Autonomous Mobile Robot Localization and Mapping for Unknown Construction Environments

Pileun Kim[1]; Jingdao Chen[2]; and Yong K. Cho[3]

[1]Ph.D. Student, Dept. of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, GA 30332-0355. E-mail: pkim45@gatech.edu
[2]Ph.D. Student, Institute for Robotics and Intelligent Machines, Georgia Institute of Technology, 777 Atlantic Dr. N.W., Atlanta, GA 30332-0355. E-mail: jchen490@gatech.edu
[3]Associate Professor, Dept. of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, GA 30332-0355.
E-mail: yong.cho@ce.gatech.edu

Abstract

With the rapid advancement of laser scanning and photogrammetry technologies, geometric data collection at construction sites by contractors has been increased to improve constructability, productivity, and onsite safety. Especially, the latest laser scanning technology provides faster scanning-speed, longer ranges, and higher accuracy and resolutions. However, the conventional static laser scanning method suffers from operational limitations due to the presence of many occlusions commonly found in a typical construction site. Full scanning without information loss requires that the scanning location should be changed several times, which also leads to extra work for registering each scanned point cloud. Alternatively, this paper presents an autonomous mobile robot which navigates a construction site and continuously updates a progress of 3D scanning with point clouds. This mobile robot system uses the 3D simultaneous localization and mapping (SLAM) technique to determine its navigation paths in an unknown environment, capture the survey-quality RGB mapped point cloud data, and automatically register the scans for geometric reconstruction of a construction site. The performance of the overall system was tested in indoor environments and validated with promising results.

INTRODUCTION

Laser scanning and photogrammetry technologies for point cloud are widely used in many construction job sites to obtain a 3D reconstruction of buildings and infrastructures. It is used extensively in the field of construction management, structural damage assessment, urban planning, historical building restoration, building renovation, facility management, and building energy analysis to render actual size objects or environments in the form of dense point cloud datasets (Cho et al. 2012; Wang and Cho 2015). In previous studies, 3D reconstruction of the work environment contributed to improvements in material tracking, scheduling, and construction defect control, but it still faces challenges in unstructured and unpredictable environments, which made it difficult to collect 3D reconstruction data (Cho and Martinez 2009). Current commercial 3D laser scanners that collect data under static conditions can accurately and safely collect millions of 3D points in a short time. However, the point cloud registration process, an important step in the post-processing phase, is still a labor-intensive and time-consuming process. This is because the complete point cloud data for construction sites without missing areas can only be obtained by scanning multiple times at different scanning locations. Then, the operator needs to register these collected data under a common coordinate system. However, the current laser scanning methods provide limited feedback to the operator during the scan process and registration process (Chen and Cho 2016), thus operators do not know if the data collected is affected by incomplete scans, disruptions, or occlusion until the end of the scanning process. On the other hand, simultaneous localization and mapping (SLAM) technology have been actively studied in various engineering fields to dynamically estimate the current scan position and automatically generate an environment map for 3D reconstruction. However, this dynamic solution has difficulties with low point cloud resolution, high noise due to motion distortion, and RGB-mapped point cloud acquisition. Therefore, in this study, we propose a framework for constructing a 3D high-resolution RGB-mapped point cloud registered in real time using a hybrid laser scanning system mounted on a mobile robot.

