Towards BIM-based robot localization: a real-world case study

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Abstract -

Conventional mobile robots rely on pre-built point cloud maps for online localization. These map points are generally built using specialized mapping techniques, which involve high labor and computational costs. While in the architectural, engineering and construction (AEC) industry, as-planned building information modelings (BIM) are available for management and operation. In this paper, we consider the use of the digital representations of BIM for robot localization in built environments. First, we convert BIM data into localization-oriented point clouds, which is easy to implement and operate compared to relatively complex SLAM systems. Then, we perform iterative closest point (ICP)-based localization on the metric map using a laser scanner. The experiments are tested using collected laser data and BIM in the real world. The results show that ICP-based localization can track the robot pose with low errors (< [0.20m, 2.50°]), thus demonstrating the feasibility of BIM-based robot localization. In addition, we also discuss the reasons for errors, including the deviations between as-planned BIM and as-built status.

Keywords -

BIM; Robot Localization; LiDAR; Deviation

1 Introduction

Precise localization is a fundamental capability for mobile robots. Almost all mobile robots, whether teleoperated or autonomous, require the robot pose to be estimated by the localization module to achieve safe human operation or self navigation in complex environments. In the robotics community, many simultaneous localization and mapping (SLAM) systems [1, 2] have been developed to achieve both mapping and localization when the robot is traveling in the real world.

For some long-term robots that operate under stable conditions such as a quadruped robot working on building inspection, the mapping process of SLAM is redundant because the generated map is almost invariant in each time of SLAM. To solve this problem, researchers in the robotics community proposed to achieve mapping first and then robot localization in the known map [3, 4]. In this context, map building is required only once and localization in the map could handle the pose estimation for long-term operation, reducing the complexity of repetitive SLAM processes. This two-step workflow has been widely used in various fields of robotics and a typical application is self-driving cars [5].

The mapping step in this workflow is generally based on SLAM or other techniques, which can be considered as a measuring or sensing process of the environment. However, some modeling or representations are directly available in the AEC industry, such as computer-aided design (CAD) or BIM. These map-like representations also contain informative measurements. Thus, we hypothesize SLAM may not always be necessary when these are available. Moreover, BIM has been raised to replace CAD in recent years. We believe that robot localization in a as-designed BIM could be a good choice in built environment.

One might argue that BIM is designed for construction and building management, which is not a localization-oriented map essentially. In this paper, we present a BIM-to-Map process to convert the digital representations of BIM into point cloud maps for robot localization. We also utilize a point-to-plane ICP-based method to localize the robot on the BIM-generated map, thus bridging the gap from design modeling to robotic navigation in the real world. In addition, there are deviations between as-planned BIM and as-built buildings in the real-world, which brings potential difficulties to online robot localization. To address this problem, we present a real-world case study to test BIM-based robot localization using a rotating Light Detection and Ranging (LiDAR) scanner. Overall, the contributions can be summarized as follows:

- A BIM-based robot localization workflow is presented to achieve precise pose estimation in the built environment. The prior maps are built with BIM-to-Map conversion without complex SLAM systems.
- We conduct experiments in the real world. The experimental results show that the proposed workflow can track the robot pose with only a LiDAR scanner

