Occupancy Grid Map to Pose Graph-based Map: Robust BIM-based 2D-LiDAR Localization for Lifelong Indoor Navigation in Changing and Dynamic Environments

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ABSTRACT: Several studies rely on the de facto standard Adaptive Monte Carlo Localization (AMCL) method to localize a robot in an Occupancy Grid Map (OGM) extracted from a building information model (BIM model). However, most of these studies assume that the BIM model precisely represents the real world, which is rarely true. Discrepancies between the reference BIM model and the real world (Scan-BIM deviations) are not only due to the presence of furniture or clutter but also due to the usual as-planned and as-built deviations that exist with any model created in the design phase. These Scan-BIM deviations may affect the accuracy of AMCL drastically. This paper proposes an open-source method to generate appropriate Pose Graph-based maps from BIM models for robust 2D-LiDAR localization in changing and dynamic environments. First, 2D OGMs are automatically generated from complex BIM models. These OGMs only represent structural elements allowing indoor autonomous robot navigation. Then, an efficient technique converts these 2D OGMs into Pose Graph-based maps enabling a more accurate robot pose tracking. Finally, we leverage the different map representations for accurate, robust localization with a combination of state-of-the-art algorithms. Moreover, we provide a quantitative comparison of various state-of-the-art localization algorithms in three simulated scenarios with varying levels of Scan-BIM deviations and dynamic agents. More precisely, we compare two Particle Filter (PF) algorithms: AMCL and General Monte Carlo Localization (GMCL); and two Graph-based Localization (GBL) methods: Google's Cartographer and SLAM Toolbox, solving the global localization and pose tracking problems. We found that in a real office environment (under medium level of Scan-BIM deviations) the translational RMSE of AMCL increases by a factor of four (from 8.5 cm in the empty environment to 33.7 cm in the real one). On the contrary, pose Graph-based algorithms demonstrate their superiority in contrast to particle filter (PF) algorithms, achieving an RMSE of 7.2 cm, even in the real environment. The numerous experiments demonstrate that the proposed method contributes to a robust localization with an as-designed BIM model or a sparse OGM in changing and dynamic environments, outperforming the conventional AMCL in accuracy and robustness.

1 INTRODUCTION

An accurate localization system is crucial for successful autonomous mobile robot deployment in indoor GPS-denied environments.

The indoor localization problem has been approached by applying several techniques. While some rely on the known position of landmarks, such as AprilTags or textual cues, others depend on sensors that must be installed strategically on the building, such as Beacons or WiFi access points. However, in most cases, the exact location of specific landmarks is not known in advance. On top of that, having additional sensors increases the cost of the navigation stack.

A BIM model, available for most of the current architecture, can be used as a reference map for LiDAR localization.

Moreover, the additional semantic information of the model can be exploited to create advanced automated robotic tasks, like object inspection (Kim & Peavy 2022) or painting (Kim et al. 2021) which simultaneously depend on an accurate localization system.

Scan-BIM deviations are the central issue of using a BIM model or a floorplan as a reference map for 2D-LiDAR localization. These deviations can be caused by furniture or clutter not present in the model, as-planned and as-built variations, and dynamic or "quasi-static" changes in the environment. To address this challenge, we contribute with a system that creates OGMs from BIM models and allows their automatic transformation in Pose Graph-based maps. These maps are leveraged for quick, memory efficient, and accurate localization in indoor GPS-denied environments, enabling safer autonomous navigation.

More specifically, the following are the main contributions of this paper:

- A method to extract OGMs from complex multi-story BIM models allows robot path planning and autonomous navigation in indoor GPS-denied environments.
- An efficient open-source method[1] to convert these 2D OGMs into Pose Graph-based maps for accurate 2D-LiDAR localization.
- An extensive quantitative comparison of various state-of-the-art 2D LiDAR localization algorithms in three carefully designed simulated scenarios with different levels of Scan-BIM deviations and with and without dynamic agents.

