

OPTIMIZING CONSTRUCTION SITE SURVEYS: BIM-BASED POSITION PLANNING FOR ROBOTIC INDOOR SCANNING

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Abstract

The traditional method of positioning scans to document existing building geometry relies on expert surveyor experience. This research emphasizes the need for optimal scan positioning in automated scanning using autonomous robots. The study introduces a framework for planning scans in a stop-and-go mapping process with a quadruped walking robot, leveraging Building Information Modeling (BIM). The framework consists of four phases: generating scan-position options, determining optimal positions, organizing the positions, and collecting data using an autonomous scanning system. Experimental results demonstrate that this approach outperforms conventional methods. It significantly reduces the number of scan positions and operation time in real indoor environments, compared to manual scanning by skilled surveyors. Future work will focus on automating the registration process and improving computational efficiency.

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1. Introduction

In recent years, laser-scanning technology has significantly advanced, enabling precise 3D data acquisition over long distances with millimetre accuracy [1, 2]. This progress has led to the widespread adoption of terrestrial laser scanning (TLS) in various fields, such as construction assessment, historic preservation, facility management (FM), and as-built 3D modelling [3, 4, 5, 6, 7]. In the context of FM, TLS-generated point clouds facilitate the representation of existing 3D environments and help identify defects and discrepancies in comparison to new designs [8, 9]. However, conducting large-area TLS surveys is time-consuming and labour-intensive due to manual interventions required by surveyors, such as positioning the scanner and scanning the target site.

To address the challenges associated with large-area TLS, researchers have proposed automated systems like the stop-and-go system, utilizing mobile robots to collect precise 3D geometric data [10, 11, 12]. These robots navigate autonomously to specific positions, conduct static laser scanning, and generate 3D point clouds, minimizing scanning time and human involvement. A crucial aspect of these stop-and-go systems is determining optimal scan positions that maximize coverage and minimize time consumption.

Currently, determining scan positions in the field relies on the expertise of laser scanning professionals and lacks certainty that these positions meet quality constraints, such as the number of scans and the distance between positions. Additionally, the scan coverage may not be maximized using these manual methods [13]. Researchers have explored computer vision techniques to address this challenge, known as the next-best-view (NBV) problem. NBV solutions fall into non-model-based methods, which lack prior scene knowledge, and model-based methods, which utilize an initial scene model [14]. While non-model based NBV solutions have been proposed [15, 16], they have limitations in completely scanning

large target spaces [17]. Therefore, robust optimal scan positioning requires prior knowledge of the building, exemplified by a BIM.

This paper aims to determine the optimal scan plan for a quadruped walking robot, leveraging BIM as prior knowledge. Furthermore, the proposed framework is validated by conducting real-world experiments in indoor environments.

2. Related Studies

Various studies have explored methods to determine optimal scan positions for laser scanning, with an emphasis on model-based approaches utilizing prior knowledge of the scanned scene [12, 13, 16, 17]. While some studies utilized UGVs with wheels [8, 10, 11], quadruped walking robots like Boston Dynamics Spot [18] and Unitree Go1 [19] (Fig. 1) were introduced as promising platforms for scanning and mapping indoor environments, owing to their unique mobility capabilities and stability in challenging terrains [20].



Fig. 1. SPOT [18] (left) & Unitree Go1 [19] (right).

Blaer and Allen [10] optimized the scan plan for a stop-and-go system using unmanned ground vehicles (UGVs) and TLS based on this approach. Other researchers like Soudarissanane and Lindenbergh [21] utilized a similar process, although their scan-position candidates were generated from all possible points on a 2D grid map, leading to computational inefficiency. Elzaiady and Elnagar [22] performed 2D line-of-sight analysis using obstacle polygons extracted from a 2D occupancy grid map. Jia and Lichti [23] proposed a more efficient method employing a hierarchical strategy-based weight greedy algorithm to minimize candidate numbers. However, these methods were limited by their 2D-based approach, lacking consideration for the actual 3D environment.

Recent research has explored utilizing 3D point clouds as prior knowledge. Mozaffar and Varshosaz [24] employed 3D voxel models from an initial scan, determining visibility through line-of-sight analysis. Prieto et al. [11] adopted a similar approach for the stop-and-go system with UGV and TLS. Wakisaka et al. [13] estimated the point cloud using structure from motion (SFM) for visibility analysis, while an unmanned aerial vehicle (UAV) [8] was used for 3D voxel mapping in another study. However, these 3D point-cloud-model-based approaches assumed prior knowledge of the as-is state, overlooking the as-designed state, which is crucial for facility maintenance due to the unavailability of point cloud data [25].

