A BIM-Driven Robotic Framework for Autonomous 3D Projection of Construction Layouts

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Abstract –

Robotic layout projection has been increasingly adopted to support construction layout tasks while reducing manual effort. However, existing solutions still require substantial human intervention and are largely limited to single, horizontal surfaces. To address these limitations, this paper proposes a BIM-driven robotic framework for autonomous construction layout projection. The framework consists of a planning module and an execution module, designed for a legged robotic platform equipped with a 3D LiDAR sensor and a projector. The planning module interprets construction layout tasks from 4D BIM models, determines feasible navigation goals for the robot, and generates projector pose-consistent layout images. The execution module performs BIM-to-environment alignment using partial SLAM, enabling the robot to autonomously navigate to the planned goals and accurately re-localize its pose to ensure precise layout projection. The proposed framework is preliminarily validated through a Gazebo-based virtual environment. Future work will focus on implementation on physical robotic systems and validation in real-world construction scenarios.

Keywords –

Construction layout; Building Information Modeling (BIM); Robotic construction; BIM-SLAM alignment; 3D layout projection.

1 Introduction

Setting out construction work on site constitutes a fundamental step in many construction tasks, including interior partition installation and mechanical, electrical, and plumbing (MEP) systems [1]. These tasks require the accurate marking of object locations on diverse work surfaces, including floors, ceilings, and vertical walls, before construction begins. In the current practice, construction layout is largely performed manually. Workers must interpret design drawings based on site conditions, measure target locations, and physically mark them. This process typically requires multiple workers cooperating with low-precision tools such as tapes, plumb bobs, and strings. While total stations offer higher precision, they remain costly and demand substantial setup time and specialized training.

To improve productivity, extensive efforts have been devoted to automating construction layout. Early approaches primarily adopt augmented reality (AR)-based systems, where digital layout information is overlaid onto the physical environment to assist human operators during manual measurement and marking tasks [2]. However, current AR technologies often suffer from limited fields of view, user discomfort, and the need for hands-on operation, which reduces their practicality for reliable construction layout tasks [3]. To address these limitations, robotic marking systems have been developed to automate layout execution by printing or drawing layout lines directly on site. While such systems eliminate the need for wearable or handheld devices, their operation is typically restricted to single planar surfaces per execution, most commonly clean horizontal floor surfaces. Consequently, existing robotic marking approaches treat layout as an isolated 2D task and lack a 3D layout projection capability, that is, the ability to consistently project design layouts across multiple physical surfaces, including adjacent walls, ceilings, or curved surfaces.

Furthermore, despite being described as "automated," most existing robotic layout workflows are not fully autonomous. They typically require a time-consuming manual setup phase, during which operators must drive the robot to predefined reference points to register the robot's coordinate system with the BIM model [4]. This dependence on human intervention for initialization and calibration disrupts workflow continuity and limits practical efficiency. As a result, there remains a lack of a fully autonomous robotic solution to perform 3D construction layout projection across multiple surfaces.

In this study, we propose a BIM-driven robotic framework for autonomous 3D construction layout projection. Unlike existing floor-bound or semi-automated approaches, the proposed framework integrates a mobile robotic platform with a BIM-aligned projection workflow to enable fully autonomous 3D layout projection.

The remainder of this paper is organized as follows: Section 2 reviews related work, and Section 3 details the proposed BIM-driven robotic projection methodology. Section 4 describes the experimental setup and discusses the results, demonstrating the framework's feasibility. Finally, Section 5 concludes the study and outlines directions for future research.

2 Literature review

Site layout planning has long been recognized as a critical task in construction projects, as it directly influences project cost, productivity, and safety [5]. At the scale of the overall construction site, site layout planning focuses on the organization and allocation of temporary facilities, including material storage areas, equipment zones, and other supporting infrastructures [6]. At a finer geometric scale, construction layout shifts toward object- or point-level tasks, emphasizing the precise positioning and marking of individual building elements or reference points on task-relevant construction surfaces [7]. For instance, during MEP installation, point-level layout typically involves marking the locations of fixtures, electrical outlets, or pipe penetrations on walls or ceilings to support accurate and efficient subsequent installation.