The remainder of this paper is organized as follows. Section 2 introduces the problem formulation of LiDAR localization and the main principles behind the particle filter-based and graph-based localization strategies. Section 3 describes previous work done on BIM-based LiDAR localization. Section 4 introduces our method to generate OGMs from BIM models, pose graph-based maps from OGMs, and the proposed employment of these maps for robust localization. Section 5 presents the experimental settings, followed by the results and analysis in Section 6. Finally, section 7 concludes our work.

2 THEORETICAL BACKGROUND

Before presenting current state-of-the-art methods, a brief introduction is provided to the theoretical basis behind the two main types of localization algorithms used in this research.

2.1 *Localization problem*

In this paper, we address the robot pose tracking and global localization problems, i.e., with and without approximated initial pose, respectively, given a 3D BIM model as a prior map which omits considerable information about the real environment and assuming that the robot employs a 2D-LiDAR sensor.

In the 2D problem, the pose of the robot at time t is defined as position and orientation $\boldsymbol{x}_t = [x, y, \theta]^\top$ In the coordinate system of the map. We aim to estimate the most likely robot's pose $\boldsymbol{x}_t^*$ given the measurements $\boldsymbol{z}_t$ and the map $\boldsymbol{m}$.

Formally, the goal is to compute:

$$\boldsymbol{x}_t^* = \arg\max_x p(\boldsymbol{x}_t \mid \boldsymbol{z}_t, \boldsymbol{m}) \qquad (1)$$

Two widely used methods that aim to calculate this estimate are the PF and the GBL algorithms.

2.2 *Particle Filter algorithms*

PF algorithms, also called MCL methods, are probabilistic approaches that represent the pose estimate with a set of normalized weighted particles.

Each particle $s_t^i = \langle \boldsymbol{x}_t^i, \omega_t^i \rangle$ consist of a pose $\boldsymbol{x}_t^i$ and a weight ω_t^i. Initially, a set of $\mathcal{M}$ particles is sampled from a Gaussian distribution around the possible locations of the robot.

Subsequently, three steps are repeated iteratively in the algorithm: motion update, importance weighting, and particle resampling.

For a more detailed explanation of every step, the reader is referred to Thrun et al. (2005). In this paper, we implemented AMCL (Pfaff et al. 2006) and GMCL (Alshikh Khalil & Hatem 2021) to be tested under different levels of Scan-BIM deviations.

2.3 *Graph-based algorithms*

Graph-based, also called optimization-based localization methods, use pose-graph data for pose estimation. These pose-graphs contain the environment's landmarks (which can be represented as submaps) associated with nodes (which are the poses from where the landmarks were observed).

Additionally, the nodes are bound to each other with spatial constraints.

In a sliding window manner, the method not only considers the most recent measurement but a set of them to compute the current Pose. Under the assumption that the measurements are normally distributed and i.i.d., it is possible to represent eq. 1 as a weighted least squares problem. This problem is commonly solved iteratively using the Levenberg-Marquart algorithm. In this paper, we implement Cartographer (Hess et al. 2016) and SLAM Toolbox (Macenski & Jambrecic 2021) as GBL algorithms.

While particle filter algorithms are easier to implement and can represent non-Gaussian distributions, graph-based localization algorithms, besides being deterministic, can handle delayed measurements and maintain a recent history of poses. A more exhaustive qualitative comparison is given by Wilbers et al. (2019).

3 RELATED RESEARCH

A BIM model with 3D geometric information can be used as a prior map to accurately localize robots in indoor GPS-denied environments and allow autonomous navigation.

This section will overview state-of-the-art methods which used prior building information, i.e., BIM

[1] Available at: https://github.com/MigVega/Ogm2Pgbm

models or floor plans, to find the correct robot position and orientation.

Follini et al. (2020) show that the transformation matrix between the reference system of the robot and the map extracted from the BIM model can be retrieved by applying the standard AMCL algorithm.

The same algorithm was used by Prieto et al. (2020), Karimi et al. (2021), Kim et al. (2021), and Kim & Peavy (2022) to localize a wheeled robot in an OGM generated from the BIM model.

