As-is Geometric Data Collection and 3D Visualization through the Collaboration between UAV and UGV

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Abstract –

The characteristics of dynamic construction sites increase the difficulty of collecting the high-quality geometric data necessary to achieve construction management activities. This paper introduces a new autonomous framework for 3D geometric data collection in a dynamic cluttered environment using an unmanned ground vehicle (UGV) and an unmanned aerial vehicle (UAV). This method first deploys UAV to collect photo images of a site and builds a point cloud of the 3D terrain of the site, including obstacle information. A mesh grid is then created from the UAV-generated point cloud, and simulation for laser-scan planning is conducted to determine the stationary laser-scan positions at which a mobile robot can collect data with less occluded views while capturing all crucial geometric information. Finally, optimal paths for the UGV to navigate among the estimated scan positions are generated. Promising test results regarding data accuracy and collection time show that the proposed collaborative UAV-UGV approach can significantly reduce human intervention and provide technologies for enabling construction site to be frequently monitored, updated, and analyzed for timely decision-making.

Keywords –

Mobile Robot; UGV; UAV; Point Cloud; Laser Scanning; SLAM; Path Planning

1 Introduction

Collecting accurate and complete geometric data from construction sites is essential but challenging. It is particularly crucial to obtain timely, complete, and accurate spatial information for decision-making in construction projects since inaccurate, missing, or insufficiently detailed data can lead to uncertainty in decision-making. However, the dynamic and complex properties of construction sites not only require various 3D geometric data but also increase the difficulty of efficiently and effectively collecting spatial data [1], [2]. It is also necessary to ensure that data collection activities have a minimal influence on other construction activities; interference between data collection and construction activities can cause project delays and low data quality, which results in poor decision-making and further delays [3].

Currently, the quality of 3D spatial data acquisition depends solely on the intuition or experience of the data collector. This experience-based data collection may not be practical or efficient due to the complexity of the process, which involves 3D spatial domain and the physical target placing for registration. Also, feedback is limited during the data acquisition, and registration process since the completeness of site scan is unknown until the full registration is completed. Furthermore, low-quality 3D spatial data can negatively impact effective decision-making, and duplicated data caused by largely overlapping scan ranges can result in extensive time and computational burdens for data processing. Further, it is possible that unnecessarily high-quality data may be collected for unimportant features at a job site while other geometric data necessary for making critical decisions may be missing. Therefore, a strong need exists to smoothly integrate automated jobsite inspection into the daily or weekly work cycle. If the jobsite inspection is automated, quality control measurements can be taken and reported to stakeholders automatically as well. To increase the efficiency of daily as-is data collection in the field, this study proposes a framework of the unmanned aerial vehicle (UAV)-assisted laser-scan location and path planning for an autonomous mobile robot, or unmanned ground vehicle (UGV).

2 Related Work

2.1 3D Reconstructions from UAV Images and Cooperation with UGV

Extracting 3D geometric data from the scene of interest [4] is very valuable for activities such as monitoring construction progress [5], [6] and defect analysis [7], [8]. The 3D reconstruction process has advanced dramatically due to recently developed computer vision-based technologies. One method for producing a 3D sitemap is photogrammetry. Photographs provide useful information about the construction progress that can be automatically processed and converted to 3D point clouds using Structure from Motion [7]-[9]. Due to stability and payload issues, UAVs typically use a photo camera to capture scenes and build a 3D point cloud with photogrammetry. Since a ground robot can be more easily stabilized with higher payloads than an aerial robot, it can collect a higher quality of 3D geometry data.

As a means of collecting 3D geospatial information, UAVs and mobile robots share the advantage of being able to collect geospatial information without exposing surveyors or device operators to hazardous areas. However, both technologies also have distinct disadvantages caused by their measuring positions. The ground-based measurement methods used by mobile robots have blind spots behind vertical obstacles and cannot capture horizontal surface data located higher than the robots. In contrast, UAVs generate blind spots under horizontal obstacles (e.g., roof). Furthermore, the overall accuracy of the point cloud generated by UAVs is lower than that of the ground-based generated point cloud even though UAVs possess operational advantages over the ground-based approaches regarding navigation.

