LiTAMIN2 : Ultra Light LiDAR-based SLAM

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Introduction

> Ultra Light LiDAR-based SLAM using Geometric Approximation applied with KL-Divergence

Abstract :

In this paper, a 3D light detection and ranging simultaneous localization and mapping (SLAM) method is proposed. It is available for operating upon 500~1000Hz with high accuracy (almost same as the state-of-the-art method - "SuMa"), for more precise result, it can still work on 200Hz.

TABLE IV: Absolute trajectory error for each SLAM method.

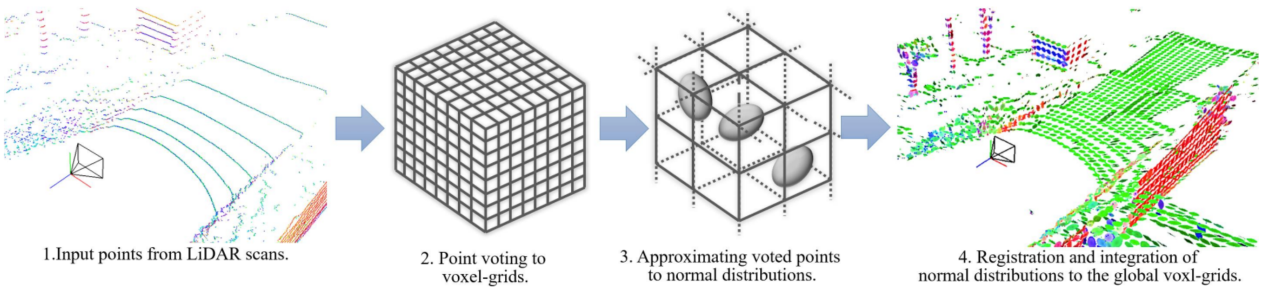
Method (Num. of frames)	Loop closure	Seq. 00 (4541)	Seq. 01 (1101)	Seq. 02 (4661)	Seq. 03 (801)	Seq. 04 (271)	Seq. 05 (2761)	Seq. 06 (1101)	Seq. 07 (1101)	Seq. 08 (4071)	Seq. 09 (1591)	Seq. 10 (1201)	Avg. of all frames [deg] / [m]
LiTAMIN2 (ICP+Cov)	–	1.6/5.8	3.5/15.9	2.7/10.7	2.6/0.8	2.3/0.7	1.1/2.4	1.1/0.9	1.0/0.6	1.3/2.5	1.7/2.1	1.2/1.0	1.8 / 5.1
LiTAMIN2 (ICP+Cov)	✓	0.8/1.3	3.5/15.9	1.3/3.2	2.6/0.8	2.3/0.7	0.7/0.6	0.8/0.8	0.6/0.5	0.9/2.1	1.7/2.1	1.2/1.0	1.2 / 2.4
LiTAMIN2 (ICP)	–	1.8/5.4	3.1/13.8	3.4/12.1	2.4/0.7	1.9/0.6	1.4/3.6	0.7/0.7	1.3/0.9	3.0/5.9	1.9/2.8	1.5/1.8	2.3 / 6.0
LiTAMIN2 (ICP)	✓	0.8/1.2	3.1/13.8	1.3/3.0	2.4/0.7	1.9/0.6	0.7/0.7	0.8/0.6	0.6/0.4	2.2/4.5	0.8/1.3	1.5/1.8	1.3 / 2.6
LiTAMIN	–	2.0/4.7	3.0/84.3	2.4/9.7	3.4/0.8	1.4/21.3	1.4/2.3	0.7/0.9	0.7/0.5	1.9/3.5	1.4/1.6	1.7/1.7	1.9 / 8.3
LiTAMIN	✓	1.1/1.5	3.0/84.3	1.8/3.7	3.4/0.8	1.4/21.3	0.9/1.0	0.8/0.8	0.6/0.3	1.6/2.8	1.3/1.4	1.7/1.7	1.5 / 6.2
SuMa (Frame-to-Frame)	–	6.4/19.7	8.2/34.9	5.4/21.3	4.1/1.2	3.4/13.4	2.9/5.1	1.5/2.0	2.1/2.9	6.2/15.9	2.4/5.0	2.4/3.4	4.8 / 14.1
SuMa (Frame-to-Model)	–	1.0/2.9	3.2/13.8	2.2/8.4	1.5/0.9	1.8/0.4	0.7/1.2	0.4/0.4	0.7/0.5	1.5/2.8	1.1/2.9	0.8/1.3	1.4 / 3.9
SuMa (Frame-to-Model)	✓	0.7/1.0	3.2/13.8	1.7/7.1	1.5/0.9	1.8/0.4	0.5/0.6	0.7/0.6	1.1/1.0	1.2/3.4	0.8/1.1	0.8/1.3	1.1 / 3.2
LeGO-LOAM	–	2.8/6.3	3.8/119.4	4.1/14.7	4.1/0.9	3.3/0.8	1.9/2.8	1.4/0.8	1.5/0.7	2.5/3.5	2.2/2.1	1.9/1.8	2.8 / 11.1
hdl_graph_slam	–	5.4/41.8	34.0/635.8	22.3/153.0	2.3/1.0	3.4/93.4	2.5/5.7	3.3/43.0	2.2/1.6	6.2/13.8	4.6/15.9	1.8/3.5	9.3 / 76.7
LOAM	–	5.8/19.4	6.1/21.0	21.7/111.6	3.3/1.0	2.2/0.5	2.2/4.6	0.9/1.1	1.2/1.3	3.0/6.7	1.9/5.3	1.5/1.9	7.0 / 29.7

LiTAMIN2 used the size of voxel as 3 m from the best accuracy result of table II. The marks ✓and – mean with (✓) and without (–) loop closure, respectively, for each method.