The main difference between these methods relies on how they create the OGM from the BIM model. While Follini et al. took the vertices of elements that intersect a horizontal plane and used the Open CASCADE viewer to generate an OGM in pgm format with the corresponding resolution and map origin information, Prieto et al. uses the geometry of the spaces in the Industry Foundation Classes (IFC) file and the location and size of each one of the openings.

Karimi et al. (2020) developed a Building Information Robotic System (BIRS), enabling the generation and semantic transfer of topological and metric maps from a BIM model to Robot Operating System (ROS). The tool was further developed in (Karimi et al. 2021) with an optimal path planner, integrating critical components for construction assessment. Kim et al. (2021) implemented a method to convert an IFC file into a ROS-compliant Simulation Definition Format (SDF) world file suitable for robot task planning. They evaluated their approach for the purpose of indoor wall painting.

Later, to incorporate dynamic objects and for the aim of door inspection, Kim & Peavy (2022) proposed a technique to convert an IFC model into a Universal Robot Description Format (URDF) building world. Once they have the URDF model, they use the PgmMap creator (Yang 2018) to create an OGM out of it.

Hendrikx et al. (2021) proposed an approach that, instead of using an OGM, uses a robot-specific world model representation extracted from an IFC file for 2D-LiDAR localization. In their factor graph-based localization approach, the system queries semantic objects in its surroundings and creates data associations between them and the laser measurements. While they demonstrated that the method could track the Pose of the robot, it was not evaluated quantitatively.

Instead of using a BIM model, Boniardi et al. (2017) use a CAD-based architectural floor plan for 2D LiDAR-based localization. In their localization system, they implement Generalized ICP (GICP) for scan matching together with a pose graph Simultaneous Localization and Mapping (SLAM) system. Later, in (Boniardi et al. 2019), they proposed an improved pipeline for long-term localization in dynamic environments.

Zimmerman et al. (2022) use an OGM obtained from a sliced TLS point cloud together with human-readable localized cues to assist localization. Their text detection-based localization technique can detect known room numbers and thus can robustly handle symmetric environments with structural changes.

While several approaches have emerged aiming to create OGMs from BIM models, none of them deal with complex non-convex models with multiple stories and slanted floors.

Moreover, most of the proposed techniques are based on the strong assumption that the BIM model represents the actual current state of the building very precisely, ignoring the presence of possible Scan-BIM deviations due to clutter, furniture, as-planned vs. as-built differences, changes due to long-term operation, or the presence of dynamic agents.

4 METHODOLOGY

As illustrated in Figure 1, our method can be divided into three main steps: Step **1**: Creation of an OGM from an IFC file employing IfcConvert and OpenCV. Step **2**: Automatic generation of a Pose Graph-based map out of an OGM with image processing, coverage path planner, and ray casting. Step **3**: Robust localization using particle filter algorithm and graph-based localization system.

4.1 *OGM generation from an IFC*

For creating suitable 2D OGMs for robot localization and navigation from complex multi-story IFC models, the IfcConvert tool of IfcOpenSchell (Krijnen 2015) and image processing techniques are used.

IfcConvert allows the creation of a 2D map in SVG format with the desired elements in the IFC model that cross a plane at the desired height.

In our case, non-permanent entities such as spaces, windows, and doors are excluded from the resulting 2D OGMs by ignoring the corresponding entity names. This exclusion is essential to filter only structural information about the building, enabling further autonomous navigation between the rooms that want to be explored.

Besides having the permanent structures in the OGMs, and with the aim of global localization and posterior correct pose graph map generation, it is crucial to differentiate between outdoor (unknown) and indoor (navigable) spaces in the OGMs. This distinction can be automated creating a second 2D map with all the entities in the IFC file (i.e., with doors and windows).

