	1.48	0.53	1.03	0.64	0.70	**0.35**	1.14	0.45	1.32	0.57	1.24	0.50
	RN [3]	1.07	0.50	1.49	0.53	1.02	0.64	0.68	0.35	1.12	0.45	1.28	0.55	1.22	0.50
GICP+CE [2]	PN++	1.08	0.51	1.52	0.54	1.06	0.65	0.70	**0.35**	1.12	0.45	1.31	0.58	1.24	0.51
	RN	1.00	0.47	1.40	0.48	0.93	0.57	0.68	0.34	1.08	0.42	1.12	0.51	1.15	0.46
GICP+DA+CE (Generalized LOAM)	PN++	**1.04**	**0.49**	**1.45**	**0.52**	**1.01**	**0.62**	**0.68**	**0.35**	**1.10**	**0.43**	**1.24**	**0.54**	**1.20**	**0.48**
	RN	**0.94**	**0.43**	**1.33**	**0.46**	**0.87**	**0.53**	**0.64**	**0.33**	**1.06**	**0.40**	**0.99**	**0.45**	**1.09**	**0.43**

[1] t_{RTE} and r_{RTE} are the translation [%] and rotation [°/m] RTEs.
[2] DA and CE mean data association and covariance matrix estimation using features, respectively.
[3] PN++ and RN mean PointNet++ and RandLA-Net, respectively.
All results are obtained by Frame-to-Model matching.

TABLE IV

COMPARISON OF THE TYPES OF SCAN MATCHING

Seq.	LOAM				GICP				Generalized LOAM (PN++)[3]				Generalized LOAM (RN)[3]			
	t_{RTE}[1] [%]		r_{RTE}[1] [°/m]		t_{RTE} [%]		r_{RTE} [°/m]		t_{RTE} [%]		r_{RTE} [°/m]		t_{RTE} [%]		r_{RTE} [°/m]	
	F-F[2]	F-M[2]	F-F	F-M	F-F	F-M	F-F	F-M	F-F	F-M	F-F	F-M	F-F	F-M	F-F	F-M
Training dataset																
01	19.46	**2.33**	3.21	0.50	3.16	3.18	0.66	0.55	2.92	3.16	0.63	0.51	2.64	2.91	0.57	**0.45**
03	24.82	4.18	10.38	1.87	1.15	1.06	0.68	0.58	1.10	1.04	0.62	0.55	1.08	**0.95**	0.75	**0.51**
05	21.95	5.34	9.92	2.30	0.91	0.90	0.47	0.45	0.84	0.82	0.41	0.41	0.78	**0.76**	0.48	**0.37**
07	12.95	2.02	8.43	1.24	0.67	0.57	0.44	0.45	0.67	**0.53**	0.41	0.41	0.66	**0.53**	0.49	**0.34**
09	27.83	7.35	9.39	2.33	1.15	1.26	0.46	0.55	1.10	1.15	0.44	0.50	**0.97**	1.00	**0.36**	0.43
Mean	21.40	4.24	8.26	1.65	1.41	1.40	0.54	0.52	1.33	1.34	0.50	0.48	**1.23**	**1.23**	0.53	**0.42**
Test dataset																
00	16.87	3.51	7.73	1.48	0.98	1.11	0.49	0.52	1.06	1.04	0.48	0.49	0.98	**0.94**	0.52	**0.43**
02	22.55	10.80	7.43	3.41	1.66	1.54	0.54	0.55	1.51	1.45	0.49	0.52	1.43	**1.33**	0.48	**0.46**
04	31.74	3.40	6.72	1.50	1.88	1.07	1.00	0.67	1.82	1.01	0.92	0.62	1.51	**0.87**	0.84	**0.53**
06	8.00	1.19	2.59	0.41	0.69	0.72	0.41	0.36	0.67	0.68	0.39	0.35	0.65	**0.64**	0.41	**0.33**
08	21.88	4.66	9.06	1.89	1.27	1.15	0.53	0.47	1.22	1.10	0.52	0.43	1.30	**1.06**	0.49	**0.40**
10	3.71	4.08	1.37	2.06	0.98	1.40	0.48	0.61	**0.89**	1.24	**0.37**	0.54	**0.89**	0.99	0.48	0.45
Mean	17.46	4.61	5.82	1.79	1.24	1.17	0.58	0.53	1.19	1.09	0.53	0.49	1.13	**0.97**	0.54	**0.44**

[1] We adopt the RTE as a metric for evaluating pose estimation provided by the KITTI dataset [7]. t_{RTE} and r_{RTE} are the translation and rotation errors for all possible subsequences of length (100,...,800) meters.

[2] F-F and F-M mean Frame-to-Frame matching and Frame-to-Model matching, respectively.

[3] PN++ and RN mean PointNet++ and RandLA-Net, respectively.

All methods are implemented by ourselves, and common parameters are standardized.