In current practice, point-level layout tasks remain largely manual. Workers interpret design drawings under dynamic site conditions and rely on tape- and ruler-based measurements, which are prone to cumulative errors that often lead to rework and schedule delays [7]. For higher-accuracy requirements, total stations integrated with BIM models are sometimes used [8]. Although effective in terms of geometric precision, such approaches depend on expensive equipment, extensive setup, and trained operators, limiting their efficiency and scalability for routine interior construction tasks.

To improve layout efficiency and accuracy, prior studies have explored AR techniques to directly transfer digital design information onto physical construction surfaces [9, 10]. Early efforts primarily relied on head-worn AR or wearable projection systems to support on-site information visualization, requiring workers to wear head-mounted displays (HMDs) such as Google Glass or Microsoft HoloLens [11]. For example, Yeh et al. [10] developed a wearable BIM-based projection system, termed iHelmet, which demonstrated improved efficiency compared to traditional two-dimensional drawings for accessing construction information. However, prolonged use of head-worn AR devices may introduce physical discomfort and occupational health concerns on construction sites [12].

To address these limitations, projector-based AR approaches have been proposed, using conventional digital projectors to overlay design information directly onto physical workspaces. Doshi et al. [13] demonstrated that projector-based AR can enhance manual spot-welding precision in automotive manufacturing by guiding workers' aiming points. In the construction domain, Ahn et al. [14] developed an AR approach using a camera-projector system that achieved sub-centimeter projection accuracy under controlled shop-floor conditions. Building upon projector-based AR, Xiang et al. [4] proposed a mobile projective augmented reality (MPAR) framework using a robot-mounted camera-projector system to project BIM models under motion for on-site visualization. However, MPAR primarily targets visualization rather than execution-level construction layout and does not address layout feature processing or accuracy requirements.

Targeting construction layout tasks, Degani et al. [1] developed a portable projector-based system. By integrating BIM with laser-based localization, the system projects processed layout information onto interior surfaces, reducing manual layout effort. Nevertheless, this system requires manual projection setup and mainly supports projection on planar horizontal surfaces, which limits its applicability in realistic construction scenarios. In parallel, industrial projector-based systems, such as LightYX [15], demonstrate the feasibility of high-precision projection in indoor construction environment. However, similar to Degani et al. [1], these systems rely on manual setup and static deployment, limiting mobility and autonomous execution. Conversely, mobile robotic solutions such as HP SitePrint [16] and Dusty Robotics' FieldPrinter [17] provide the necessary mobility to automate layout execution. While these systems significantly reduce manual labor, their operational scope remains fundamentally constrained to horizontal surfaces due to their reliance on physical ink-jet marking. This surface-bound mechanism lacks the flexibility required to map design information onto vertical walls or overhead ceilings, leaving a critical gap in comprehensive 3D construction layout scenarios.

In summary, previous studies have explored various approaches to automate construction layout execution, including AR-based visualization, projector-based AR systems, and mobile robotic solutions. Despite these advances, existing methods either rely on laborious manual setup, exhibit limited mobility, or are constrained to clean floor surfaces. As a result, a fully autonomous solution capable of executing 3D construction layouts on multiple surfaces remains lacking. To address this gap, this study investigates the feasibility and performance of a BIM-driven, robotic framework for autonomous 3D construction layout projection.

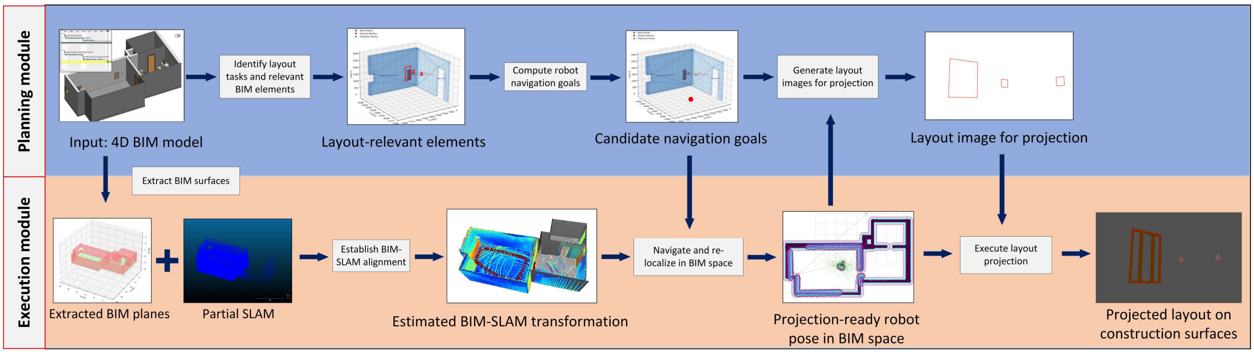


Figure 1. The proposed framework.