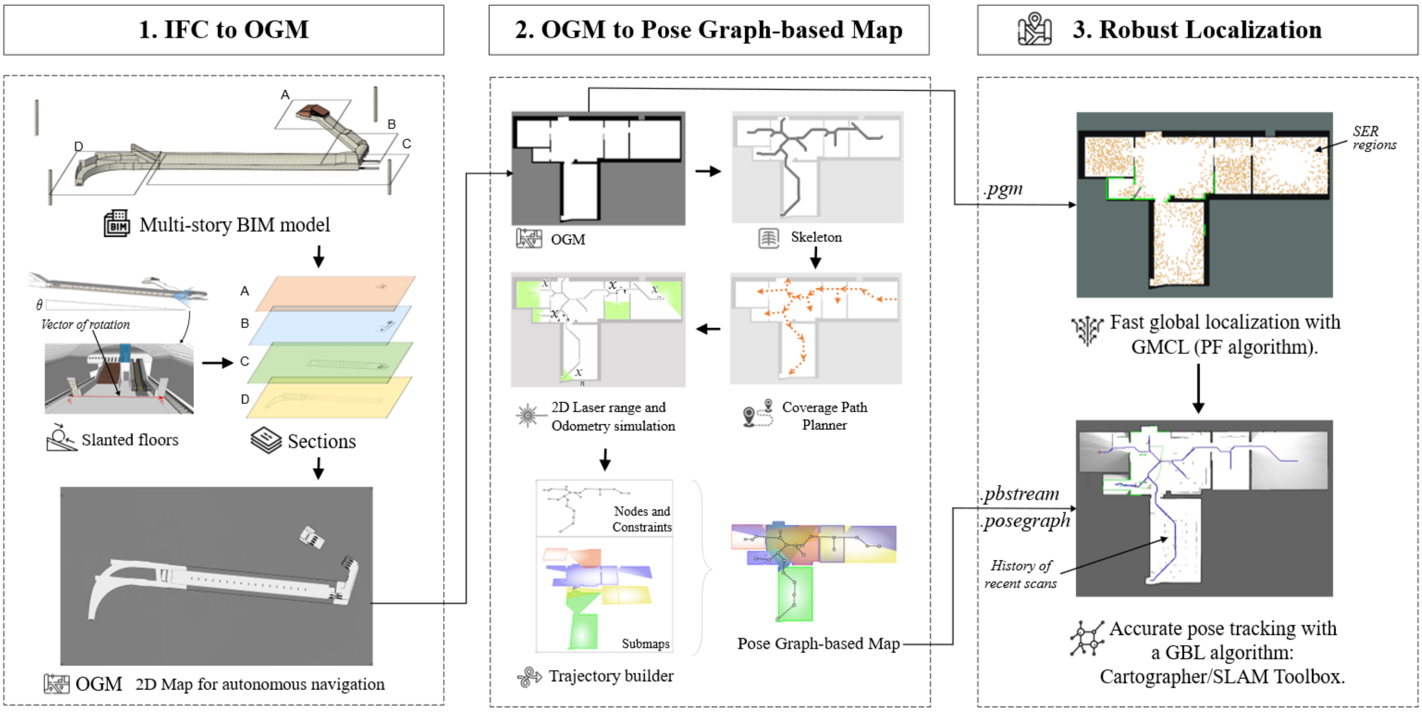


Figure 1: Proposed IFC to Pose Graph-based map for robust 2D-LiDAR localization. In the first step, an OGM is created from Multi-story non-convex BIM models which can have slanted floors, this map is suitable for path planning and autonomous robot navigation. In the second step, a Pose Graph-based map is generated from the OGM. Finally, in the third step, these maps allow fast global localization and robust pose tracking in changing and dynamic environments.

The final separation of outdoor (gray color), indoor (white), and obstacle (black) is done based on the contours in the SVG image. OpenCV allows the processing of the contours depending on their hierarchy, i.e., depending on if they are inside (child contours) or outside another contour (parent contours).

The resulted file is finally converted to *.pgm*, which, together with its properties (the resolution and origin) in a *.yaml* file, can then be loaded into the robotic system as prior environment information, allowing robot localization, and path planning, and autonomous navigation.