LITERATURE REVIEW

One way to achieve 3D-reconstructed maps is to use photogrammetry. Photographs provide useful information about the construction progress, which can be processed automatically and converted to 3D format using Structure from Motion techniques (Navon 2007). The advantage of image-based modeling methods is the availability of texture information that enables material recognition (Dimitrov and Golparvar-fard 2014) and CAD model-based object recognition (Kim et al. 2013). However, it is difficult to obtain consistent image analysis in photography because of weather and lighting conditions and geometric inaccuracy when there are few common features among multiple images (Fathi and Brilakis 2012). Compared to photographs, laser scanning allows the measurement of a wider range with higher resolution and accuracy and is generally not limited by surrounding conditions during the data acquisition process (Jaselskis et al. 2003). Researchers in the construction and facility management field have conducted laser-scanning related studies including rapid workspace modeling for equipment operations (Fang et al. 2016), construction progress monitoring (Rebolj et al. 2008), fault detection (Bosche and Guenet 2014), assembled modeling (Wang et al. 2015), thermal object recognition (Kim et al. 2017) and bridge deflection evaluation (Xiong et al. 2013). However, laser scanning requires considerable time to complete a full scan. This is because multiple scans must be registered at different locations due to limited data capture coverage and occlusions on the site to generate an as-built model for construction projects (Atasoy et al. 2009), which is costly, labor intensive and time-consuming. Although there has been significant progress in automating the point cloud data collection workflow, building a complete as-built model during the construction process has not yet been fully supported. Even state-of-the-art data acquisition devices require engineers to manually adjust data acquisition parameters and determine where to collect data, which depends on their experiences and skills. On the other hand, automated robot laser scanning systems enable more accurate, holistic data collection and modeling for as-built conditions of construction sites.

To automate a robotic laser scanning system, the robot needs to know information about its position and the surrounding environment. SLAM (Simultaneous Localization and Mapping) is a way to allow robots to estimate their current position and orientation as well as the environment map. SLAM technology has been well developed, but still faces some limitations. For example, Davison et al. (2007) restored the 3D trajectory with a monocular camera in an unknown environment. The Visual SLAM method was unable to handle sudden movements and was limited in getting detailed maps of the surrounding environment. Roca et al. (2013) created a 3D model of a building using a Kinect sensor and compared the results to the other models generated by a laser scanner. However, the generated point clouds are noisy and uneven. This is because the vision-based system is vulnerable to errors accumulating over long distances and is heavily influenced by material and lighting conditions. There have been many studies to create 3D maps using SLAM in unknown environments using laser scanners. Chong et al. (2013) studied precise localization in 3D urban environments using 2D Light Detection and Ranging (LiDAR) and mileage data. However, this work is focused on localization only, and not on generating accurate 3D models. Chen and Cho (2016) developed a mobile platform using orthogonal pairs of LiDAR to create a 3D point cloud map for the indoor environment. This method yielded a high-accuracy map but did not include the visual information in the reconstructed 3D map. Another approach to solving the SLAM problem is to utilize multiple robots and integrate the robot's attitude estimation and individual maps to create more accurate world models (Chang et al. 2007). However, this method does not allow an operator to observe the real-time map until the exploration and optimization process are completed.

In summary, it is still difficult to solve the problems discussed above although 3D data collection and processing has been greatly improved. In particular, there have been limited attempts to automate the robot sensor setup and control process to ensure data quality and comprehensiveness. Therefore, the primary objective of this paper is to develop an automated framework to provide 3D-reconstructed maps for the construction industry with reduced time and effort, and the outcome is a complete registered point cloud with color information. The scope includes the integration of robotic SLAM technology to the data collection and registration framework, which is limited to indoor environments in this paper.

MOBILE ROBOT SYSTEM AND NAVIGATION ALGORITHM

A robotic hybrid LiDAR system, Ground Robot for Mapping Infrastructure (GRoMI), was used for this study. GRoMI is composed of two major parts, a hybrid laser scanning system and an autonomous mobile robot platform as shown in Figure 1. The upper part is a laser scanning system, and the lower part is mobile robot platform. The advantages of this system are: 1) data acquisition is possible while the robot is moving; 2) RGB-mapped high-resolution point cloud can be obtained through the DSLR camera, and 3) robot navigation and data collection can be carried out remotely or autonomously. Figure 2 describes the flowchart of the proposed approach. There are four main procedures; static scan, dynamic scan, autonomous navigation and point cloud registration. The detail of each process is described in the following sections.

