Let the Robot Decide: Adaptive Scan Planning in cluttered and Unknown Terrains

Pileun Kim, Seongyong Kim, and Yong K. Cho

***Abstract*— Autonomous 3D scanning in cluttered and unknown environments is essential for applications like construction monitoring and disaster response. This study presents a robotic framework that automates scan view planning and navigation for efficient point cloud data acquisition. By integrating SLAM, frontier-based exploration, and a scan view evaluation module, the system identifies optimal scanning locations while navigating unstructured terrain. The framework was implemented on a mobile robot equipped with LiDAR and RGB sensors and tested in a simulated disaster site. Experimental results demonstrated high-resolution mapping with minimal data loss, low registration error (RMSE: 2.66 cm), and robust navigation through complex terrain. This research significantly reduces human intervention and redundant scanning, enabling cost-effective, high-fidelity 3D modeling in dynamic, real-world scenarios.**

I. Introduction

Accurate 3D mapping is a critical capability for robots operating in dynamic and unstructured environments, such as construction sites, disaster zones, or post-industrial facilities. These settings are often cluttered, hazardous, and difficult for human surveyors to access, requiring robots to autonomously sense, plan, and navigate through unknown spaces. High-resolution 3D models generated from LiDAR data are essential for enabling progress monitoring, structural assessment, rescue operations, and digital twin creation [1].

Traditional methods of acquiring such 3D models often rely on static terrestrial LiDAR scanning (TLS), which requires human operators to manually select scan locations and ensure adequate coverage. This approach is labor-intensive and prone to occlusion errors due to the scanner's limited field of view. More critically, it is unsuitable for time-sensitive or dangerous environments where human presence is not feasible. Autonomous robotic systems offer a promising alternative, but most existing solutions depend on pre-mapped environments or manual waypoint selection, limiting their adaptability in unknown or dynamic terrains.

This paper presents a fully autonomous scan planning and navigation framework for mobile robots equipped with 3D LiDAR (Fig. 1). The proposed system addresses the challenge of occlusion by dynamically evaluating scan quality, terrain conditions, and spatial coverage to identify optimal scan paths. The core contributions include a visibility-aware scan evaluation method, a cost function that balances spatial and directional criteria, and seamless integration with a SLAM-based localization and frontier exploration strategy. The robot incrementally builds high-resolution point clouds while navigating unknown environments in real time.

II. Related Work

A. Mobile Scanning Platform

Autonomous mobile scanning systems have evolved significantly over the past two decades. Early efforts, such as Ariadne [2] and the 3D rangefinder platform by [3], focused on structured indoor spaces with limited autonomy and resolution. These systems often required prior maps or fixed scanning trajectories. Later platforms like PR2 [4], Irma3D [5], and MoPAD [6] introduced multi-modal sensors—including RGB-D cameras, 3D LiDAR, and thermal imaging—to enrich environmental modeling and automate object recognition. The MoPAD system, for instance, emphasized multi-perspective fusion to reconstruct occluded interiors in cluttered rooms.

More recently, robotic systems have tackled outdoor and industrial applications. [7] introduced a cooperative multi-robot system for indoor-outdoor scanning using a parent-child framework. The quadruped-based system from [8] demonstrated autonomous scaffold mapping on construction sites, offering robust mobility and dense point cloud acquisition without prior maps. UAV-based platforms have also contributed to the field; [9] and [10] proposed real-time exploration strategies using stereo cameras and depth sensors, focusing on obstacle-rich or large-scale environments. Despite these advances, many approaches still rely on partial prior knowledge or require operator intervention during mission setup, limiting their generalizability.

Figure 1. Top-down view showing optimized scan location and robot trajectory during field experiments at a simulated disaster site. Trajectory color indicates scan quality based on visibility fitness: red= good, green= acceptable, black= poor

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B. Next-Best-View (NBV) Planning

The Next-Best-View (NBV) problem is central to active 3D perception, aiming to select the most informative next viewpoint to improve scene coverage while minimizing redundancy. Classical NBV approaches, such as frontier-based exploration [11], identify the boundary between known and unknown space using 2D occupancy grids. While computationally efficient, these methods often struggle in cluttered 3D environments where occlusions and complex geometries obscure critical features.