A similar procedure can be followed for multi-story level buildings. In the case of non-overlapping stories, the different OGMs can be merged into a single one if the relative position between them is known. To maintain this spacial relationship, while obtaining the OGMs, reference auxiliary elements with a height equal to the maximum building's height can be included in its surroundings. With these additional elements, all the OGMs will have the same dimensions allowing its merging.

Creating 2D OGMs with IfcConvert is relatively straightforward when the desired section is horizontal (parallel with the XY plane). However, if the model has a ramp or a slightly slanted floor, the model must be rotated before the occupancy map is generated. Favorably, IfcConvert also allows the rotation of the model in the desired angle given a quaternion calculated from the vector of rotation.

4.2 *OGM2PGBM: OGM to Pose Graph-based map conversion*

The automatic generation of data suitable for GBL methods from BIM models implies the simulation of sequential laser data in the entire navigable space in the model with the corresponding odometry data. For this aim, the previously generated 2D OGMs are used.

Applying the skeleton method proposed by Lee et al. (1994) enables the interconnection of all the rooms in a smooth trajectory. Subsequently, a Wavefront Coverage Path Planner (Zelinsky et al. 1993) is applied over the navigable area inside a dilated version of the skeleton, allowing finding the waypoints over which the laser will be simulated. Then, using a ray casting algorithm and without a real-time simulation engine (such as Gazebo), laser sensor data and odometry are simulated following the waypoints found in the previous step. Finally, a trajectory builder merges these sensor data creating an accurate pose graph-based map, serialized as a *.pbstream* file for Cartographer or a *.posegraph* file for SLAM Toolbox.

This pipeline allows the efficient automatic generation of Pose graph-based maps from 2D OGMs. As our OGM2PGBM workflow does not require Gazebo for data simulation, it is faster and more portable than a Gazebo-based pipeline, allowing its execution in an isolated manner. Moreover, since the technique does not consider the complete 3D model but only a 2D OGMs, it is very efficient. In addition, it can be used from any given OGMs, which besides of been generated from a BIM model (with the method presented in the previous section), can be generated out of a floor plan or a previously scanned map. Graph optimization is not required since every scan's position is known accurately from the simulation.

4.3 *Robust Localization*

Once the different needed map representations (OGM and pose graph-based maps) are generated from a BIM model, they can be used for robust localization in changing environments.

We propose to take advantage of the Self-Adaptive PF of GMCL to spread particles only in the SER regions and solve the global localization problem efficiently. As it is shown later (in Section 6), PF algorithms being able to represent non-Gaussian distributions can solve the global localization faster than graph-based algorithms.

Once an estimated pose is found with a covariance smaller than 0.05, the nodes of GMCL are stopped, and a GBL algorithm can be started.

For example, to track the Pose of the robot accurately, Cartographer can be activated with the *start_traj* service at the time when GMCL converges and using the *.pbstream* map generated with the method proposed in Section 4.2.
Similarly, SLAM Toolbox can be started with an initial pose, however with a prior *.posegraph* map.

5 EXPERIMENTS

This section presents the evaluation scenarios designed to evaluate the various techniques and details of the implementation and evaluation.

5.1 *Evaluation Scenarios*

As illustrated in Figure 2, three different scenarios were conceived to evaluate the different methods.

Each scenario increases the level of clutter present in the environment and, therefore, decreases the level of overlap that a perception sensor would have with permanent building objects (such as walls, columns, floors, and ceilings). The latter are the elements that are usually present in a BIM model.

Additionally, to increase the simulation's realism level, we added animated walking human models (also called dynamic agents) moving in the environment. In scenarios 1 and 2, five humans walk from each Room to the closest exit of that Room. In the scenario Nr. 3 (“Disaster”), a total of six people move faster, trying to escape through the main door. Once the agents reach their goal, they start again, moving from their initial planned position in an infinite loop.

(a) 1 (b) 2 (c) 3

Figure 2: Evaluation Scenarios. (a) Empty Room: represents a typical BIM Model, without furniture; (b) Reality: represents a standard office environment and is based on real-world TLS data; (c) Disaster: is an environment after a simulated disaster with large Scan- BIM deviations.