BIM has also been proposed as a valuable resource for optimal scan planning. Biswasa et al. [26] utilized BIM for simple concrete structures, but computational time was a challenge. Zhang et al. [27] developed a scan planning method for large construction environments based on manually extracted points of interest from BIM, but accuracy depended on skilled engineers. Frías et al. [12] proposed a comprehensive framework for optimal scan planning, discretizing the construction site's BIM into a 2D grid and employing grid-based and triangulation-based distribution for generating scan-position candidates. A 2D ray-tracing algorithm determined optimal scan positions, and an optimal path was determined using the ant colony optimization algorithm. Tan et al. [28] integrated UAV and BIM for scan planning, employing a genetic algorithm for coverage path planning, suitable for outdoor environments.

2.1. Challenges in the Existing Work

Previous research faced significant limitations: first, experiments in indoor spaces predominantly utilized simplistic Manhattan world settings, such as rectangular rooms, which lack the complexity necessary

for practical applications [11, 12, 13]. Second, most visibility analyses were conducted on 2D grids or 3D voxels, failing to accurately represent real-world geometry, and all potential scanning locations were considered without regard for precise obstacles [8, 12, 13, 28]. Third, while some researchers addressed scan ordering optimization, their approach focused solely on the shortest straight-line paths between scan positions, ignoring obstacles, rendering it impractical [10, 22]. Lastly, only a few studies employed autonomous robot platforms take advantage of BIM as a valuable resource that has become an industry standard, with a quadruped walking robot for field applications, and there was a lack of validation for acquired scanning data from these robot platforms [10, 11, 29].

3. Methodology

The methodology employed in this study involves a systematic process of detecting corners or vertices in the costmap, identifying vertices that scan the maximum number of edges in the polygon, and iteratively finding additional vertices to cover the remaining unscanned edges until the entire polygon is scanned comprehensively. The following steps comprise the methodology.

3.1. Corner Detection

The first step involves processing the costmap image to identify the corners or vertices of the polygon. The following procedures are undertaken:

- The costmap image is loaded and converted into grayscale to simplify the processing.
- A thresholding technique is applied to create a binary occupancy grid map, highlighting the occupied and unoccupied regions.
- The OpenCV function *cv2.goodFeaturesToTrack* is utilized to detect corners in the binary occupancy grid map. This function identifies key feature points that represent corners within the map.
- Detected corners are filtered to eliminate nearby duplicates. Euclidean distances between corner points are calculated, and duplicates are removed, ensuring an accurate representation of distinct corners.

3.1.1. Finding a Vertex (V_i) Scanning Maximum Edges of the Polygon

In this step, scan locations (V_i) are identified based on a convolution operation and careful analysis of corners. The process is as follows:

- A convolution operation is performed on a binary occupancy grid map using a 10×10 kernel. This operation helps in identifying regions with high edge density, indicating potential locations for efficient scanning.
- The function *find_scan_locations* iterates through the detected corners and identifies scan locations (V_i) that are not visible from any existing scan location. These locations correspond to vertices that scan the maximum number of edges of the polygon.

3.1.2. Searching for Unscanned Edges by Previous Vertex (V_i)

In this step, the focus is on ensuring that all corners are visible from scan locations (V_i) and identifying edges that remain unscanned. The following procedures are implemented:

- Utilizing the occupancy grid map and previously detected scan locations, a function named *is_visible* checks if a corner is visible from a given scan location. This visibility check is performed using Bresenham's line algorithm, ensuring accurate determination of visibility between corners and scan locations.
- The function identifies edges that remain unscanned by the previous vertex (V_i), ensuring that the scanning process is comprehensive.

3.1.3. Finding Another Vertex (V_j) Scanning Max. Unscanned Edges

In this step, new scan locations (V_j) are identified to cover the remaining unscanned edges effectively. The following procedures are followed:

- Another function iterates through the remaining unscanned edges, identifying new scan locations (V_j) that maximize the scanning coverage.
- The visibility check using the *is_visible* function ensures that the new scan locations effectively cover previously unscanned edges.

3.1.4. Continuing the Process Until All Edges Are Scanned

Steps 3.1.2 and 3.1.3 are repeated iteratively until all edges of the polygon are scanned. The iterative process ensures that each new scan location selected is strategically positioned to maximize the coverage of unscanned edges, thereby forming an optimal set for efficiently scanning the entire polygon represented by the occupancy grid map.

3.2. Challenges in the Current Approach

In the process of optimizing scan locations for the autonomous scanning platform, several challenges have been identified, particularly in the context of room image capture. These challenges significantly impact the quality and uniformity of the captured data and pose constraints on the robot's ability to effectively scan room corners. The challenges are as follows:

- **Robot Dimensions:** One of the primary challenges faced pertains to the physical dimensions of the robot, restricting its ability to access and reach room corners effectively. This limitation poses a significant obstacle as the robot's placement away from the corners hinders its ability to capture detailed information from these critical areas. Consequently, the captured data lacks comprehensive coverage of room corners, leading to incomplete and potentially inaccurate representations of the room layout.
- **Data-Capture Quality and Uniformity:** Another critical challenge arises from the placement of the robot in the corner of the room, impacting the quality and uniformity of the captured data. Specifically, the data captured from the walls near the corner appears overly zoomed-in, lacking context and detail.