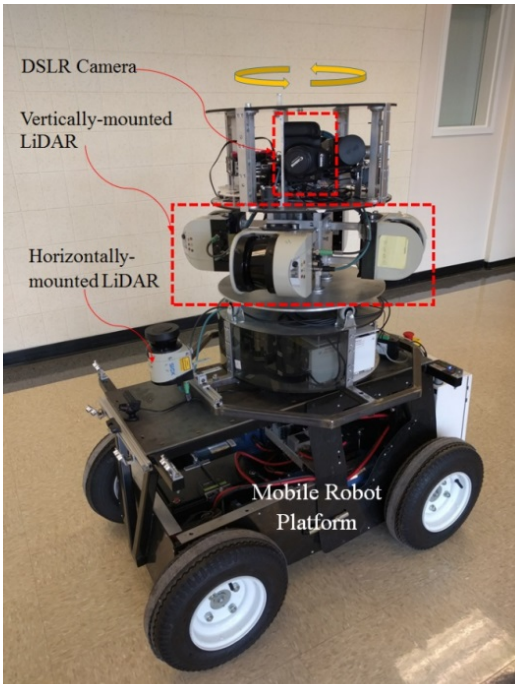


Figure 1. Mobile robot platform with a hybrid 3D scanning system

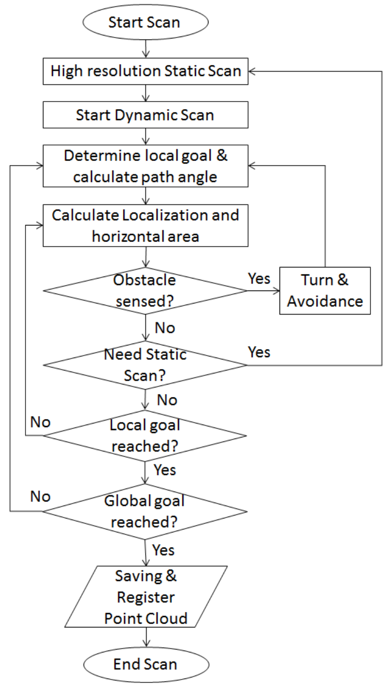


Figure 2. Flowchart of proposed framework

The algorithm for navigation of the autonomous mobile robot is shown in Figure 2. The robot calculates the current position and orientation from the currently estimated map and a previously built map of the environment with LiDAR scanners. Then, it determines a local goal position within the scanned area and finds the shortest path between the current position and the goal. When it senses any obstacles, including stationary and moving one, while it travels through the shortest path, it selects the new path based on the previously selected shortest path. If the mobile robot reaches the local goal, it computes a new local goal position and moves toward it. This process is repeated until it reaches the global goal position.

In the differential drive configuration, there are four individual drive wheels, placed on each corner of the mobile platform as shown in Figure 3. The number of rotations during each sampling time can be obtained by encoders placed on each wheel. The wheels on the same side are mechanically coupled respectively. Therefore, the encoders provide two distinct speeds; one is for the left pair of wheels and other for the right pair of wheels. The platform is moved by applying different velocities at each side for the drive wheels. The kinematics of GRoMI are given in Equation 1.

$$
\begin{aligned}
x_{k+1} &= x_k - \left(\frac{V_R + V_L}{2}\right) dt \sin \theta_{k+1} \\
y_{k+1} &= y_k + \left(\frac{V_R + V_L}{2}\right) dt \cos \theta_{k+1} \\
\theta_{k+1} &= \theta_k + \left(\frac{V_R - V_L}{a}\right) dt
\end{aligned}
\qquad (1)
$$

Here, b is the vehicle axle length, while V_R and V_L are the velocities of the right and left wheels respectively. x_k and y_k represent the position of the center of axle C. θ is the yaw angle between the vehicle axle and x axis. For this paper, the frame of reference is chosen such that the start location of the robot is the origin facing the positive y direction.