2.2 Scan Planning and Autonomous Scanning

A widely used technology in many field applications, Light Detection and Ranging (LiDAR) can measure a wide area with higher resolution and accuracy compared to photographs and is generally not limited by surrounding lighting and weather conditions during its operation. However, multiple scans from different locations must be taken and registered because of limited data capture coverage and occlusions. To register multiple scans in one coordinate system, many physical targets or markers are typically pre-installed in the overlapping scan area, which requires substantial cost, labor, and time [9]. A well-designed scanning plan minimizes data collection time while capturing all required geometric information. Latimer et al. [10] have used the concept of "sensor configuration space" to automate laser-scan planning. The configuration space is a 3D volume in which specific geometric features, or "information goals," are displayed on an imaging sensor. Their algorithm clusters information goals and generates configuration spaces for each cluster. It then selects sensing locations and plans the "minimum-time" path for moving the scanner to this location. Some studies have shown that the laser-scan planning problem can be solved using as-designed models [11], [12]. However, current practices still manually collect and process the 3D point clouds of large-scale environments, which requires many scans and often results in high labor and time costs, human errors, and inconsistent data quality. Automating some or all of the data collection and registration processes can mitigate these problems.

Automatic scanning has recently gained strong interest among academics and industry technology developers. Various sizes and types of LiDAR have been equipped to vehicles and mobile or aerial robots, and the simultaneous localization and mapping (SLAM) technique has been utilized in their approaches in generating dynamic point clouds[13], [14]. In robotics, SLAM is a popular method for enabling a robot to estimate its current position and orientation from a map of the environment created by LiDAR or cameras. The problem with this approach is that most SLAM systems are commanded manually; humans must decide where to go and how to perform complete scanning of a large site [15], [16]

3 Objective

The objective of this study is to explore a methodology that carries out multiple automation including robot navigation, laser scanning, and registration of multiple point clouds collected by 3D laser scanners mounted on UGV. To achieve the research objective, the following primary tasks are proposed. First, UAV is deployed to obtain an initial 3D map of the cluttered site. Second, optimal scan locations are estimated by simulation, using a mesh grid applied to the UAV-generated map and an occupancy map generated based on the gradient value of the terrain. Finally, the optimal navigation path is determined from among the simulated scan locations. The overall framework of the proposed approach is shown in Figure 1.

4 Methodology

4.1.1 System Architecture

In this study, a UAV (DJI Mavic Pro) equipped with a 1/2.3" complementary metal-oxide semiconductor sensor and a hybrid LiDAR system mounted on the Ground Robot for Mapping Infrastructure (GRoMI) are used, as shown in Figure 2. The two major parts of GRoMI are a laser scanning system and a mobile

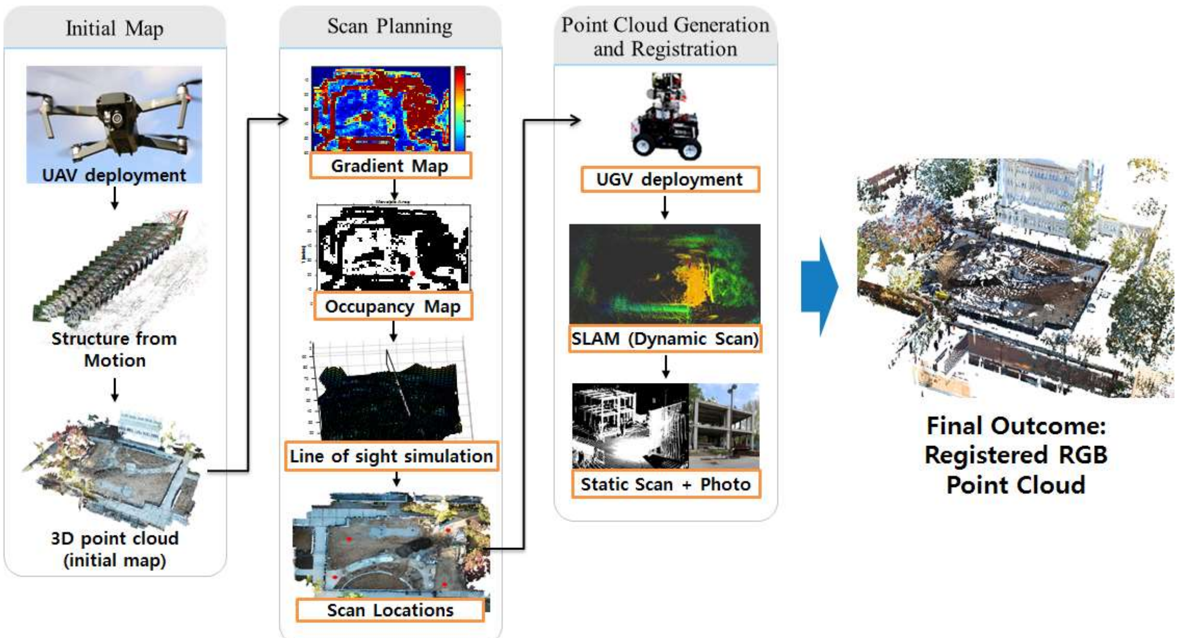

Figure 1. The overall framework of the collaborative UAV-UGV data collection and visualization