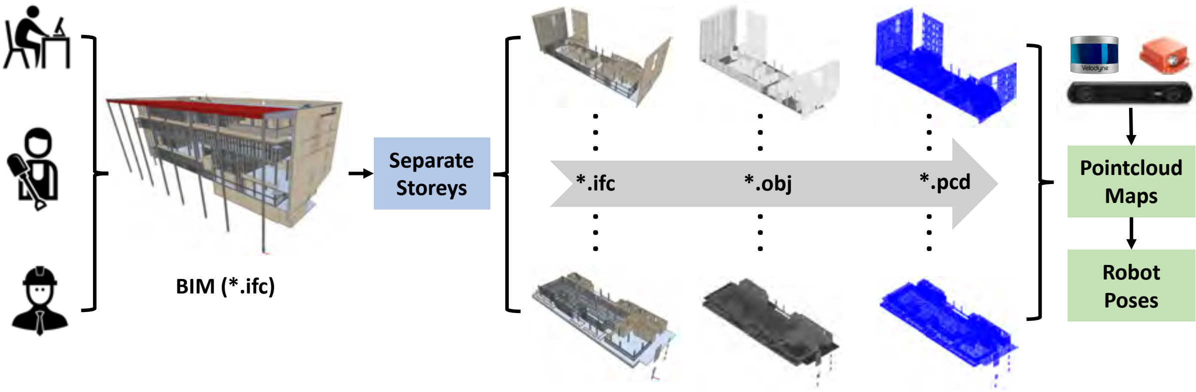


Figure 1. The workflow of BIM-based localization in this paper. We first convert BIM to metric point cloud maps storey by storey. Then based on the localization-oriented maps, mobile robot localization can be achieved using sensor units. In this paper, we perform a case study on 3D LiDAR localization in BIM at NUS campus.

and BIM.

2 Related Work

Many research publications have reviewed related robot navigation topics from different standpoints, including deep learning-based [6], specific sensor-based [7, 8, 9], etc. In this paper, we present some related work on CAD or BIM-based mobile robot navigation.

Intuitively, floor plans or 2D points can be generated from CAD models for lightweight 2D localization. In [10], point clouds were extracted from CAD models to achieve radar localization via multi-modal registration. Researchers in [11] proposed to localize a 2D laser scanner on floor plans and hand-drawn maps using stochastic gradient descent. As for localization in 3D space, ICP-based alignment is considered as an effective method to track the robot pose [12]. Despite the point-based method, meshes were also used for robot global localization without initial guess in [13]. Recently, researchers in [14] proposed a novel interface to connect building construction and map representation, which could also detect deviations between as-designed and as-built models via localization results.

Compared to traditional CAD models, BIM is more interoperable in the construction industry and contains more semantic information for robot navigation. For visual-based pose estimation, photogrammetric point clouds can be aligned to BIM model [15] for camera pose estimation from scratch. With sequential input images, visual-based pose tracking was demonstrated to be effective [16], in which camera poses were estimated by aligning images to BIM models. However, visual-based localization methods are easily affected by illumination changes, while LiDAR-based is more robust in long-term operation. In [17], BIM was combined with LiDAR SLAM system to localize the robot, but the experiments were conducted in simulated environments. Researchers in [18] extracted semantic features of BIM and achieved robot localization using 2D laser scans in the real world. The results showed that the robot can track its pose in BIM but the localization performance was not evaluated quantitatively.

Inspired by the related works above, we can conclude that it is feasible to use BIM for robot localization tasks. However, in some previous works [16, 17], robot localization modules were built on existing SLAM systems, which makes the localization module complicated for real robot applications. To address the problems, we propose to localize the robot in BIM-based maps using lightweight point cloud registration. Besides that, we evaluate the localization accuracy quantitatively in the real world.

3 Workflow Description

As shown in Figure 1, the proposed workflow consists of two parts: offline point cloud map generation from BIM and online ICP-based localization.

3.1 BIM to Point Cloud Map

As a promising direction in the construction industry, BIM is supported by many tools and used in various construction processes, such as building inspection [19] and quality management [20]. For mobile robot localization, metric maps are required rather than digital representations. In this context, the first challenge is that how to generate localization-oriented maps from BIM files.

In this paper, we propose to convert BIM to localization-oriented maps in three steps. The pipeline is shown in Figure 1. Given a whole BIM of one building, we first split the whole BIM into several separate BIM according to different storeys. After that, we use the open source tool IfcOpenShell [1] to convert multiple BIM to CAD files. Finally, 3D point clouds are sampled from triangular meshes with a density [21]. There are many other sampling strategies in some software [2] [3], such as Monte-Carlo Sampling. Considering that density value is easy to be understood and tuned, we decide to use this strategy in this paper. The final point cloud maps can be regarded as submaps of each floor in the building.