More advanced NBV strategies incorporate volumetric representations—e.g., voxel maps [12], octrees [13], or probabilistic fields [14]—to quantify information gain and occlusion likelihood. Hybrid 2D–3D planners, like those proposed by [5], transition between coarse global plans and fine-grained local adjustments based on visibility constraints. Aerial platforms often apply sampling-based receding horizon methods [9] or semantic-aware NBV planning [15] for structural inspection tasks.

However, many of these methods are computationally expensive and assume structured environments or uniform terrain. The approach proposed in this paper avoids such limitations by using a lightweight, geometry-driven visibility scoring metric based on real-time LiDAR data. It integrates seamlessly with SLAM and frontier exploration to offer adaptive viewpoint selection that is robust to environmental complexity and sensor limitations.

This paper contributes a lightweight, geometry-driven NBV approach tailored for ground robots in cluttered environments.

III. METHODOLOGY

The proposed framework consists of five core modules: (1) SLAM-based localization, (2) frontier-based navigation, (3) scan view evaluation, (4) stationary scanning, and (5) point cloud registration. These modules are integrated into a unified system enabling a mobile robot to autonomously explore and map cluttered, unstructured environments.

A. System Overview

The process begins with the robot receiving a user-defined boundary of the target scan region. The robot uses the LeGO-LOAM SLAM algorithm to perform localization and construct an evolving map of its surroundings. Fig. 2 presents the complete system architecture, from environmental perception to 3D scan registration.

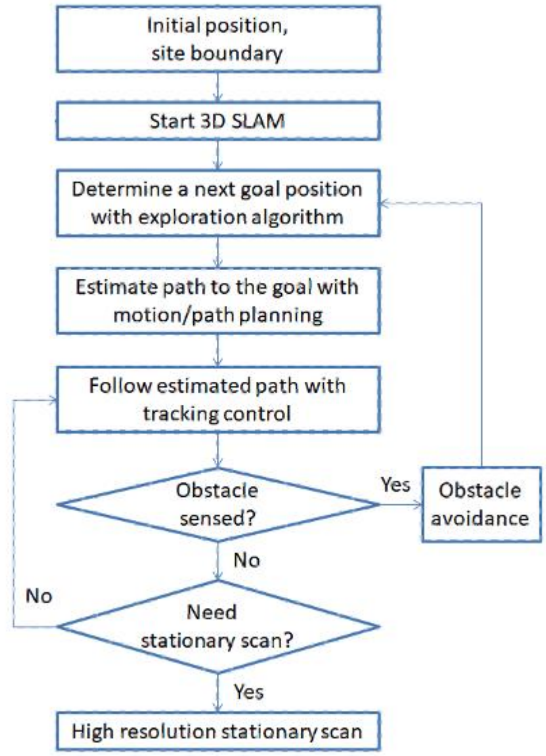


Figure 2. Flowchart of the proposed architecture

B. Scan View Evaluation

During navigation, the robot evaluates candidate scan positions in real time using a fitness score based on visibility. The robot dynamically computes heading angles and distances to prioritize scan targets with optimal visibility and spatial distribution, enhancing coverage and navigation efficiency.

Each potential scan point (x, y) along the robot's trajectory is evaluated using a visibility-based fitness score R(x, y), which reflects the quality of the viewpoint based on occlusion and line-of-sight. The score is computed by summing the radial distances measured by the 3D LiDAR at that location across a range of beam angles:

$$R(x,y) \approx \sum_{\theta=\theta_{min}}^{\theta_{max}} \sum_{\emptyset=\emptyset_{min}}^{\emptyset_{max}} d(x,y,\theta,\emptyset)$$

Higher scores indicate less occlusion and better spatial visibility. As shown in Fig. 3, these scores are visualized on a color map, where trajectory segments are classified as "good," "acceptable," or "bad" scan locations based on their fitness values.