5.2 *Gazebo Simulation*

To simulate the experimental data, we use Gazebo. Once the IFC model is converted to Collada format using IfcConvert, it can be imported into Gazebo.
While importing complex IFC models in Gazebo is essential to ensure that every element has its own geometric representation. One way to avoid instantiating multiple objects from the same data is using the export capabilities of Blender.

For trustworthy data simulation, we separate between collision and visual models. Since LiDAR sensors cannot perceive glass materials, windows and glass doors were removed in the collision models.

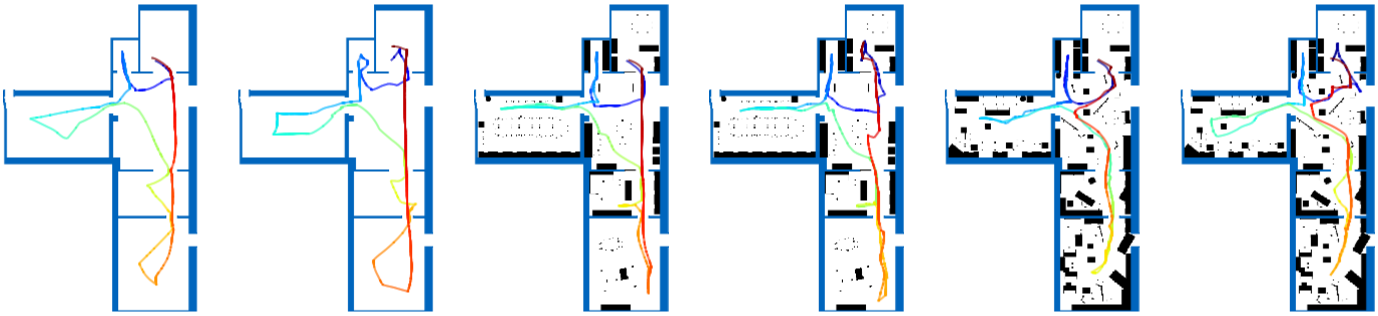
5.3 *Robot Simulation*

The robot used for the simulated experiments was the holonomic Robotnik SUMMIT XL equipped with a 2D LiDAR Hokuyo UST-10LX.

It was commanded with stable linear and angular velocities at approximately 1 m/s and 1 deg/s, respectively.

Using the URDF model of this robot, it is possible to leverage the different packages of the ROS Navigation Stack for RViz. One of these packages is NAVFN which assumes a circular robot and allows to plan a path from a start point to an endpoint in a grid based on a Costmap. A Costmap is an inflated version of the given 2D OGMs with a specified amplification radius created to avoid the robot colliding with obstacles while navigating through the environment.

The Gazebo Plug-in PgmMap creator (Yang 2018) was also implemented to speed up the usage of the OGMs for robot simulation, allowing the creation of maps with known origin positions. This step is not required in practice since the alignment between the real world, and the map can be retrieved as a localization system result. It is worth mentioning that using navigational goals instead of single movement commands is very convenient for data simulation since it significantly reduces the probability of collisions, which can make the entire sequence useless.



(a) 1-1 (b) 1-2 (c) 2-1 (d) 2-2 (e) 3-1 (f) 3-2

Figure 3: Sequences of data with the respective OGMs. (a) and (b) correspond to an empty environment (i.e., without furniture) with and without dynamic agents resp.; (c) and (d) similar but in a scenario with furniture as it is in the real world; (e) and (f) in the disaster environment. To better visualize the different levels of Scan-BIM deviations, the OGM of the empty environment is presented over the other OGMs in blue color. The change in color of the trajectory represents the initial and end position of the robot, with dark blue being the start and red the endpoint.

Following this approach, 2D LiDAR, Inertial Measurement Unit (IMU) measurements, Wheel odometry, and ground truth odometry were simulated in the six scenarios (three models with and without dynamic agents). The resulted trajectories of the simulation are presented in Figure 3.

5.4 *Experimental details*

Due to the stochastic nature of PF algorithms and similarly as done by Alshikh Khalil & Hatem (2021), these methods were executed 30 times in each sequence, and the average values were calculated.