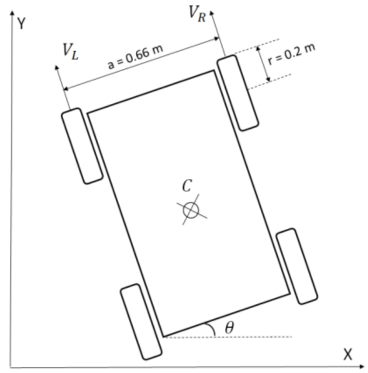


Figure 3. GRoMI odometry model

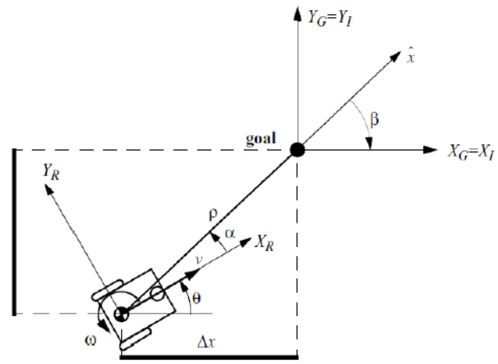


Figure 4. Distance and angle calculation

Figure 4 shows that how the mobile robot reaches a local goal from the current position, and Equation 2 demonstrates the distance and angle relationship between a local goal position and the current position of the mobile robot.

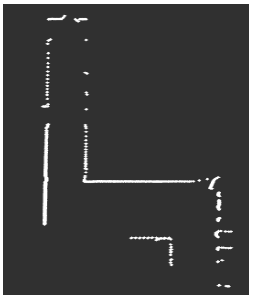
$$\begin{gathered} \rho = \sqrt{\Delta x^2 + \Delta y^2} \\ \alpha = -\theta + atan2(\Delta y, \Delta x) \\ \beta = \theta - \alpha \end{gathered} \tag{2}$$

Here, ρ is the distance between a local goal position and the current position, and α is the angle between a local goal position and current orientation. Once the local goal is determined, the mobile robot rotates α degrees and moves forward ρ meters. The linear controller for mobile robot velocity v and rotation speed w is designed by Equation 3. In this paper, the gain values k_ρ, k_α, k_β are selected as 3, 8, and 1.5.

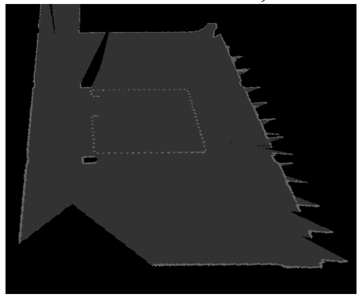
$$\begin{gathered} v = k_\rho \rho \\ w = k_\alpha \alpha - k_\beta \beta \end{gathered} \tag{3}$$

PRE-SCANNING WITH SLAM

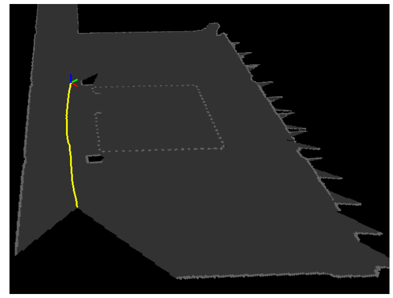
The laser scan data from the horizontal LiDAR is used by the SLAM algorithm to calculate the position and orientation of the mobile robot on the horizontal plane. The Hector SLAM algorithm, developed by Kohlbrecher et al. (2011), was adopted in this paper to perform laser scan matching between current LiDAR scan and incrementally-built map to obtain the pose estimation and horizontal map of the surrounding environment. The SLAM algorithm is performed as shown in Figure 5. Figure 5a shows the current raw scan data from horizontal LiDAR. Then, scan matching is performed with the currently estimated map and previously built map of the environment in order to obtain translation and rotation parameters, which is shown in Figure 5b. This is continuously repeated as the mobile robot moves to compute both the position and orientation of the robot at each step along its trajectory as well as the 2D map of the environment, which is shown in Figure 5c.