platform. The upper laser scanning system includes four vertically mounted 2D SICK line laser scanners to collect 3D mapping information. A horizontally mounted 2D line laser scanner is to estimate the robot's location and pose information on a 2D plane and a regular digital camera to obtain the RGB data of the scenes. The lower mobile platform system, used primarily for navigation, has object avoidance sensors, an IMU, and a navigation camera. The robotic system offers the following functionalities: 1) point-cloud data acquisition while the robot is moving; 2) RGB data collection through a DSLR camera, and 3) autonomous navigation.

The proposed framework allows the robot to automatically collect the geometry data for construction progress monitoring and analysis through LiDAR-based SLAM and automatic point cloud registration methods. To avoid the potential of interfering with construction workers and other activities, the data collection has been done after daily work is completed. In addition, collecting scan data during construction work is not meaningful because the site geometry is rapidly changing and blocked by moving objects (e.g., workers and equipment). In this study, the tested environment is limited to the outdoor construction site since this approach is using UAV-generated map data as prior information for UGV's scan and path planning.

4.1.2 UAV Scan

The factors affecting the performance of the photogrammetry created from UAV include 1) ground control points (GCPs); 2) ground sampling distance (GSD); 3) overlapping ratio; and 4) image processing methods.

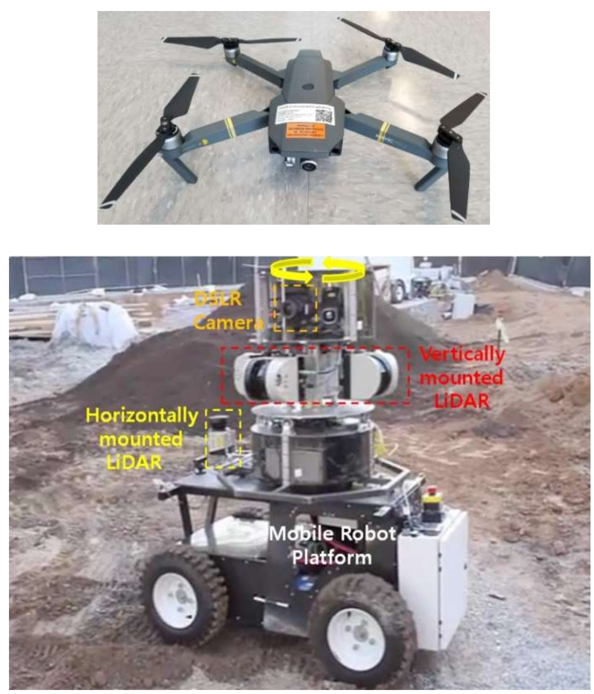

Figure 2. UAV (top) and ground robot systems (below)

Because this study is intended for autonomous 3D as-is data collection in which there is no human intervention, and GCPs were not considered. Referring to the number of pixels per unit length, GSD is a factor related to the flight level, focal length, and resolution of the camera. The GSD can be written as the following Equation (1):

$$\mathrm{GSD} = \frac{H}{f}\,\mu \tag{1}$$

Where H is flight height above ground level (m), f is a focal length (mm), and μ is pixel size (μm). Since the GSD value directly affects the results of the photogrammetry, it is important to determine the flight altitude. The overlapping ratio also affects the accuracy of the photogrammetry. Both GSD and overlapping ratio should be determined when the flight plan is made. In this study, flight altitude was set to 30 m above ground level to determine the GSD to be 1 cm. Using the images obtained from the UAV, this study processed photogrammetric data to generate a point cloud, as shown in Figure 3.