Note that it is better not to change the sequence of this conversion. If we convert the whole BIM to CAD model first without separation, the storey information of BIM is not used. It is more challenging to split large CAD or point cloud maps into storey-based submaps in the follow-up steps. To simplify the conversion process, a promising research direction is to generate point clouds or features directly from the original BIM, which we conclude as a future work in Section 5.

3.2 ICP-based Localization

With generated point cloud maps, there are many existing methods to localize the robot based on the onboard sensors of mobile platform [4, 22]. Generally, a classical robot localization consists of two parts: odometry as a motion module and data matching as a measurement model. In this paper, to validate the effectiveness of the proposed BIM-to-Map conversion process, the localization system is simplified without odometry, which makes the validation easy and efficient to use.

We use a mobile LiDAR scanner to validate the proposed workflow. With the measured LiDAR scans, an ICP algorithm is performed to register the laser points to generated maps from BIM. ICP is a widely used point cloud registration method in the robotics community [23, 24]. Specifically, we use a point-to-plane ICP to achieve pose estimation since there are many planar structures in the building environment. Overall, the point-to-plane ICP-based pose estimation can be formulated as follows:

$$(\mathbf{R}, \mathbf{t}) = \underset{(\mathbf{R},\mathbf{t})}{\arg\min} \left(\sum_{k=1}^{K} \|(\mathbf{R}\mathbf{p}_k + \mathbf{t} - \mathbf{q}_k) \cdot \mathbf{n}_k\|_2 \right) \quad (1)$$

where K is the number of matched data associations; $(\mathbf{R}, \mathbf{t})$ is the rotation and translation of estimated robot pose; $\mathbf{p}$ is the lidar points reading; $\mathbf{q}$ and $\mathbf{n}$ are the map points and normal vectors respectively. At each timestamp, ICP will minimize the error metric in Equation 1 as close to zero as possible within a number of iterations.

As for implementation, open source library libpointmatcher [25] [4] is utilized. At each timestamp s, we use the estimated pose at timestamp $s-1$ as the initial guess of ICP registration. Random sampling on $\mathbf{p}$ is also used to accelerate the online localization process.

[1]https://github.com/IfcOpenShell/IfcOpenShell
[2]https://www.meshlab.net/
[3]https://www.cloudcompare.org/
[4]https://github.com/ethz-asl/libpointmatcher

Figure 2. The devices that we used for data collection and experimental validation.

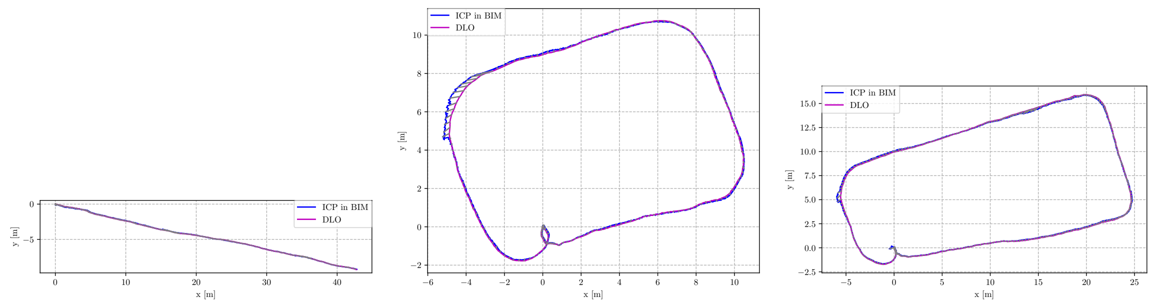
Figure 3. Interior scenes in NUS SDE4 building

4 Experiments

In this section, we first introduce the devices for data collection and the places where we collected the data. Then localization accuracy is evaluated by comparing it to state-of-the-art LiDAR SLAM methods.