3 Methodology

This study presents a BIM-driven robot-enabled framework for autonomous construction layout projection. It transforms BIM-defined design information into executable layout projection actions.

This framework is developed for a mobile robotic system to enable autonomous layout projection in indoor construction environments. The targeted physical system mainly consists of a legged robot platform equipped with a 3D LiDAR sensor and a projector. The legged robot platform is adopted to maintain reliable mobility in complex indoor construction sites that are often characterized by uneven surfaces and obstacles. The LiDAR provides stable perception, localization, and mapping in indoor spaces with variable lighting and limited visual texture. The projector serves as the execution device, projecting BIM-derived layout information onto task-relevant construction surfaces.

Figure 1 illustrates the framework, which comprises two primary modules: a BIM-driven layout projection planning module and a robotic layout projection execution module. The planning module performs three key functions. First, given a scheduled construction task, it automatically derives the corresponding layout task by identifying the target objects for layout and their associated hosting surfaces from the BIM model. Second, it computes an optimal navigation goal for the robot to carry out the derived layout projection task, by jointly considering the layout objects' geometries, the robot's geometric features, and the projector's parameters. Third, after the robot reaches the navigation goal and the projector is calibrated, the planning module will generate a layout image consistent with the projector's pose, enabling accurate layout projection.

In the execution module, the system first aligns the BIM model with the physical environment using partial Simultaneous Localization and Mapping (SLAM) and semantic plane-based registration, yielding a rigid transformation between the robot navigation frame and the BIM coordinate system. The robot then localizes in BIM space and navigates to the planning-defined goal. After arriving, it performs re-localization to refine its pose and updates the projector pose based on the known robot-projector relationship. Finally, the updated projector pose is sent to the planning module to generate a pose-consistent layout image, which is projected onto the target construction surfaces to complete the layout projection task.

3.1 BIM-driven layout projection planning

3.1.1 Identify layout-relevant elements

Given a 4D BIM model as input, the proposed method performs layout projection planning in a task-driven manner by leveraging construction schedule information. At a given time point, the construction schedule is queried to identify the upcoming construction tasks. For projection tasks, two types of BIM objects are involved: projection objects, representing the BIM elements to be projected, and base objects, which provide supporting surfaces for projection. Projection objects are automatically extracted from the input 4D BIM model based on current or specified construction tasks, by leveraging the pre-established links between tasks and their associated BIM elements in the model. The base objects are inferred by topological analysis with the extracted projection objects. More specifically, the BIM objects that spatially contact or intersect the projection objects are identified as the base objects. This task- and time-aware selection reduces manual specification of layout targets and ensures that layout planning is synchronized with the actual construction sequence.

Once the projection objects are identified, their corresponding base objects, which refers to the physical construction elements providing surfaces for receiving projections, are determined based on topological relationships within the BIM model. Specifically, boundary representation (B-rep)-based geometric queries are performed to evaluate intersection or touching relationships between projection objects and candidate base objects, following established BIM topology processing principles [18]. A base object is considered valid when a projection object is found to intersect with or be in contact with its geometry, indicating a physically meaningful support relationship on site.

3.1.2 Compute robot navigation goal

In this study, the robot navigation goal is defined as an optimal robot location and orientation that allow the robotic system to perform an accurate layout projection. The procedure for computing the navigation goals is as follows:

First, a 2D preliminary feasible region is defined on the floor plane based on the spatial distribution of all projection objects. Specifically, all projection objects are projected onto the floor plane, and their bounding boxes are expanded by a predefined margin. The overlap of these expanded areas defines a region within which the robot can be positioned to observe the targets. A grid-based sampling strategy is then applied to discretize the region with a predefined resolution, generating candidate robot positions.