Figure 3. UAV-generated 3D point cloud map of the construction site using image data

4.1.3 Scan-Spot Selection for the Mobile Robot

The scan planning method proposed by this study is to locate satisfactory stationary scanning locations for GRoMI by evaluating the candidate scan locations with a line-of-sight simulation of a 3D laser scanner. Considerations for selecting these locations include 1) the surface point with a large field-of-view of the surroundings with minimal obstructions; 2) the minimal overlapped area between scans; and 3) the most complete possible scan areas for the entire site. Evaluation criteria include a quantity of point data and the amount of occlusion, which differ depending on each scan location. Based on these criteria, a number of scans and data collection time can be reduced while maintaining satisfactory area coverage and level of detail. The scan-spot selection process is accomplished through the following four steps:

1) Divide the job site into cells (1 m by 1 m each) and compute the gradient between neighbor cells for each cell,
2) Create a 2D gradient map and an occupancy map to find the movable area at a site,
3) Run a line-of-sight simulation for every candidate scan location cell and count how many points and how few occlusions can be achieved, and
4) Find candidate scan locations where more point-cloud data and less occlusion can be obtained.

These four steps are described in detail below.

A. Gradient Map Generation

The first stage of the scan planning process requires obtaining an initial 3D terrain model of the target site. In general, it is difficult to use existing or as-designed 3D data because as-is site conditions are generally different from the existing information. Therefore, the UAV-generated point cloud is used as a guidance map to compute the scan locations and to generate a navigation path for GRoMI. The gradient-based map is used to simulate a series of scan views for the robotic scanning system at all scan locations before GRoMI conducts any data acquisition tasks. At first, the UAV-generated point cloud of the construction site is divided into 1 m by 1 m cells. Gradients between neighbor cells are then computed. Figure 4 demonstrates the gradient map of a test site. It can visualize which cells are flattened, tilted or occupied by obstacles. The blue color area is relatively flat with a small gradient value where the mobile robot can be better balanced horizontally for laser scanning, and the red color area is relatively inclined with a more considerable gradient value where the mobile robot should avoid.

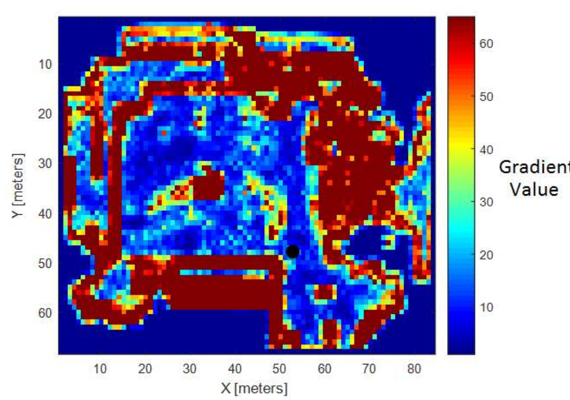

Figure 4. Gradient map of a test site

B. Occupancy Map for Candidate Scan Locations

Based on the generated gradient map, the movable and flat areas in the site are defined by setting a specific gradient threshold value. The movable area is the place where GRoMI can move around because the area has a relatively small gradient value, and it is used for path planning for GRoMI. A reference point is required for selecting optimal locations. This study uses the starting position of GRoMI as the reference point. Figure 5 shows the occupancy map of the movable areas, while GRoMI's initial location is shown as a small red dot in the target site. Occupancy means whether the obstacle is present at each cell.

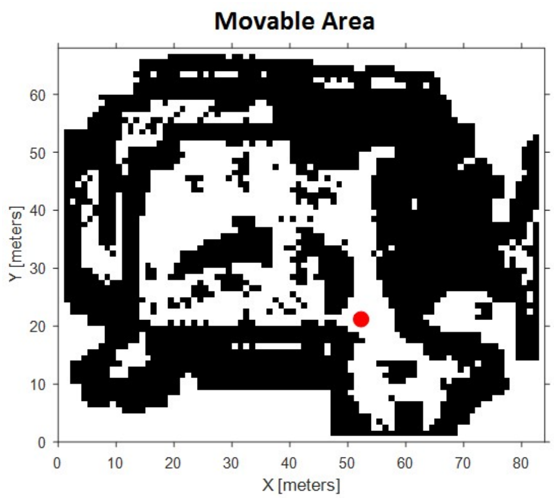

Figure 5. Occupancy map for the movable area

C. Line-of-Site Simulation

The next step is to compute the visibility of each candidate scan location. The ray tracing algorithm [17] is used to calculate the line-of-sight visibility. At first, the mesh grid is created from the UAV-generated point cloud. The 3D ray tracing for each laser line is then simulated. It is possible to find the cross points between laser lines and contour of the terrain. These points can be classified into two groups. The first is the simulated laser points, which are the minimum distance points from the specific scan location, has one point per laser line. The others are occluded points. This simulation lists the scan locations with the maximum number of points from the laser scanner and the minimum number of occlusion points. In addition, the greedy cover algorithm [18] is utilized to select an approximation for the optimal number of scan locations necessary to cover the entire site. It chooses the scan location that can see the largest amount of the boundary and then continues selecting the scan locations to cover the remaining area from the potential viewpoints. This process repeats until either the entire site has been covered or the iteration reaches the approximation for the optimal number of scans.