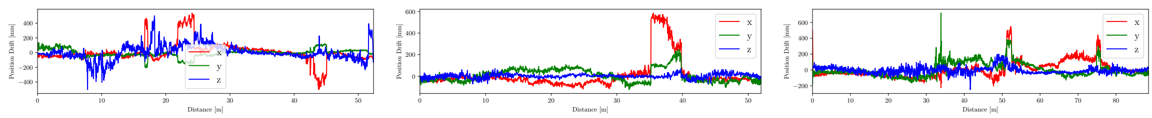
4.1 Set-up

To validate the effectiveness of the proposed workflow, we collect several sequences using a handheld Velodyne VLP-16 sensor in the real world. The data collection devices are shown in Figure 2. All the data Sequences are collected in the School of Design and Environment 4



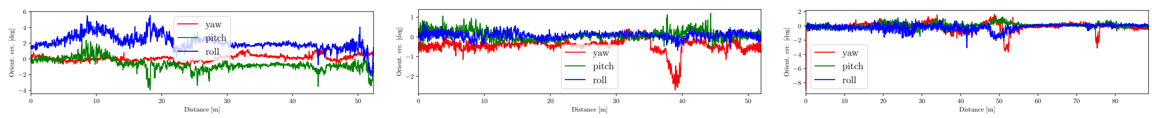
(a) Sequence-1 in 2nd floor (b) Sequence-2 in 3rd floor (c) Sequence-3 in 3rd floor

Figure 4. BIM-based localization trajectories compared to DLO



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

Figure 5. Translation Errors



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

Figure 6. Rotation Errors

Table 1. Localization Errors Compared to DLO

Sequence	Translation Error (m)				Rotation Error (°)			
	Max	Mean	RMSE	Std	Max	Mean	RMSE	Std
1	0.56	0.13	0.17	0.12	6.82	2.37	2.50	0.80
2	0.60	0.09	0.14	0.10	2.70	0.57	0.64	0.30
3	0.76	0.11	0.14	0.08	9.00	0.61	0.84	0.58

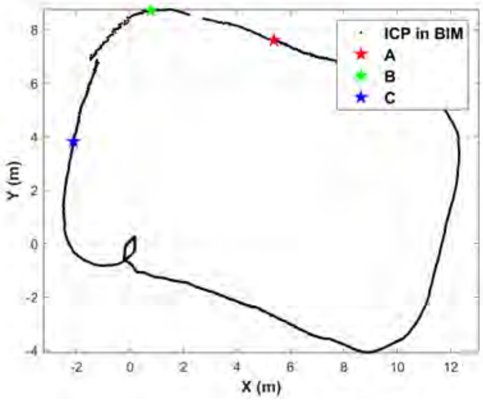
(SDE4) building at NUS. The traveled distance is tens of meters in each Sequence. We present some interior scenes in Figure 3. The SDE4 BIM can be viewed in Figure 1. All the online localization experiments are performed using a laptop with Intel I5-8265U and 16G RAM.

Ground truth poses are required to evaluate the ICP-based localization. However, compared to outdoor autonomous vehicles equipped with GPS/INS, it is challenging to collect ground truth poses in indoor scenes, especially for traveling across rooms and corridors in this paper. We notice that a state-of-the-art lidar SLAM system, direct LiDAR odometry (DLO) [26] [5], can provide accurate pose estimation in DARPA Subterranean Challenge. According to the error analysis in [26], DLO achieves the best performance compared to other LiDAR SLAM systems. Thus, we set DLO as the "ground truth" for evaluation in this paper.

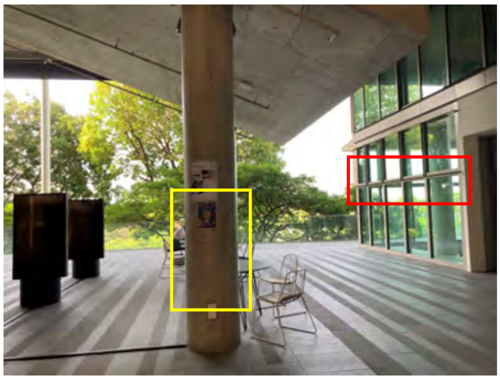
4.2 Performance Evaluation

An open source toolbox rpg_trajectory_evaluation [27] [6] is used to measure the quantitative results. All poses

[5]https://github.com/vectr-ucla/direct_lidar_odometry
[6]https://github.com/uzh-rpg/rpg_trajectory_evaluation