(a) raw scan data from LiDAR



(b) incrementally-built 2D map



(c) trajectory with position and orientation of the mobile robot

Figure 5. Scan matching with horizontal LiDAR

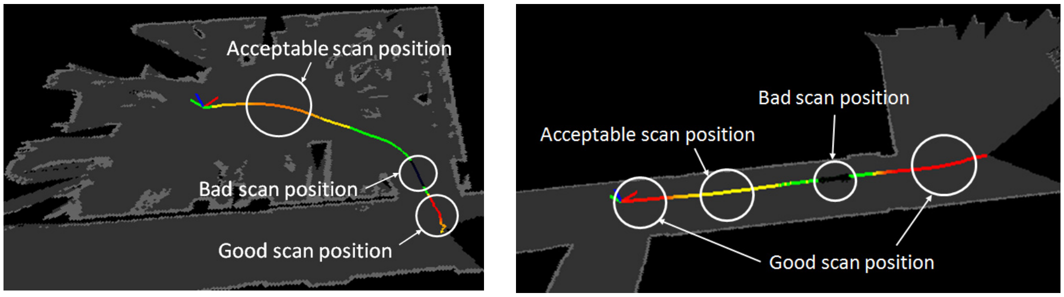
The position and orientation information, obtained from the 2D Hector SLAM algorithm, can be utilized to generate the 3D map by adding vertical scanning information. The vertical scans are first registered in the local coordinate frame of the mobile robot based on the angular displacement of the revolving frame of the vertical LiDAR. Then, each scan is added to the global coordinate frame by the corresponding transformation and rotation parameters estimated by the Hector SLAM. Therefore, 3D maps are gradually built up by stacking multiple planar scans.

AUTOMATED SCAN VISIBILITY EVALUATION

Determining the optimal position where the mobile robot should stop and acquire a high-resolution static scan is one of the main problems to be addressed in this paper, which relies on the horizontal laser scanner data. For each potential scan point along the robot trajectory, a fitness number is calculated based on the visible area of the 2D map from that scan point, denoted by A(x, y). This fitness number is obtained by summing up the horizontal distances of the scan data over different scan angles, θ relative to the scan origin point (x,y), shown in Equation 4.

$$A(x,y) \approx \sum_{\theta=\theta_{min}}^{\theta_{max}} d(x,y,\theta) \tag{4}$$

A visualization of the fitness score evaluated in real indoor environments is shown in Figures 6 (a) and (b). Each figure shows a scanned 2D world map together with the robot trajectory highlighted according to the fitness score. High-intensity regions correspond to “good” fitness scores, where the points along the path will be strongly considered as the next scan origin for a high-resolution static scan (corridor region in Figure 6a). Moderate intensity regions correspond to “acceptable” fitness scores, where the points along the path may be considered for the next scan point. Low-intensity regions correspond to “poor” fitness scores, where the points along the path will not be considered for static scanning (obstructed doorway in Figure 6a).



(a) (b)

Figure 6. Evaluation for scan positions along the robot trajectory

An additional step is required to determine the final scan positions used for static scanning. Two criteria were utilized in this study: (i) static scans should be carried out in "good " or "acceptable" scan positions, with priority given to "good" scan positions, and (ii) two static scans should not be separated by more than the range of the laser scanner.

RESULTS

A building floor was selected as a testbed for validating the proposed framework. As can be seen from the flowchart in Figure 2, the high-resolution static scan is performed at the start, and then the pre-scanning process is initiated. The horizontal scanner collects the horizontal distance information, performs localization and builds a 2D map using Hector SLAM. Then, the four vertical scanners simultaneously collect 3D information to avoid obstacles and perform pre-scanning in 3D to perceive the surroundings. Figure 7 shows the process of dynamic pre-scanning and localization where the coordinate axes in the circle represent the current position of the mobile robot.

