Preprint of the paper:
Tiozzo Fasiolo, D., Scalera, L., Maset, E., Gasparetto, A. (2022)
Experimental evaluation and comparison of LiDAR SLAM algorithms for mobile robotics.
In The International Conference of IFToMM ITALY (pp. 795-803).
Cham: Springer International Publishing.

Experimental evaluation and comparison of LiDAR SLAM algorithms for mobile robotics

Diego Tiozzo Fasiolo, Lorenzo Scalera, Eleonora Maset, and Alessandro Gasparetto

Abstract This paper presents an experimental evaluation and comparison of LiDAR SLAM algorithms for mobile robotics. We analyze the performance of four state-of-the-art methods for localization and mapping in terms of the capability in reconstructing a point cloud of the surveyed environment and of the required computational effort. More in detail, the cloud-to-cloud distance with respect to a ground-truth reference model and the density of the final point cloud are evaluated and compared. Experimental tests are conducted by performing repeated autonomous surveys on two different scenarios with a mobile robot, showing the advantages and disadvantages of the considered methods in reconstructing a 3D map.

1 Introduction

Over the last few years, a growing number of mobile robotics applications involving the acquisition of 3D information have been developed. Examples range from mapping of hazardous environments [2], cultural heritages sites [3], as well as agricultural lands [13, 15]. One particular field of application of mobile robotics for 3D mapping is the analysis and digitization of buildings, as shown in [7].

Robotics, indeed, is increasingly applied as an aid to acquire 3D data for the subsequent creation of as-is Building Information Models (BIMs) [1]. In this context, the availability of efficient, cost-effective and user-friendly surveying techniques for semi-structured and unstructured environments is crucial. Moreover, novel algorithms may be used when speed and simplicity take priority over accuracy, for instance in rescue application [16], or in building construction monitoring [6].

The acquisition of 3D information on buildings could be automated mounting a Light Detection and Ranging (LiDAR) sensor on a robotic platform [11, 12]. Indoor

Diego Tiozzo Fasiolo, Lorenzo Scalera, Eleonora Maset, and Alessandro Gasparetto
University of Udine, 33100 Udine, Italy, e-mail: {diego.tiozzo,lorenzo.scalera, eleonora.maset,alessandro.gasparetto}@uniud.it

environments are challenging as the Global Navigation Satellite System (GNSS) is frequently not available, due to signal blockage and reflection. Consequently, different localization methods are needed. The core of these technologies is Simultaneous Localization and Mapping (SLAM), which was born for autonomous navigation but can also estimate the trajectory of a moving scanning device, while acquiring maps of the area of interest. It is worth noting that a complete autonomous system should perform navigation, 3D data acquisition and processing, with the minimum human intervention. Thus, the computational capability of the on-board computer cannot be exhausted by the standalone SLAM algorithm.

Most SLAM methods are either visual or LiDAR-based. Visual-based methods use RGB, stereo or time-of-flight cameras as inputs and store image frames, which are used to compute the robot position and update the map. LiDAR-based methods rely on LiDAR and store distance and angular measurements instead of image frames. Comparative analysis (benchmarks) of SLAM algorithms can be easily found in the literature for different environments: vineyards [8], indoor offices [5], outdoor cities [10]. However, that works report results as root mean square error in the trajectory estimation, and few information is given regarding 3D reconstruction capability.

In this paper, we present an experimental evaluation and comparison of four state-of-the-art SLAM algorithms, which rely on LiDAR data only. Analysis are conducted to assess the accuracy of the obtained 3D model with respect to a ground-truth point cloud, the repeatability of the generated map and its points density. Furthermore, the computational requirements are monitored, with the aim of finding out which of the proposed mapping algorithms could be a trade off between the quality of the final map and the computational effort. Experimental tests are carried out performing the survey of two different indoor scenarios with a mobile robot that autonomously follows closed-loop paths across a series of predefined way points. The maps obtained from these data with the SLAM algorithms are compared with a ground-truth point cloud provided by a terrestrial laser scanner (TLS) system.

The paper is organized as follows: in Sect. 2 the LiDAR-based SLAM algorithms chosen for the comparison are briefly recalled. In Sect. 3 the materials and methods are described, and Sect. 4 presents the results. The paper is concluded in Sect. 5.

2 LiDAR SLAM algorithms

SLAM is the process of building a map of an unknown environment while concurrently estimating the location of an autonomous robot. The key process of LiDAR SLAM methods is point cloud scan matching. It consists of calculating a best-fit rigid transformation that minimizes the error across corresponding matching points between two point clouds (typically a non-linear optimization problem).