3.3. Revised Approach

To calculate the optimal scan positions, we used centroid computation and point selection criteria. The objective is to strategically determine scan positions within a room, ensuring comprehensive coverage while maintaining an even distribution across the environment.

Taking the centroid as the reference point for determining optimal scan positions offers several advantages in terms of achieving comprehensive coverage and even distribution across the environment.

- **Geometric Balance:** The centroid represents the geometric center of the polygonal environment. By placing scan positions around this central point, it ensures a balanced distribution of coverage throughout the space. This geometric balance helps in minimizing redundancy and maximizing efficiency in scanning.
- **Maximized Coverage:** Scan positions placed around the centroid facilitate maximum coverage of the environment. Since the centroid is equidistant from all corners of the polygon, scan positions strategically located around it can effectively capture details from all directions, ensuring no area is left unscanned.
- **Distance Optimization:** By utilizing the centroid as a reference point, the distance between scan positions can be optimized. This optimization ensures that scan points are neither too close nor

too far apart, striking a balance between coverage and resource utilization. It helps in avoiding overlapping scans while ensuring that no area is left unexplored due to large gaps between scan positions.

- **Simplicity and Robustness:** Calculating the centroid is a straightforward geometric operation that provides a single reference point for scan position determination. This simplicity enhances the robustness of the scanning methodology, making it less prone to errors or inaccuracies associated with more complex algorithms.
- **Adaptability to Polygon Shape:** Regardless of the shape of the polygonal environment (here, the room), the centroid serves as a consistent reference point. This adaptability ensures that the scanning approach remains effective across various room geometries without the need for significant modifications or adjustments.

Incorporating centroid computation into the methodology for determining optimal scan positions thus enhances the efficiency and effectiveness of the autonomous scanning platform. It not only ensures comprehensive coverage of the environment but also contributes to the generation of detailed and reliable maps by strategically placing scan points for thorough data collection.

3.3.1. Centroid Computation

The first step in our methodology involves the calculation of the centroid using the optimal corner points identified through the initial approach.

3.3.2. Point Selection Criteria

To strategically choose new scan positions, a set of specific criteria are applied to ensure an even distribution of points while maintaining a certain distance between them.

By integrating centroid computation and stringent point selection criteria, our methodology facilitates the calculation of optimal scan positions, which are strategically placed within the room, ensuring both comprehensive coverage and an even distribution across the environment. This approach enhances the efficiency and accuracy of the autonomous scanning platform, enabling it to generate detailed and reliable maps of the scanned space.

4. Results

4.1. BIM Data

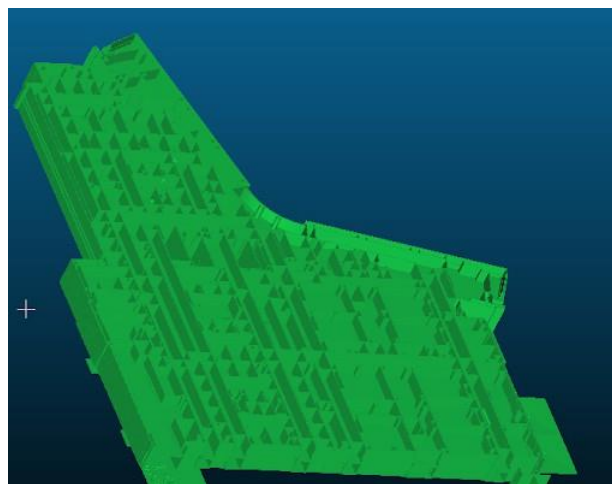


Fig. 2. Sample BIM model of a floor at office space.

In our study, we selected a specific floor within an office space as our experimental site due to its considerable size, necessitating multiple scan positions for thorough coverage. Office spaces typically include elongated corridors with architectural elements such as windows, doors, and stairs. Notably, the

chosen office space also features a semi-circular corridor, adding complexity to the environment (Fig. 2).



Fig. 3. (a) corresponding occupancy map(top-view) calculated using ROS [30]; (b) detected corners using OpenCV function.

The office space data provided for our research was in the .obj format, a widely used commercial BIM format characterized by a standard triangular mesh structure. To facilitate our analysis, we automatically extracted the BIM geometry from the .obj file. Using the Robot Operating System (ROS) [30], this geometry was then converted into the .png file format (Fig. 3(a)), enabling further processing.