This paper uses a novel ICP metric to speed up the registration process while maintaining accuracy. However, Reducing quantity of point cloud can drop the accuracy, to avoid this issue, symmetric KL-divergence is introduced to the ICP cost that reflects the difference between two probabilistic. The cost function includes not only the distance between points but also differences between distribution shapes.

Main works

- Reduction of the number of points
    1. Voted a group of input points into the voxel grids.
    2. Aligned them using the means of the voting points.
    3. Integrated the point clouds into voxel map.



- ICP cost function applied with symmetric KL-divergence

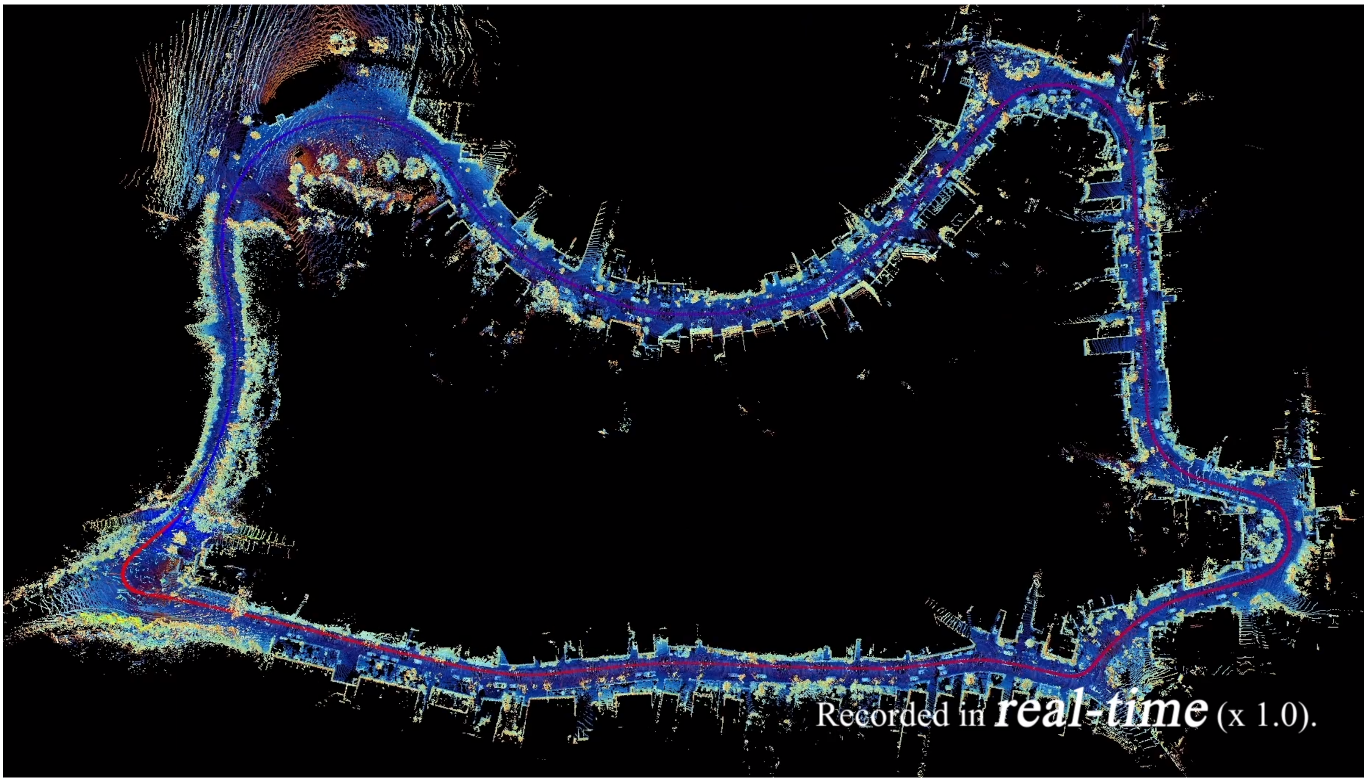
TABLE I: Comparison of the ICP cost functions for local approximation with a cluster of normal distributions.

Method	ICP cost function per point-assosiation
Standard ICP	$(q-(Rp+t))^T(q-(Rp+t))$
NDT	$(q-(Rp+t))^T C^{-1}(q-(Rp+t))$
Generalized ICP	$(q-(Rp+t))^T(C_q+RC_pR^T)^{-1}(q-(Rp+t))$
LiTAMIN	$(q-(Rp+t))^T \frac{w(C+\lambda I)^{-1}}{\|(C+\lambda I)^{-1}\|_F}(q-(Rp+t))$
LiTAMIN2 (proposed method)	$w_{ICP}\left[(q-(Rp+t))^T \frac{(C_q+RC_pR^T+\lambda I)^{-1}}{\|(C_q+RC_pR^T+\lambda I)^{-1}\|_F}(q-(Rp+t))\right]+w_{Cov}\left[\mathrm{Tr}(RC_p^{-1}R^TC_q)+\mathrm{Tr}(C_q^{-1}RC_pR^T)-6\right]$

Reference :

Video

- LiTAMIN2 (ICRA 2021) Youtube



Links

- MR2T lab official web
- LiTAMIN2: Ultra Light LiDAR-based SLAM using Geometric Approximation applied with KL-Divergence
- LiTAMIN2 introduction
- ICRA2021 LiTAMIN2的復現