The following state-of-the-art algorithms are considered in this paper: Real-Time Appearance-Based Mapping (RTAB-Map) [10], Lightweight and Ground-Optimized Lidar Odometry and Mapping (LeGO-LOAM) [14], Direct LiDAR Odometry (DLO) [4], *hdl_graph_slam* [9]. These algorithms are chosen for the comparison as they rely on LiDAR data only, without the needs of an Inertial Measurement System (IMU) or other additional odometry sources (e.g., encoders or GNSS). Moreover, they present: (a) different down sampling and scan matching approaches that lead to different results in the final point cloud; and (b) different data structures, to store and access data, during the mapping process, which can affect the efficiency of the code. Furthermore, these algorithms are suitable for embedded system and, thus, for mobile robotics applications.

RTAB-Map implements a voxel grid as down-sampling method. A voxel grid is a set of 3D boxes over the point cloud data. In each voxel, all the present points are approximated with their centroid.

Instead of using the down-sampled cloud one can resort only on relevant points to perform SLAM: this idea is exploited in LeGO-LOAM. With a clustering process, points belonging to the same objects, or to the ground, are labeled. Edges and planes features are then extracted from clustered points, and used as input for SLAM. LeGO-LOAM exploits loop closure: the ability of recognizing if the vehicle has returned to a previously visited location, and to use this information to correct the map.

DLO, similarly to RTAB-Map, exploits directly a down sampled cloud. However, DLO uses a local map instead of performing scan matching with the whole point cloud. This algorithm is particularly suited for computationally limited robotic platforms because of the innovative data structure it introduces.

Finally, *hdl_graph_slam* uses Normal Distribution Transform (NDT) scan matching. NDT method represents the point cloud as a voxel grid, at whose cells is associated a normal distribution, which locally models the probability of measuring a point. Moreover, ground plane constraint are applied in order to avoid drift along the z axis, due to the accumulated error.

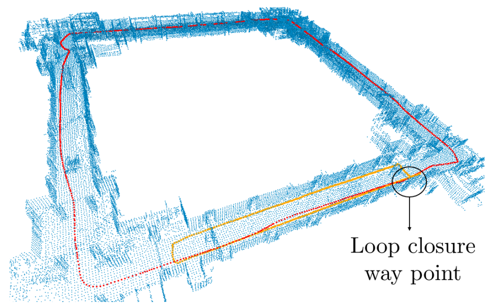
These algorithms are usually adopted for navigation purposes of mobile robots, as they manage to provide a six degrees of freedom pose with respect to a fixed reference frame, with high frequency, in indoor as well as outdoor environments. However, to the best of our knowledge, the focus of the application of these algorithms is not the 3D reconstruction of buildings, but rather the localization of the robot in a map of the surrounding environment.

3 Materials and methods

In this work, a Scout Mini mobile robot by Agile-X Robotics (Fig. 1a), equipped with a NVIDIA Xavier computer and a Velodyne VLP-16 laser scanner, is employed to acquire data for the benchmark. The VLP-16 measurement range is up to 100 m with an accuracy of $\pm 3\ cm$. The vertical field of view is $30°$ $(\pm 15°)$, and the horizontal field of view is $360°$. The laser provides a vertical angular resolution of $2°$ and an horizontal resolution of $0.2°$, as the rotation rate is set to 10 Hz. Thanks to the ROS Navigation Stack [1] , the mobile robot can autonomously navigate from a

[1] http://wiki.ros.org/navigation

(a)



(b)

Fig. 1: (a) Agile-X mobile robot in the corridor of test case (1); (b) point cloud of the surveyed environment obtained with LeGO-LOAM. The path followed by the robot is shown in yellow for test case (1), in red for test case (2).

starting location to a goal one, if a 2D map of the surroundings is provided. The 2D map is previously built with the *gmapping* [2] SLAM package, moving the robot by teleoperation with a wireless joystick, while employing *rf2o* [3] as odometry source.