4.2. Optimal scan planning result

The proposed optimal scan planning framework determines optimal scan positions, or waypoints, for an autonomous scanning system through a line-of-sight simulation that evaluates candidate scan positions.



Fig. 4. (a) optimal scan corners; (b) optimal scan locations using revised approach.

In the conducted analysis, Fig. 3(b) presents the output obtained from the OpenCV function, displaying all the corners detected within the given dataset. Notably, the green points in Fig. 4(a) represent optimal corner positions. These specific corners play a critical role in detecting other corners within the environment. However, it is important to acknowledge the practical limitations that hinder data capture from these specific corner points. Despite their significance, capturing data from these optimal corner positions is challenging due to these limitations. The study highlights the importance of these corners for further corner detection, emphasizing the challenges researchers face in practical data capture from these crucial points.

Furthermore, the optimal scan positions were identified and denoted by cyan points in Fig. 4(b). These positions were calculated using the centroids of the optimal corner points determined in Fig. 4(a). These

scan positions were strategically located away from walls, ensuring a strategic placement within the indoor space.

A critical aspect of this approach was the careful selection of new scan positions. To achieve this, a specific distance threshold was established, ensuring that the new scan positions remained within a certain distance from each other. This distance criterion played a crucial role in evenly spreading the scan positions across the room. By preventing the positions from being too close to one another, this method aimed to guarantee comprehensive coverage of the environment.

The systematic spacing of scan positions not only facilitated effective data capture but also enhanced the subsequent analysis process. By strategically placing the scan positions and adhering to the distance threshold, the approach significantly contributed to ensuring the thorough and accurate capture of data, enabling robust analysis and interpretation of the indoor environment.

The key advantage of employing the optimal scan planning process with BIM lies in its ability to offer a reliable job site scan through automated planning, eliminating the reliance on human intuition and experience. Manual scanning methods necessitate more time due to leveling and relocating the TLS. Additionally, manual results may lack certainty in scan coverage due to the surveyor's skills and experience. In contrast, our proposed framework maintains scan completeness while reducing operation time, thanks to optimal scan positioning and robot mobility.

Furthermore, this study highlighted the advantages of using a quadruped walking robot in automated scanning frameworks. While it is widely acknowledged that mobile robot-based data acquisition is more efficient in terms of time and cost compared to traditional TLS-based methods, the limitation lies in the applicability of general wheeled or caterpillar robots, which require flat, obstacle-free indoor environments. In contrast, a quadruped walking robot is suitable for repetitive scanning tasks in challenging spaces where ordinary robots cannot operate, enabling the implementation of a fully automated scanning system.

5. Conclusions

In this research paper, we present a novel approach to optimizing scan planning in 3D indoor spaces using a BIM-based autonomous scan planning framework with a quadruped walking robot. Traditional scan operations, reliant on a surveyor's intuitive decision-making, often suffer from inefficiencies. Our proposed framework addresses this challenge through a systematic four-phase approach.

Firstly, in the scan-position candidate generation phase, a set of potential scan positions is generated from a binary navigable map. Then, utilizing the ray-tracing algorithm, optimal scan positions are selected based on the visibility of these candidates. Finally, automated data collection is achieved through the stop-and-go scanning process with the autonomous scanning system.

Our contributions are multifaceted. Firstly, our framework's scan positions exhibit superior coverage performance in indoor spaces which is achieved by strategically positioning scan points away from walls and ensuring even distribution across the room. Secondly, our approach proves to be significantly more efficient than manual methods involving skilled surveyors, as it reduces manual scan operation time while conserving the coverage of the acquired point cloud.

Moreover, our research includes the validation of the proposed framework using an autonomous scanning system with a quadruped walking robot. The results from real-world job site scans corroborate the effectiveness of our optimal scan planning methodology. Notably, our work represents the pioneering effort in addressing optimal scan planning using BIM and a quadruped walking robot. This innovative approach is poised to contribute significantly to the development of robot-based fully automated scanning systems, marking a crucial step forward in the realm of autonomous data acquisition in complex indoor environments.

6. Future Work

In the upcoming stages of our research, several key areas will be explored to further enhance the capabilities of our autonomous building scanning system:



Fig. 5. future work: A1 and A2 denote scan points to be excluded.

- **Refinement of Exterior Points Exclusion:** The research will delve into advanced techniques for the precise identification and exclusion of data points located outside the building premises, as highlighted in A1 of Fig. 5. This meticulous filtration process is essential to ensure the accuracy and reliability of our analysis.
- **Enhanced Obstacle Detection Algorithms:** Building upon our obstacle-enclosed scan locations approach, we will develop and refine sophisticated algorithms to detect and exclude scan points surrounded by obstacles, as highlighted in A2 of Fig. 5. These algorithms will be designed to facilitate seamless navigation and enhance data accuracy, even in complex and cluttered environments.

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