C. Goal Selection and Cost Function

To avoid repetitive or suboptimal scanning, the system incorporates a cost function that combines spatial and directional criteria to balance efficient navigation with high data quality. These criteria include:

- Distance from current robot position
- Deviation in heading from prior scans
- Penalty for proximity to previous scans
- Inverse of scan visibility score

D. Autonomous Navigation

The optimal scan goal is transmitted to the ROS *move_base* stack, which handles global/local path planning and real-time obstacle avoidance. As the robot travels, it updates its map and reevaluates scan fitness. Once it reaches

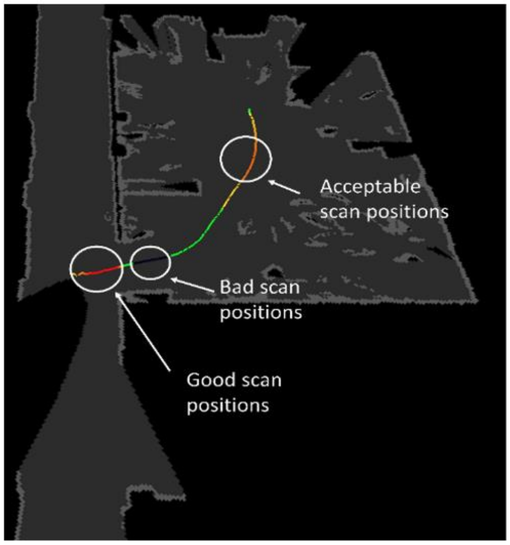


Figure 3. Evaluation of fitness score for scan positions along the robot trajectory

the scan position, the robot performs a high-resolution stationary scan and proceeds to the next goal.

IV. EXPERIMENTAL VALIDATION

To validate the proposed framework, a series of field experiments were conducted at a full-scale outdoor disaster training site, approximately 90 m × 90 m in size. The testbed was designed to simulate post-disaster environments, featuring collapsed concrete structures, scattered debris, irregular terrain, and enclosed spaces. These conditions presented realistic challenges for autonomous navigation and 3D data acquisition.

A custom-built mobile robot, the Ground Robot for Mapping Infrastructure (GRoMI), was used as the experimental platform (Fig. 4). It was equipped with a rotating 3D LiDAR for environmental sensing, multiple 2D LiDARs for obstacle detection, and a panoramic RGB camera for visual mapping. The onboard computation system executed the full autonomous scanning framework, including SLAM, scan view evaluation, path planning, and point cloud registration. No prior maps or manual interventions were used throughout the mission.

A. Experiment Setup and Workflow

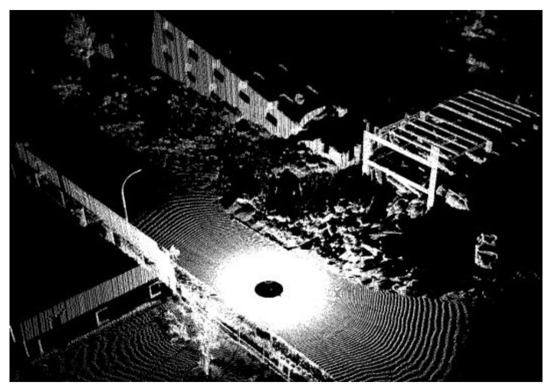
The scanning mission began with dynamic exploration, during which the robot performed SLAM-based localization while collecting point cloud data on-the-fly. This initial phase allowed the robot to identify obstacles, update its map, and evaluate the visibility and fitness of potential scan viewpoints. The robot then proceeded through the site, adaptively selecting high-visibility scan regions based on the proposed cost function and visibility scoring method.