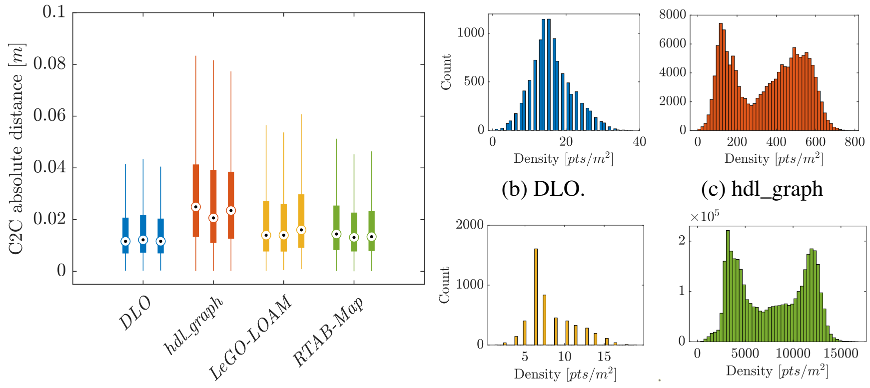
Experimental tests are carried out in two different scenarios of the main building of the scientific campus of University of Udine (Italy): (1) a single corridor of the squared plant of the west wing of the building (40 m long, 8 m wide and 4 m high); (2) the whole squared plant (80×80 m, measured along the center line of the corridors). To quantify the results in terms of repeatability, in test case (1), three data sets (referred to as (1.1-3)) are acquired by the robot while moving through five way points that define a closed path inside the corridor (Fig. 1b). Nevertheless, test case (2) was performed only once. The robot traveled a path 112 m long in about 9 minutes in test case (1), 324 m in about 12 minutes in test case (2).

During each autonomous survey the robot records raw data from the Velodyne sensor in the standard file format used for storage in ROS, the so called *ROS Bags*. Reproducing these files simulates the LiDAR sending the same data in real-time at the same rate they were recorded. According to this method, in this experimental campaign, the aforementioned SLAM algorithms are run, at a subsequent stage, using the *ROS Bags* as input on a workstation mounting an Intel Core i9-10900 CPU and 32 GB of RAM. The analysis of the required computational effort is made by monitoring the RAM usage of the workstation over time.

We acquired the ground-truth reference model of the corridor of test case (1) by means of the RIEGL Z390i TLS, placing the instrument vertically in three positions along the corridor axis. In order to register the three obtained scans, reflecting landmarks were located in the corridor and their coordinates measured using a Leica TCRA 1201+ total station. Since the robotic and TLS point clouds

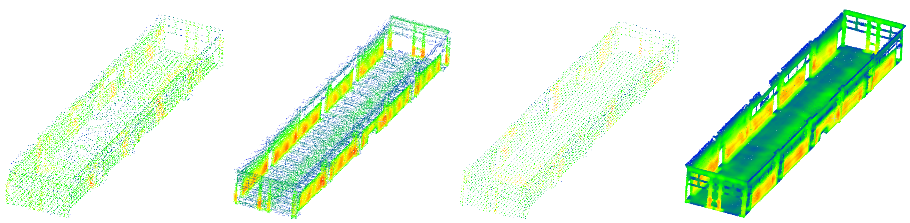
[2] `http://wiki.ros.org/gmapping`

[3] `http://wiki.ros.org/rf2o`



(a) (b) DLO. (c) hdl_graph (d) LeGO-LOAM. (e) RTAB-Map.

Fig. 2: (a) Box plots of C2C absolute distance; (b)-(e) histograms of surface density for test case (1), data set (1.1).



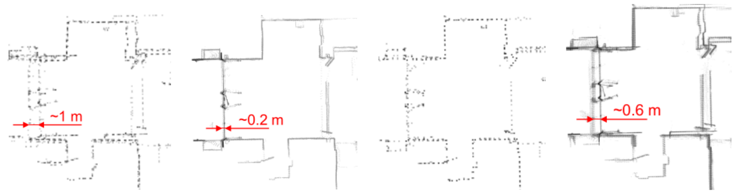
(a) DLO. (b) hdl_graph. (c) LeGO. (d) RTAB-Map.

Fig. 3: Point clouds obtained for test case (1), data set (1.1). Colors indicate density, blue for lower, red for higher values.

Table 1: Experimental results in terms of mean ± standard deviation.

	Test case (1), data set (1.1)				**Test case (2)**	
	Points $[pts]$	**C2C** $[mm]$	**Density** $[pts/m^2]$	**RAM** $[MB]$	**Points** $[pts]$	**RAM** $[MB]$
DLO	39, 310	21 ± 34	16 ± 6	1789 ± 45	139, 746	2166 ± 71
hdl_graph	383, 920	35 ± 37	353 ± 180	1663 ± 133	1, 179, 703	2587 ± 389
LeGO-LOAM	24, 111	27 ± 45	8 ± 3	1858 ± 103	95, 813	2219 ± 123
RTAB-Map	10, 240, 867	22 ± 24	7780 ± 3668	3317 ± 1079	14, 723, 532	6181 ± 1712

are expressed in arbitrary reference frames, the comparison with the ground truth requires a preliminary alignment to the reference model that was performed in CloudCompare software, using the Iterative Closest Point method.