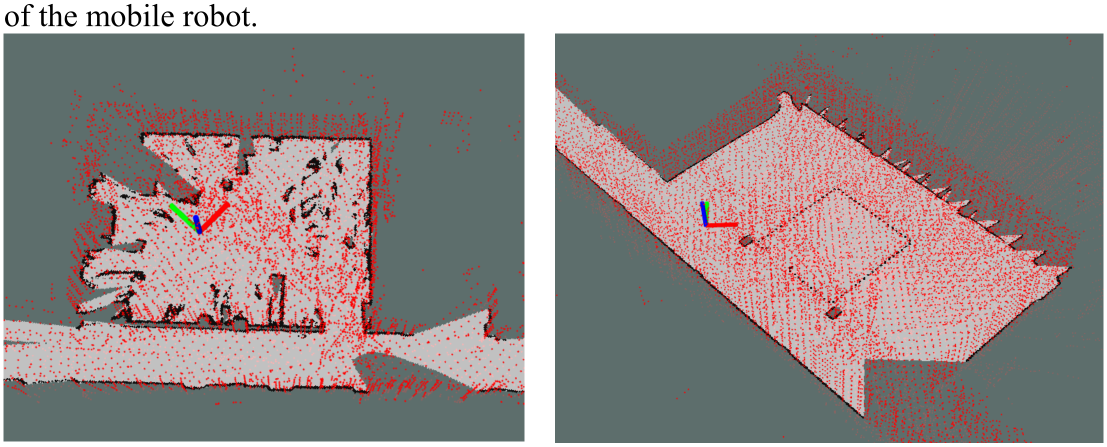


Figure 7. Dynamic 3D pre-scanning and localization

During the pre-scanning process, the mobile robot finds the optimal static scan position by the evaluation of fitness according to Equation 4. Once the robot finds the best static scan position, it calculates the coordinate transformation from the previous static scan position to the current position using localization data and then moves to the next static scan position. Once the scanning process is completed at the global goal position, a final registered point cloud is simultaneously generated. Figure

8 shows the registered RGB-mapped point clouds for the test environment, and Table 1 represents the registration results of the proposed framework. To verify the result for this testbed, the higher scan ID was assumed as a ground truth, and the deviation angle from each reference axis in degree and root mean square error (RMSE) in meters were measured. As shown in Table 1, the translation and orientation data obtained from SLAM can be directly applied to the transformation between each scan. It can be observed that the measured RMSE of the final registration data is 0.035 meters, and the deviation angle is less than 0.08°.

Figure 8. Registration of RGB mapped point cloud

Table 1. Registration result between each static scan with SLAM

Scan ID			#1 - #2
Before Registration	Translation	X axis	-7.52 m
		Y axis	8.83 m
		distance	11.59 m
	Orientation		5.406 °
After Registration	RMSE		0.035 m
	Deviation angle	X axis	0.072 °
		Y axis	1.375 °

DISCUSSION AND CONCLUSION

In general, reconstructing a 3D map of the environment is challenging because it requires targets or invariant common features and sufficient overlapped area. To overcome these problems, this paper proposed a SLAM-based autonomous mapping and registration framework through a hybrid robotic data collection system, which combines dynamic and static scan processes. The advantages and contributions of this framework are: 1) to automate the target-free data fusion and registration process, 2) to reduce the effort and time of the point cloud data collection and registration process for ensuring construction quality and safety, and 3) to provide a high-resolution RGB-mapped point cloud.

The proposed framework would enable robots to robustly collect high-quality site data regardless of job site conditions for improved construction site supervision, thereby enhancing site monitoring capability and saving tremendous time and cost. Furthermore, frequently updated construction site information modeling data can be used for several construction applications including defect management, safety, legal dispute, supply chain management, as-built BIM, and more. To explore such applicability, the proposed robotic framework will be tested on complex construction sites for future study.

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