For each sampled location, robot geometric constraints are evaluated by checking the robot footprint against surrounding structures from the BIM model. Locations that would cause collisions with walls, columns, or other elements are discarded, ensuring that only collision-free positions are retained.

For each remaining location, the robot orientation is determined based on the locations of all projection objects. Specifically, the orientation is constrained such that all target objects lie within both the horizontal and vertical fields of view of the projector. Among all feasible candidates, the selected orientation is the one that is most centrally aligned with respect to the spatial distribution of these objects.

At this stage, a set of feasible poses is obtained, each defined by a location and its corresponding optimal orientation. The final navigation goal (pose) is selected using a scoring function that jointly optimizes two objectives with equal weights: (1) minimizing the total projection distance between the robot and all projection objects; and (2) maximizing the average angle between the projector orientation and the centroids of all projection objects. The ensures that the selected pose is both close to the projection objects and avoids skewed projection angles, thereby improving projection accuracy.

3.1.3 Generate layout images for projection

After the robot reaches the navigation goal and re-calibrates its pose (see Section 3.2.2), a layout image consistent with the projector and its current pose is generated to enable accurate layout projection, following the procedure described below.

First, the projector pose for layout projection in the BIM coordinate system (T_{proj}^{BIM}) is derived from the robot pose obtained from the re-localization step (Section 3.2.2) and the known extrinsic transformation of the projector relative to the robot platform (T_{proj}^{robot}):

$$T_{proj}^{BIM} = T_{robot}^{BIM} \cdot T_{proj}^{robot} \tag{1}$$

Next, the projection objects are transformed into surface-aligned projection geometry for layout image generation. Based on the established projection-base object associations (Section 3.1.1), the volumetric B-rep geometry of each projection object, is orthogonally projected onto its associated planar substrate surface and merged into a planar polygon. For a substrate surface of a base object defined by a normal vector n and a reference point p_0, each vertex v of the face of projection object is projected onto the surface by:

$$v' = v - [(v - p_0) \cdot n] \cdot n \tag{2}$$

The method to merge all the projected faces into a single polygon can be found in [18].

Lastly, the resulting surface-aligned layout geometry is rendered using a virtual camera, which projects the layout geometry onto the camera image plane to generate the desired layout image [19]. To ensure consistency with the onboard projector, the virtual camera is configured with the same intrinsic parameters and pose in the BIM coordinate system, i.e. T_{proj}^{BIM}. The projected layout is then rasterized with a predefined color to produce the final projection image, which is subsequently provided to the execution module (Section 3.2.3) for physical projection onto the target construction surfaces.

3.2 Robotic layout projection execution

Once the system enters the execution module, the robotic platform is deployed in the physical environment, where its initial pose with respect to the BIM model is generally unknown. Although the BIM model provides a global and semantically rich spatial reference, it does not directly offer real-time localization of the robot in the as-built environment. Therefore, an online perception and localization mechanism is required to anchor the robot within the BIM coordinate system.

3.2.1 Semantic plane-based BIM-SLAM alignment

To establish spatial consistency between the physical workspace and the BIM model, a partial SLAM strategy is adopted to focus on task-relevant regions. This reduces mapping overhead while maintaining sufficient accuracy for layout projection.

Planar features are extracted from both the BIM model and the local SLAM map. From the BIM model, structural surfaces (e.g., walls and slabs) are represented as polygonal planar surfaces with unit normal vectors. These surfaces are further augmented with semantic attributes (e.g., element type) obtained from the BIM model. In parallel, dominant planes are segmented from the local SLAM point cloud using RANSAC [20] and represented by their centroid and normal vector. To improve plane correspondence with the BIM model, vertical SLAM planes are classified as solid, door, or window categories using rule-based heuristics. Specifically, inlier points are projected onto a local 2D plane to detect void regions corresponding to structural openings, which are then evaluated based on their size and vertical position (e.g., whether the opening originates from the bottom region and exceeds predefined size thresholds). This enables direct semantic consistency with BIM-derived plane attributes during alignment. Based on the extracted geometric and semantic plane sets, a semantic plane-based BIM-SLAM alignment is performed to estimate a rigid transformation mapping the SLAM coordinate frame to the BIM coordinate frame:

$$T_{BIM}^{SLAM} = [R|t] \tag{3}$$

The alignment is performed in two steps. First, vertical alignment is estimated using horizontal plane correspondences (e.g., floor or ceiling) to determine the vertical offset. Then, in-plane translation and yaw rotation are estimated using a RANSAC-based matching procedure over vertical planes. Two planes are considered a match based on geometric and semantic consistency. Geometric consistency is evaluated using normal vector similarity and point-to-plane distance. The angle between two planes is computed based on their normal vectors:

$$\cos(\theta) = n_1 \cdot n_2 \tag{4}$$

where n_1 and n_2 are unit normal vectors. Two planes are considered consistent if $\cos(\theta) \geq 0.98$ and the point-to-plane distance is below a predefined threshold (e.g., 0.2 m). Semantic labels (e.g., wall, door, window) are used as an additional constraint.

The alignment quality is evaluated using a scoring function based on the number of matched planes. Each geometrically consistent plane pair contributes one point, and an additional point is added if the semantic labels are consistent. The total score is defined as:

$$S = N_{geom} + \lambda N_{sem} \tag{5}$$

where N_{geom} is the number of geometrically consistent plane pairs, N_{sem} is the number of pairs with matching semantic labels, and λ is a weighting factor. In this study, λ is set to 0.6 to balance geometric consistency and semantic agreement.

Once established, the BIM-SLAM transformation allows the robot to localize in the BIM coordinate system, which is used for navigation and layout projection.

3.2.2 BIM-based navigation and re-localization

Once the BIM-SLAM transformation T_{BIM}^{SLAM} is established, the robot can be directly localized within the BIM coordinate system. The robot's current pose estimated from partial SLAM is transformed into the BIM frame using the estimated alignment, enabling automatic initialization in BIM space without manual pose specification.

Navigation to projection viewpoints is carried out using the robot's native navigation stack (e.g., Nav2 [21]), which performs path planning, obstacle avoidance, and motion control based on the aligned map representation. Navigation goals are generated in the BIM coordinate system during the planning stage (Section 3.1.2) and transformed into the navigation frame using the same BIM-SLAM transformation before being dispatched to the navigation system.

To ensure accurate layout projection, a re-localization step is performed after the robot reaches each navigation goal. Once the robot arrives at the target position, it remains stationary for a short duration to eliminate motion effects. A static point cloud is then collected using the onboard LiDAR and point cloud registration is performed to align it with the BIM model and refine the robot pose. Since the robot is static, the re-localization process becomes more stable and accurate.

The updated pose is treated as the final projection-ready camera pose, which helps reduce accumulated navigation and odometry errors. It is then used for layout image generation (Section 3.1.3).

3.2.3 Layout image projection

After the robot reaches the navigation goal and complete re-localization, the system proceeds with physical layout projection. At this stage, the layout image has already been generated in the planning module (Section 3.1.3) based on the corresponding projection-base pair and the projector pose after re-localization. The pre-generated layout image is transmitted to the onboard projector and projected onto the target construction surface.

4 Simulation-based validation and preliminary results

4.1 Experimental setup

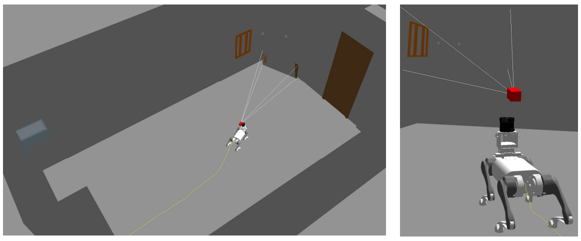
The feasibility of the proposed framework was validated through simulation. An indoor environment was modeled in Gazebo based on a BIM model of a research laboratory, with a layout task involving two electrical sockets and a vertical grille on two perpendicular walls (Figure 2(a)).

As shown in Figure 2(b), the system is implemented on a simulated quadruped robot (Unitree Go1) equipped with a trunk-mounted 3D LiDAR sensor (Ouster OS1-32) for localization and mapping. Since projector modeling is not supported in Gazebo, a forward-facing RGB-D camera (Intel RealSense D435i) is used as a proxy to simulate projection and verify alignment accuracy.