(a) DLO. (b) hdl_graph (c) LeGO-LOAM. (d) RTAB-Map.

Fig. 4: Results for test case (2): zoom on the orthophotos near the loop closure. For LeGO-LOAM, the drift along the x axis is not appreciable from the point cloud.

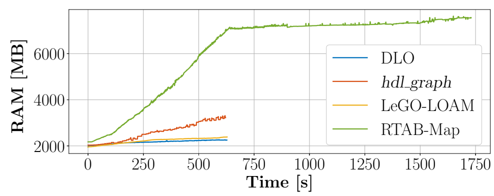


Fig. 5: Memory usage over time in test case (2).

4 Experimental results

In this section, the experimental results and the comparison between the considered SLAM algorithms are described. The first quantitative evaluation regards the point clouds accuracy, obtained with each algorithm, which is evaluated by measuring the cloud-to-cloud absolute distance (C2C) with respect to the ground-truth model of the corridor. Fig. 2a illustrates a graphical representation of the results of test case (1) in the form of box plots. Fig. 2a shows that a good repeatability of the results can be achieved in multiple tests across the same sequence of way points. The second column of Tab. 1 shows that the best results in terms of C2C absolute distance are obtained by RTAB-Map and DLO (with an average value of 2 *cm*). Moreover, from a visual inspection it can be seen that point clouds from RTAB-Map and *hdl_graph* are noisy, mostly on floor. RTAB-Map and sometimes also *hdl_graph* maps present scans not properly aligned to the global point cloud, which results in few points deviating from the real surface even tens of centimeters.

Subsequently, the surface density that characterizes the point clouds of test case (1) is evaluated. From the first and third columns of Tab. 1, it can be noticed that RTAB-Map guarantees the higher density, followed by *hdl_graph*. On the other hand, the individual peaks in histograms of DLO and LeGO-LOAM (Fig. 2b and Fig. 2d, respectively) demonstrate that the final maps result in a regular distribution of points, because of the voxel filter exploited in the final point cloud. Meanwhile, *hdl_graph* and RTAB-Map histograms present two peaks (Fig. 2c and Fig. 2e respectively). Thus, the higher density is reached for walls points and on the contrary, ground and roof present a low density, as shown in Fig. 3b and Fig. 3d. This is due to the horizontal placement of the LiDAR on top of the robot and its angular resolution.

The main characteristics of the point clouds obtained from test case (2) (Fig. 1b) are reported in the two last columns of Tab 1, which confirms the results in terms of density. Furthermore, from test case (2) it can be noticed that the drift along z axis does not present significant values, except for RTAB-Map. In this last case, the map is affected by an offset in correspondence to the loop closure, which was estimated to be roughly 30 cm. On the other hand, Fig. 4a-4d report drift along x and y axis, which is visibly reduced in *hdl_graph* and LeGO-LOAM thanks to their loop closure capability, meanwhile in DLO and RTAB-Map drift is approximately $0.6 \div 1$ m.

Finally, the computational effort of each SLAM algorithm is evaluated. The fourth and last columns of Tab. 1 report the obtained results for data set (1.1) and for test case (2), respectively. Moreover, the RAM usage over time in test case (2) is shown in Fig. 5. RTAB-Map takes approximately 19 minutes more than the *ROS Bags* file duration to process the LiDAR data and concurrently build the map. This algorithm, when used for navigation, employs a memory management solution that implies the deletion of the oldest point in the global map. However, for environment reconstruction purposes, all points must be kept and this tool must be disabled. Consequently, the algorithm slows down and stores LiDAR data in a buffer for further processing. This is demonstrated by the slope change in Fig. 5 at the instant corresponding to the end of the *ROS Bags*. Moreover, RTAB-Map is likely to saturate the embedded system memory when running also the navigation framework. Nevertheless, the memory usage of the other SLAM algorithms is similar between each other and suitable for online 3D mapping.

In contexts when a rapid survey is necessary, and mobile scanning system are preferred to TLS, *hdl_graph* proved to be the best trade-off in our test cases, because of its good results in terms of memory usage and point cloud density. Moreover, the accuracy provided by *hdl_graph* (despite it is the lowest among the other algorithms) is still suitable and comparable with the accuracy of the sensor.