As Zimmerman et al. (2022), we consider that a method converges when its pose estimate is within 0.5 m from the ground truth pose. If, after the first 95 % of the sequence, convergence does not happen, then it is considered a failure.

Unfortunately, SLAM Toolbox could not be evaluated for global localization since it does not provide this service. The lifelong mapping mode of SLAM Toolbox was also tested for completeness; however, it yielded unwanted results with poor performance.

6 RESULTS AND ANALYSIS

The libraries provided by Grupp (2017) were used to calculate the error metrics of the various methods on the different sequences.

6.1 *Pose tracking*

In Table 1 we present the translational and rotational Root Mean Square Error (RMSE) for each sequence for each method evaluated on the pose tracking problem with the ground truth from the simulation.

Figure 4 presents a summary of the statistics of the translational errors for all the methods in all sequences.

Overall, it can be seen that GBL methods always perform better than PF algorithms in the pose tracking problem.

Among the tested PF algorithms, GMCL performs most of the time better than AMCL. Only in the scenarios 2-2, 3-1, and 3-2, AMCL achieves lower RMSE. In scenarios 2-2 and 3-2 GMCL has a very high translational RMSE. This shows that the additional filters of GMCL cause the method to be more sensitive to dynamic environments in changing environments.

Regarding the GBL algorithms, SLAM Toolbox achieves the best performance in scenarios 1 and 3. As expected, scenario 3 (with the most significant Scan-BIM deviations) was the most challenging scenario for all the methods. On top of that, in this scenario, the pure localization mode of Cartographer always found wrong data associations, resulting in wrong relative constraints that cause localization failure. Therefore, Cartographer could not be quantitatively evaluated in this environment, even when an initial approximated pose was provided. Nonetheless, Cartographer achieved an impressive performance in scenario 2 (real-world scenario), accomplishing a translational RMSE four times lower than SLAM Toolbox in the environment without dynamic agents (7.19 cm and 28.69 cm, respectively) and almost six times lower in the scenario with dynamic agents (4.11 cm and 23.57 cm respectively).

6.2 *Global localization*

The performance of the different methods regarding convergence time is presented in Figure 5 GMCL, thanks to its Self-Adaptive PF, performs the best in the global localization problem. Only in scenario 1-2 Cartographer shows a slight superiority. Meanwhile, AMCL always takes at least twice as long compared to the other methods to converge to a good pose. In addition, it does not converge in scenario 2-1.

Due to the high level of Scan-BIM deviations, none of the implemented methods converges while trying to solve the global localization problem in scenario 3.

Table 1: Summary of the quantitative evaluation results for each sequence. Translational RMSE in centimeters and angular RMSE in degrees, respectively.

Method	1-1		1-2		2-1		2-2		3-1		3-2	
AMCL	8,49	0,44	8,47	0,50	33,68	2,71	37,44	3,26	63,04	3,29	65,12	3,37
GMCL	8,27	0,24	7,86	0,24	24,27	2,57	52,38	4,37	66,60	3,70	126,91	4,46
SLAM Toolbox	**3,69**	**0,17**	**3,95**	**0,17**	28,69	1,50	23,57	1,50	**37,84**	**1,34**	**37,96**	**1,70**
Cartographer	11,89	0,22	4,04	0,21	**7,19**	**0,15**	**4,11**	**0,21**	-	-	-	-

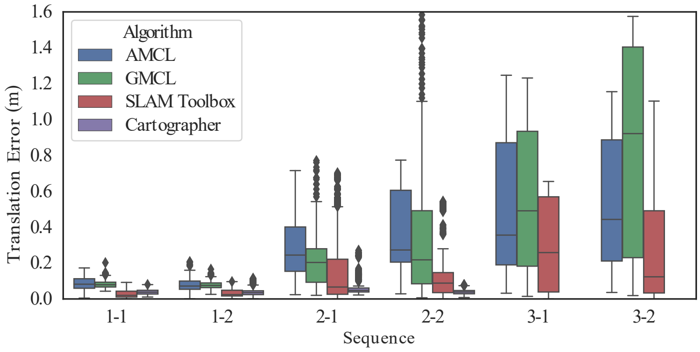


Figure 5. Statistics of the pose error estimates in translation for each method on the six evaluation scenarios.