D. Find Satisfactory Scan Locations

The scan planning simulation calculates the number of laser points and occlusion points during the previous steps. Among these locations, removing some of the scan locations within a specific distance is required to minimize the overlapped area caused by the redundancy. The specific distance differs depending on the size of the target site; a 10 m distance is used for our test bed. After the simulation, four of the optimized scan locations were estimated as shown in red dots in Figure 6.

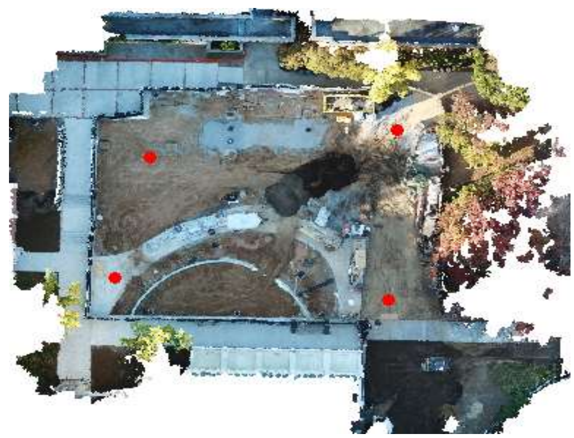

Figure 6. Identified scan locations from the scan planning simulation with UAV's point cloud (top view)

4.1.4 Automatic Registration of Scans

The laser-scan data from the horizontal LiDAR is used by the Hector SLAM algorithm to estimate the position and orientation of GRoMI on the horizontal plane. The Hector SLAM algorithm, developed by Kohlbrecher et al. [19], is employed in this study to perform laser-scan matching between the laser scans and progressively built maps to estimate the robot's postures and planar maps of the environment. In addition, the SLAM-driven localization approach is used to automatically register the point clouds obtained from each stationary scan location [20].

5 Results

In this study, a real-world construction site at the Georgia Tech campus was selected as a cluttered environment for the test. Three devices, UAV, GRoMI, and a commercial laser scanner, were used to build 3D point clouds of the site. To generate a 3D point cloud, UAV used the photogrammetry technique, and a commercial laser scanner used sphere targets for point