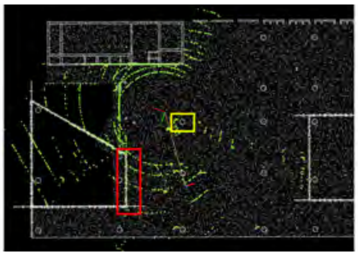


(a) Localization trajectory of Sequence-2

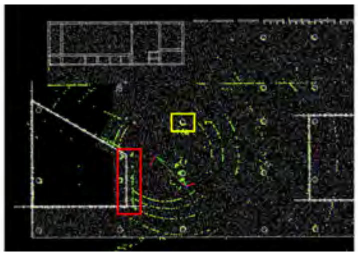


(b) pillar and window ledge

(c) Pose-A



(d) Pose-B



(e) Pose-C

Figure 7. We find that deviations between as-planned and as-built cause a sudden "jump" in the localization trajectory. In 7b, the pillar is shown in the yellow box and the window ledge is shown in the red box for clearance. In 7c, 7d and 7e, the green points represent measured LiDAR points and white points are generated map points from BIM.

$(\mathbf{R}, \mathbf{t})$ are used to align the trajectories of DLO and BIM-based localization. The initial robot poses are manually fixed in the point cloud maps.

As shown in Figure 4, three data sequences are collected for localization evaluation. Among the three sequences, one is collected on the 2nd floor of SDE4 building and two with loops are collected on the 3rd floor. We also present numerical errors of entire trajectories in Table 1, in which mean error is the mean of the absolute value of each error. The translation and rotation error variations are also presented in Figure 5 and Figure 6 with respect to the traveling distance.

As observed from the errors, the proposed BIM-based localization method can track the lidar scanner successfully with minor errors. In Table 1, the rotation errors of Sequence-1 are larger than errors of Sequence-2 and 3. We consider this is due to several reasons, such as the differences in map point distributions, traveling trajectories, etc. Overall, most of the translation errors are below 0.2m and rotation errors are below 2°, which is acceptable for indoor positioning systems, but still needs to be improved for navigation applications in the future. Compared to previous BIM-based pose estimation methods [15, 17], the proposed LiDAR localization can track the sensor pose continuously and more accurately, even though only scan matching is involved in our method.

4.3 As-Planned vs As-Built

We also notice that there are two large discrepancies in Sequence-2 during robot localization, resulting in the large errors seen in Figure 5b and Figure 6b. Three robot poses A, B and C are selected in chronological order for investigation, as shown in Figure 7a. Specifically, Pose-B exhibits a large error compared to the ground truth. The bird's-eye-view of aligned LiDAR points and map points are presented in Figure 7c, 7d and 7e for visualization.

In Figure 7c and 7e, the point cloud of the pillar (yellow box) is aligned correctly but points of the window ledge (red box) are not aligned. While in Figure 7d, the pillar points are unaligned. We measure the distance between the unaligned ledge points using ROS Rviz and the deviation distance is around 0.7m. Based on the analysis above, we conclude that there is a deviation between as-planned BIM and as-built construction status on the 3rd floor which lead to the large localization errors in Sequence-2. On the other hand, compared to SLAM-based maps, we consider that BIM-to-Map conversion will not involve measurement and estimation errors, which will provide higher-quality local point clouds.

5 Conclusion and Future Work

A workflow of BIM-based robot localization is presented in this paper. We first convert BIM to metric point cloud maps and then perform ICP- based localization to localize a LiDAR sensor. In the experimental section, we conduct a real-world case study at NUS campus. We also find that the deviations between as-planned BIM and as-built buildings bring localization errors in this workflow.

We consider there are several research directions to improve the workflow, categorized as follows:

- More robust point cloud registration or alignment to overcome the deviations from BIM. We consider the semantic information of BIM could help build robust registration. On the other hand, the registration algorithm can be improved using fine-tuned parameters or other outlier filters.
- Multi-sensor fusion for a more accurate localization system. Generally, inertial measurement unit or other odometry modules can help build a more complete system, i.e., providing a high-frequency motion model, which will definitely improve the localization performance.

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