The framework is implemented in a modular manner, with both the planning and execution modules developed in Python within a ROS 2-based robotic system. In the experiment, the grid resolution for candidate robot position sampling is set to 0.5 m × 0.5 m.

The simulation procedure is as follows. The robot is first placed at a random location and performs partial SLAM to align with the BIM model and localize in BIM space. Navigation goals are automatically generated, and the robot navigates to these goals using Nav2 [22]. After arrival, a re-localization step is performed by collecting a static point cloud and aligning it with the BIM model. The LiDAR pose in the BIM coordinate system is obtained, and the camera pose is derived using a fixed transformation. Layout images are then generated and compared with the camera images to evaluate geometric consistency.

The experiments evaluate the framework in terms of BIM–site alignment accuracy and layout projection accuracy. Accurate localization is required for navigation and projection, while projection accuracy is essential for reliable layout execution.



a) Simulated construction scene b) Robotic system

Figure 2. Experimental setup in the Gazebo simulation environment (The red cuboid represents a virtual camera used as a proxy for the projector).

4.2 Evaluation of BIM-site alignment accuracy

To enable navigation and layout projection in BIM space, accurate alignment between the SLAM map and the BIM model is required. This experiment evaluates whether the proposed plane-based BIM–SLAM alignment provides sufficient accuracy for localization.

The robot autonomously traversed the task-relevant workspace to collect point-cloud data using its onboard LiDAR sensor. A graph-based SLAM pipeline (RTAB-Map [22]) was employed to construct the local map and estimate the robot pose. Dominant planar features were extracted from both the SLAM map and the BIM model and matched to estimate a rigid BIM-SLAM transformation.

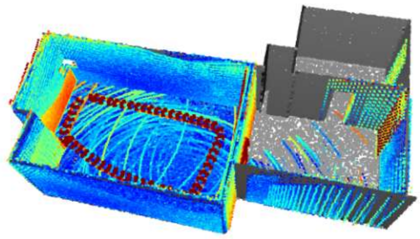


Figure 3. Qualitative result of BIM-SLAM alignment. The SLAM-generated point cloud is overlaid with extracted BIM planar surfaces (grey).

Figure 3 presents a qualitative visualization of the alignment result, where the SLAM-generated point cloud is overlaid with BIM-derived planar surfaces. As shown in the figure, major structural elements, including walls and the floor, exhibit consistent spatial correspondence in both position and orientation.

Quantitative results are summarized in Table 1. A total of 19 planar surfaces were detected from the SLAM map, among which 17 planes were successfully matched with BIM-defined planes, resulting in a matching ratio of 89.45%. For the matched plane pairs, the mean plane-to-plane distance error is 12.51 cm with an RMSE of 21.50 cm, while the mean normal vector angular error remains low at 2.09° with an RMSE of 5.18°. Most plane pairs exhibit distance errors below 10 cm and angular deviations below 5°, demonstrating consistent geometric alignment in both position and orientation.

This level of alignment accuracy is acceptable, as the BIM-SLAM alignment is mainly used for robot localization and navigation. To improve accuracy for projection, a re-localization step based on static point cloud is performed after the robot reaches the navigation goal. Experimental results in Table 1 show that the alignment error is reduced to approximately 0.48 cm after re-localization, representing a substantial improvement compared to the initial BIM-SLAM alignment.

Table 1. Quantitative evaluation of BIM-SLAM alignment and re-localization accuracy.

Metric Category	Metric	BIM-SLAM	Re-localization
Number of matched planes	Total	19	6
	Matched	17	6
	Ratio	89.45%	100%
Plane-to-Plane distance	Mean	12.51 cm	0.48 cm
	RMSE	21.50 cm	0.71 cm
	Maximum	47.65 cm	1.49 cm
Normal deviation	Mean	2.09 deg	0.30 deg
	RMSE	5.18 deg	0.34 deg
	Maximum	9.46 deg	0.51 deg

4.3 Evaluation of projection accuracy

Projection accuracy is evaluated using Intersection over Union (IoU), which measures the overlap between the projected region A_p of an object and its ground truth counterpart A_g . This metric reflects the area-level geometric consistency of the projected layout, making it suitable for evaluating projection accuracy on construction surfaces. The IoU is computed as:

$$IoU = \frac{|A_g \cap A_p|}{|A_g \cup A_p|}$$

Figure 4 shows the IoU-based regional overlap between the projected layouts and the ground-truth regions in the camera image. Among the three projection objects, objects 1 and 2 are located on the same planar surface, while object 3 is projected on a different surface.