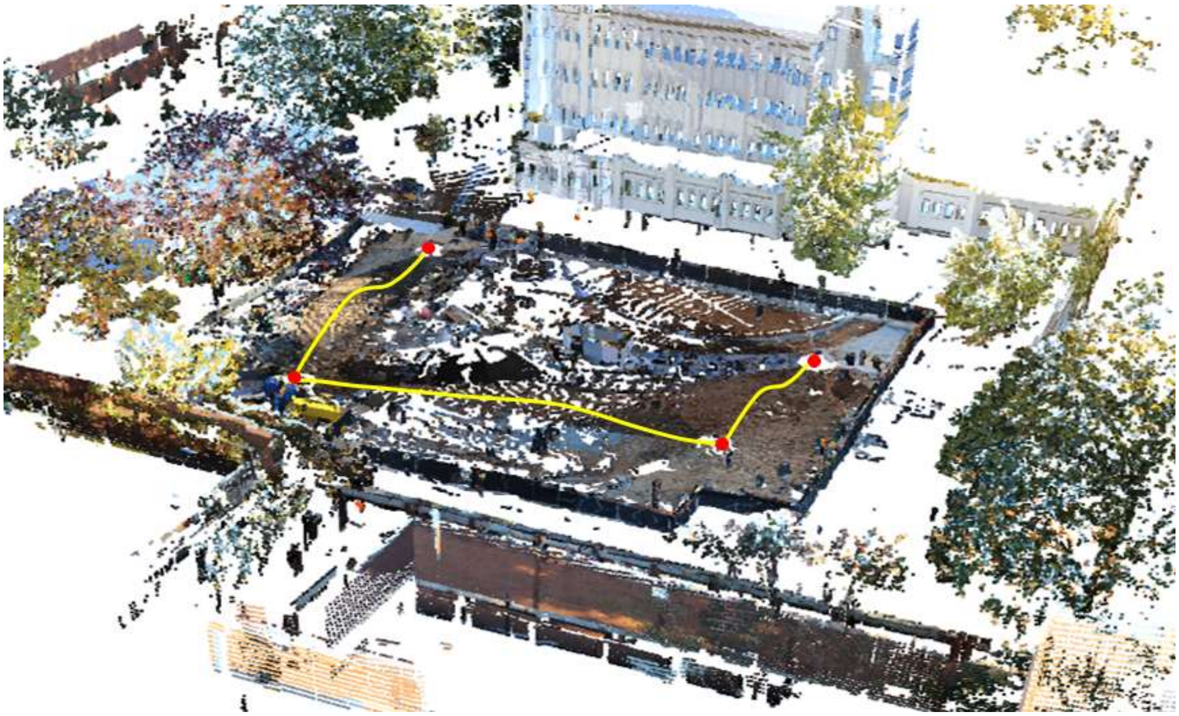

Figure 7. Registered 3D point cloud of the test site and GRoMI's scan and moving paths

cloud registration. As previously described, GRoMI conducted the SLAM-based automatic registration. Figure 7 shows the automatically registered RGB point clouds of the target site made by GRoMI.

Table 1. Error assessment

	GRoMI
Mean absolute error (MAE)	1.97 cm
Root mean square error (RMSE)	2.31 cm

Table 2. Required time from data collection to registration

	GRoMI	Commercial laser scanner
Pre-processing	35 min	10 min
Operation	30 min	40 min
Post-processing	0 min	40 min

In this study, the commercial laser scanner is considered the ground truth to measure the registration error of the registered point cloud collected by GRoMI since the terrestrial laser scanner has the highest accuracy of ±3 mm. As shown in Table 1, the mean absolute error (MAE) between the GRoMI and commercial laser scanner point clouds is 1.97 cm, and the root mean square error (RMSE) is 2.31 cm; MAE is an average distance between two point cloud sets, and RMSE is a standard deviation between two data sets.

Table 2 shows the required time to build a 3D registered point cloud with each device. The pre-processing includes the UAV's scanning time and path-planning processes for GRoMI and a target placing and laser preparation time for the commercial laser scanner. Operation refers to the data collection process with each device, and post-processing is the point-cloud registration process. During the 35 min of pre-processing for GRoMI, 10 min of UAV operation, 20 min of point-cloud generation, and 5 min of scan planning are included. The clear advantage of using GRoMI with UAV is the shortened processing and operation time. A commercial laser scanner has slightly higher accuracy but requires significantly more time than GRoMI for the target relocation and manual point clouds registration. Also, it cannot guarantee the complete scan of the job site since selecting scan locations is based on human intuition. Conversely, the advantage of using GRoMI is the planning scan locations and paths created by using a UAV-generated point cloud. Thus, it can realize more favorable results. Also, it does not need post-processing (registration) because it is registered automatically using the robot localization data (i.e., SLAM). Therefore, the proposed aerial mobile robot-based autonomous data acquisition approach resulted in higher time and cost efficiencies compared with the traditional terrestrial LiDAR-based data acquisition method.

6 Discussion and Conclusion

In general, effective mobile robot path planning for unknown and clustered environments is challenging because no a priori information of site conditions exists. To overcome these problems, this paper introduces an autonomous method for 3D point-cloud generation through the collaboration between UAV and UGV. From the test results, both commercial laser scanner and UGV yielded satisfactory accuracy. However, the proposed method, with UGV (GRoMI), is more effective in post-processing for point-cloud registration using the SLAM-driven robot localization data. The advantages of using the proposed approach over traditional methods include (1) to automate the point-cloud acquisition process by finding the robot's preferred scan locations and planning navigation paths with the aid of UAV's site map; (2) to remove redundant scans and reduce time and cost for data collection; (3) to reduce missing areas of the target site; and (4) to automatically register multiple scans.

The proposed framework enables mobile robots to robustly and effectively collect high-quality site data, thereby enhancing site inspection and monitoring capabilities and reducing necessary time and cost. Since the robot can frequently update the geometric information of a site, it can be used for several construction management applications including virtual site access from remote places, progress monitoring, defect management, safety, legal dispute, supply chain management, as-built BIM, and more.

However, the implementation of the proposed method is still limited by its dependence on UAV's generated map data. As such, pre-processing for the proposed approach requires more time than the traditional 3D scanning process. For future study, the current robotic approach should be further investigated for cases when UAV data is not available (e.g., indoor construction). In this case, the robot must be able to itself estimate preferred scan locations.

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