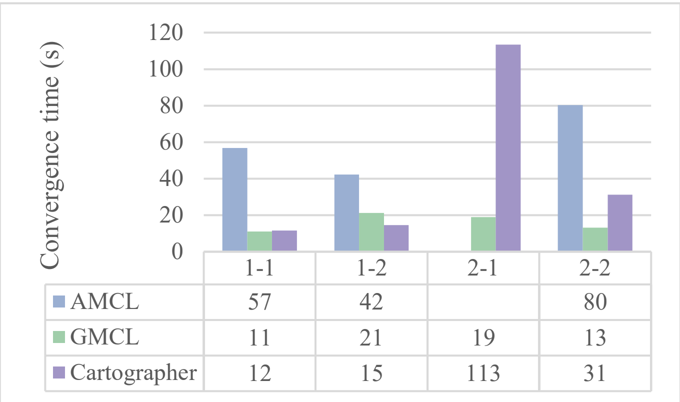


Figure 4 Convergence time in seconds for the various methods in the different scenarios.

7 CONCLUSIONS

In this paper, besides contributing with methods to create OGMs from BIM models and transforming them to pose graph-based maps for robust localization, we provide an extensive comparison of diverse state-of-the-art localization 2D-LiDAR algorithms in three different levels of Scan-BIM deviations, with and without dynamic agents.

We found that GBL algorithms overperform PF algorithms in the pose tracking problem.

In the case of a map with very low (or negligible) Scan-BIM deviations, SLAM Toolbox achieves the best performance.

On the contrary, if the map has a medium level of Scan-BIM deviations (for example, due to large pieces of furniture or as-planned and as-built differences), as in a real-world office building, Cartographer is the best performing method.

However, in a case where the level of changes in the environment is too high (such as in scenario 3), SLAM Toolbox, while with a relatively high error, would be the best option among the tested localization algorithms.

The fact that PF algorithms only consider the most recent observation to update the belief of the current Pose gives them certain robustness to deal with high ambiguity scenarios (such as scenario 3).

However, it also causes high inaccuracies when the level of Scan-BIM deviations is medium (such as in scenario 2). On the other hand, GBL algorithms taking advantage of a recent history of observations can better handle this real-world scenario and can track the robot's Pose more accurately.

Nonetheless, GMCL performs better for the global localization problem than GBL algorithms.

In general, we recommend using a GBL algorithm for accurate BIM-based (or floor plan-based) 2D LiDAR pose tracking in real-world environments and GMCL for global localization.

To facilitate the correct implementation of Graph-based Localization algorithms, we contribute with an open-source method to create accurate pose graph-based maps from any OGMs. In addition, we provide a method to create OGMs from complex multi-story BIM models, which can additionally be leveraged for path planning and autonomous navigation. State-of-the-art SLAM techniques have switched from using particle filters to graph-based optimization approaches; based on our experiments, we can conclude that it will be analogously advantageous for most localization systems.

8 FUTURE WORK

In the light of the experimental results and motivated by related research, we believe that the following are promising future research directions:

Consider not only 2D-LiDAR information but also 3D-LiDAR sensor data is a promising direction to reliably handle significant Scan-BIM deviations, as partially shown by Blum et al. (2020) and Moura et al. (2021)

Fusing multiple sensor modalities, such as IMU, RGB-D cameras, and LiDAR sensors, would increase the robustness of a localization method to deal with fast angular movements and deprecated scenarios, as demonstrated by Lin & Zhang (2021) and Xu et al. (2022).

To achieve major robustness, the extraction of detailed information from a BIM model, such as the position of room numbers labels, doors, and windows, can support solving the global localization problem even in symmetric environments, as done by Zimmerman et al. (2022) and Haque et al. (2020).

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