The IoU results reveal clear differences in projection accuracy across objects located on different planar surfaces. Object 1 achieves a high IoU of 98.98%, while Object 2 exhibits a moderate IoU of 66.23%, indicating relatively better spatial alignment between the projected layouts and the ground-truth regions. In contrast, Object 3 shows a lower IoU of 53.41%, reflecting a more obvious overlap discrepancy.

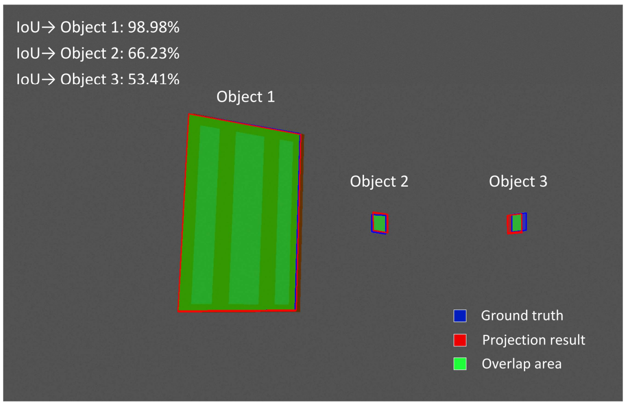


Figure 4. Quantitative evaluation of projection accuracy

The IoU variation mainly originates from LiDAR-based re-localization errors. Since the robot estimates its pose by aligning the LiDAR point cloud with the BIM model, uncertainties in the point cloud, such as sensor noise and point-cloud resolution, can propagate to the final projection results. Therefore, the projection deviation is mainly caused by localization and alignment uncertainty.

The different IoU values across objects can then be explained by two factors. First, the alignment error varies across different planes. The re-localization error is larger for the right wall (0.65cm), which contains Object 3, than for the left wall (0.02cm)., so objects located on planes with larger alignment errors show larger projection deviations. Second, projection distance and angle further amplify the effect of the same pose error. Objects farther from the projector or projected under more oblique angles are more sensitive to localization errors, which leads to lower overlap on the target surface. For future real-world deployment, using higher-accuracy LiDAR, such as Trimble X9, could help provide more accurate reference point clouds, thereby reducing the root errors and improving overall projection accuracy.

5 Conclusion

This research proposes a BIM-driven robotic framework for autonomous 3D construction layout projection in indoor environments. The framework integrates a BIM-based layout planning module with an autonomous layout projection execution module enabled by a mobile robotic platform. The main contributions are twofold. At the system level, the framework establishes a BIM-driven robotic system for fully autonomous 3D construction layout projection, overcoming the limitations of conventional floor-based and partially automated methods. At the technical level, it introduces several enabling methods for autonomous operation, including BIM-driven layout extraction, projection-oriented navigation planning for feasible robotic positioning, and semantic-enhanced BIM-SLAM alignment for robust autonomous navigation.

The framework was validated in a Gazebo-based simulation. A wall-mounted layout projection task involving two electrical sockets and one vertical grille was conducted across two wall surfaces. The results show that the framework supports automated robot-enabled layout projection based on BIM-derived information. With the incorporation of a re-localization step before projection, alignment accuracy is improved, leading to more consistent projection results across different objects and wall surfaces.

Despite these promising results, several limitations remain. First, the current framework assumes full correspondence between the BIM model and the as-built environment and does not account for differences that commonly arise in practice. Second, the framework was validated only in a simplified simulation environment, which does not fully capture the complexity of real construction sites, such as cluttered materials and dynamic obstacles. In addition, the experiment shows that projection accuracy decreases for distant targets and highly inclined projection angles. Future work will focus on improving projection position planning strategies to improve overall accuracy. Future studies will also focus on increasing the realism of the simulation environment to mimic real construction sites, followed by deployment on a real robotic platform to evaluate the proposed framework under practical on-site conditions.

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