B. Comparison with Conventional Stationary Scanning

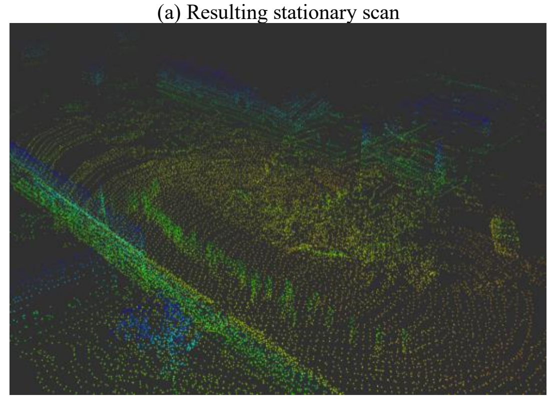
To highlight the benefit of optimized stationary scanning, a comparison was conducted between point clouds collected during dynamic motion and those acquired at stationary scan locations. In the dynamic mode, the robot performed continuous scanning while navigating, producing coarse point clouds used primarily for localization and navigation support. In contrast, stationary scans were taken at viewpoints selected based on visibility evaluation to maximize scene coverage and reduce occlusions.

As shown in Fig. 5(a) and 5(b), dynamic scans exhibited sparser and noisier geometry, with reduced resolution and increased occlusion artifacts. Meanwhile, stationary scans provided higher point density, clearer object boundaries, and more complete surface reconstruction. These results confirm that while dynamic scanning supports autonomous exploration, high-fidelity 3D reconstruction is best achieved through stationary scans taken at optimally selected positions.

Figure 4. Field deployment of the GRoMI



(a) Resulting stationary scan



(b) Resulting dynamic scan

Figure 5. Data quality comparison in the same region

C. Accuracy of Registration.

The accuracy of multi-view registration was evaluated using Root Mean Square Error (RMSE) between overlapping point clouds and angular deviation of alignment. Pose estimates provided by the SLAM module were used to register each scan frame. Across all registered scans, the framework achieved an average RMSE of 2.66 cm and angular deviation below 0.08°**,** confirming that the system maintained accurate localization and alignment throughout the mission, even in unstructured terrain.

D. Autonomy and Coverage.

The robot successfully explored and scanned the entire target region using frontier-based navigation and adaptive scan view planning. The framework dynamically adjusted to terrain conditions, avoided inaccessible areas, and selected scan locations without human oversight. Compared to stationary methods, the dynamic strategy reduced scanning time, eliminated redundant data acquisition, and maintained high spatial coverage without sacrificing quality.

These field results confirm that the proposed framework can autonomously acquire high-fidelity 3D point clouds in unknown, cluttered, and hazardous environments. The dynamic scanning method, combined with visibility-aware planning and robust localization, offers a scalable solution for real-world construction monitoring, post-disaster assessment, and autonomous mapping applications.

V. Discussion

The proposed scan planning framework demonstrates strong performance in unstructured environments by combining visibility-aware viewpoint selection with SLAM-based localization and frontier exploration. The use of a real-time fitness score based on 3D LiDAR data enables the robot to prioritize scan locations that maximize visibility and reduce redundancy, improving both coverage and efficiency.

Experimental comparisons highlight that while dynamic scans support fast navigation and coarse mapping, they produce sparse and noisier data. In contrast, stationary scans at optimized locations yield denser, higher-quality point clouds suitable for detailed reconstruction. This trade-off confirms the importance of strategic scan goal planning for applications requiring accurate 3D data.

A current limitation is the exclusive reliance on geometric visibility for scan evaluation. Environments with minimal structural features may challenge the scoring method. Additionally, terrain accessibility is handled through LiDAR-based occupancy but could benefit from incorporating surface properties for better path planning.

VI. Conclusion

Field experiments demonstrated that the proposed framework reliably generates high-quality 3D point clouds in unknown, cluttered environments. By selecting scan locations based on visibility and spatial efficiency, the system achieved accurate registration (RMSE 2.66 cm, angular deviation <0.08°) without manual intervention. Stationary scans clearly outperformed dynamic ones in data quality. Future work will explore terrain-aware planning and multi-robot deployment to improve scalability and adaptability.

Acknowledgements

The work reported herein was supported by the United States Air Force Office of Scientific Research (AFOSR) (Award No. FA2386-17-1-4655). Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the U.S. AFOSR.

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