5 Conclusion

In this paper, an experimental evaluation and comparison of state-of-the-art LiDAR SLAM algorithms for mobile robotics has been reported. The point clouds obtained with the reported algorithms have been analyzed in terms of capability of reconstructing an indoor environment and computational effort. Experimental tests have been conducted performing repeated autonomous surveys on two test cases. From the experiments, it results that DLO and LeGO-LOAM yield to a surface density not suited for 3D environment reconstruction, meanwhile RTAB-Map provides a dense map, but with a significant computational effort.

Future works will involve the integration of additional sensors as odometry sources and the test of further SLAM approaches. We will also evaluate the effects of robot path and speed on the resulting maps, especially in exploration tasks.

Acknowledgments

This research was developed within the Laboratory for BigData, IoT, Cyber Security (LABIC) funded by Region Friuli Venezia Giulia, and the Laboratory for Artificial Intelligence for Human-Robot Collaboration (AI4HRC) funded by Fondazione Friuli. The first author acknowledges support from the National Ph.D. Programme in Artificial Intelligence of University of Naples Federico II (Naples, Italy).

References

1. Adán, A., Quintana, B., Prieto, S.A.: Autonomous mobile scanning systems for the digitization of buildings: A review. Remote Sensing **11**(3), 306 (2019)
2. Agha, A., Otsu, K., et al.: Nebula: Quest for robotic autonomy in challenging environments; team costar at the darpa subterranean challenge. arXiv preprint arXiv:2103.11470 (2021)
3. Borrmann, D., Heß, R., Houshiar, H., Eck, D., Schilling, K., Nüchter, A.: Robotic mapping of cultural heritage sites. Int. Arch. of Photogr., Rem. Sens. and Spat. Inf. Sc. **40**(5), 9 (2015)
4. Chen, K., Lopez, B., Agha-mohammadi, A.a., Mehta, A.: Direct LiDAR Odometry: Fast Localization with Dense Point Clouds. IEEE Robotics and Automation Letters (2022)
5. Filipenko, M., Afanasyev, I.: Comparison of various SLAM systems for mobile robot in an indoor environment. In: Int. Conf. on Intell. Syst. pp. 400–407. IEEE (2018)
6. Follini, C., Magnago, V., Freitag, K., et al.: Bim-integrated collaborative robotics for application in building construction and maintenance. Robotics **10**(1), 2 (2020)
7. Gupta, T., Li, H.: Indoor mapping for smart cities—an affordable approach: Using kinect sensor and zed stereo camera. In: Int. Conf. on Indoor Pos. and Ind. Nav. pp. 1–8. IEEE (2017)
8. Hroob, I., Polvara, R., et al.: Benchmark of visual and 3D LiDAR SLAM systems in simulation environment for vineyards. In: Ann. Conf. Tow. Aut. Rob. Syst. pp. 168–177. Springer (2021)
9. Koide, K., Miura, J., Menegatti, E.: A portable three-dimensional LiDAR-based system for long-term and wide-area people behavior measurement. Int. J. of Adv. Rob. Syst. **16**(2) (2019)
10. Labbé, M., Michaud, F.: RTAB-Map as an open-source LiDAR and visual simultaneous localization and mapping library for large-scale and long-term online operation. Journal of Field Robotics **36**(2), 416–446 (2019)
11. Maset, E., Scalera, L., Beinat, A., Cazorzi, F., Crosilla, F., Fusiello, A., Gasparetto, A.: Preliminary Comparison Between Handheld and Mobile Robotic Mapping Systems. In: Int. Workshop IFToMM for Sustainable Development Goals. pp. 290–298. Springer (2021)
12. Maset, E., Scalera, L., Beinat, A., Visintini, D., Gasparetto, A.: Performance Investigation and Repeatability Assessment of a Mobile Robotic System for 3D Mapping. Robotics **11**(3), 54 (2022)
13. Ristorto, G., Gallo, R., Gasparetto, A., et al.: A mobile laboratory for orchard health status monitoring in precision farming. Chem. Eng. Trans. **58**, 661–666 (2017)
14. Shan, T., Englot, B.: LeGO-LOAM: Lightweight and ground-optimized LiDAR odometry and mapping on variable terrain. In: IEEE/RSJ Int. Conf. on Int. Rob. and S. pp. 4758–4765 (2018)
15. Tiozzo Fasiolo, D., Scalera, L., Maset, E., Gasparetto, A.: Recent Trends in Mobile Robotics for 3D Mapping in Agriculture. In: Int. Conf. on Rob. in Alpe-Adria Danube Region. pp. 428–435. Springer (2022)
16. Zhu, D., Ma, Y., Wang, M., et al.: LSO-FastSLAM: A New Algorithm to Improve the Accuracy of Localization and Mapping for Rescue Robots. Sensors **22**(3), 1297 (2022)