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Localization and mapping of autonomous wheel mobile robot using Google cartographer

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ABSTRACT

COVID-19 has become a world concern because of the spread and number of cases that have befallen the world. Medical workers are the first exposed group because they have direct contact with patients. So, a vehicle is needed to replace tasks such as logistics, delivery, and patient waste transportation. An autonomous wheeled mobile robot (AWMR) is a wheeled robot capable of moving freely from one place to another. AWMR is required to have good navigation and trajectory control skills. The purpose of this study is to develop an AWMR navigation system model based on the simultaneous localization and mapping (SLAM) algorithm, accurately in a dynamic environment. With this research, developing a good navigation and trajectory method for AWMR, in the future, it can be applied to produce an AWMR platform for multipurpose. This research was conducted in two stages of development. The first year is the research that is currently being carried out, focused on sensor modeling, designing SLAM-based navigation models, and making navigation system testbeds. This research produces a trajectory navigation and control system that can be implemented on an AWMR platform for the purposes of logistics, transportation, and patient waste in hospitals.

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1. INTRODUCTION

COVID-19 has become a world concern because of the spread and number of cases that have befallen the world. A total of 144,636 people died out of 4 million cases in Indonesia [1], including medical personnel. Thousands of medical personnel were exposed while carrying out their duties due to direct contact with patients, such as treating and handling patient waste [2]. This makes medical personnel at higher risk compared to others. Therefore, a logistics transportation system is needed for patient waste to avoid medical staff contact with patients.

An autonomous wheeled mobile robot (AWMR) is a wheeled robot capable of moving freely from one place to another. This has the potential for AWMR to be applied in various fields such as the warehousing industry for the transportation of goods [3], [4], the health sector [5], for healthcare in hospitals [6], surveillance for military purposes [7], and others [8], [9]. In these various applications, one thing that is fundamental is the ability to move accurately, which AWMR must have. A dynamic AWMR environment, either due to movement activities by humans or other AWMR, nonlinearity of environmental parameters, and changes in load on AWMR, is a challenge, so good navigation and trajectory control skills are needed [10].

In AWMR navigation generally uses dead reckoning with data from the wheel speed sensor. In the dead reckoning method, the position vector, which is the feedback for the trajectory control, is obtained by integrating the velocity vector with the measurement model in a deterministic manner, which results in an accumulation of measurement errors if one measurement error occurs. In contrast to the navigation method with the simultaneous localization and mapping (SLAM) method uses a probabilistic model where measurement errors will not accumulate if one measurement error occurs [11]. In addition to the navigation method, which is the feedback needed to control tracking on the trajectory, it also depends on the control method used. Although several methods have been proposed, the model and environment still use a linear model with a static environment by ignoring nonlinearity and changing parameters. In fact, the AWMR environment is a dynamic environment with nonlinearity and changing parameters, so it is necessary to develop nonlinear controls, such as robust controls [12] or intelligent controls [13], which can overcome uncertainty in the AWMR environment.

Navigation is a problem to get information about the surrounding environment, especially the position of the AWMR and surrounding objects that must be known before moving from one point to another. In general, the navigation system on AWMR uses the dead-reckoning method through the speed data from each wheel. However, it has limitations that it can only be used in static environments and errors that accumulate when one measurement error occurs due to its deterministic nature [14]. Laser sensors, such as light detection and ranging (LiDAR), are distance detection sensors based on reflected infrared, which are an option with light computation, but have limitations if the room has open sections with wide distances. Of the several specific uses of these sensors, combining measurement methods with the use of stochastic SLAM is an option [15].

Apart from dead reckoning, various sensors and methods have been developed, such as camera sensing, global positioning system (GPS), and light distance and ranging (LiDAR). Sensing with a camera is one of the natural navigation, like humans, can see visuals widely, but to process visual information into positional information, both AWMR positions and objects in the surrounding environment are required to have high computation [16]. Navigation using GPS is another option to get a global position, but GPS has limited accuracy for short distances of less than 2 meters and the absence of the ability to detect the environment as a whole [17]. LiDAR is another option for navigation by utilizing the reflection of the emitted infrared light. LiDAR gets reflections from objects and walls in the surrounding environment, which will be very suitable for dynamic indoor environments, but has limitations if there is one point of the room that is open or without wall boundaries. This resulted in the need for a special technique in navigation in a dynamic environment. SLAM, or simultaneous localization and mapping, is a navigation technique by mapping and positioning simultaneously.

In SLAM, there are two methods that are run simultaneously, namely the formation of a global map based on information from the position data of objects and walls by the sensor and the localization method, namely obtaining the position of the AWMR global coordinates on the map. The occupancy grid is one of the methods for obtaining a global map, and in the localization method, there are several methods, namely scan matching [10] and particle filter [16]. The scan matching method only relies on information data from LiDAR, so it has low accuracy because there is no data correction from other sensors, where LiDAR has limitations in rooms that have open areas without dividing walls. Particle Filter offers a combination of stochastic data because, like the Kalman filter, there are motion models (predicted) and sensor models (measured). In the motion model stage, a kinematic model with wheel speed data is used, while in the measured stage, measurement data from LiDAR is used.

The purpose of this research is to develop an accurate AWMR navigation system model based on the SLAM algorithm in a dynamic hospital environment. Furthermore, it is combined with a trajectory control system with a robust sliding mode control method that works adaptively to handle nonlinearity and parameter uncertainty and can follow trajectory changes when in a dynamic environment. With this research, developing a good navigation and trajectory method for AWMR, in the future, it can be applied to produce an AWMR platform for multipurpose.

2. METHOD

The proposed control system, as shown in Figure 1, starts with a navigation module that is responsible for determining the robot's position in relation to the global coordinate system. Accurate localization is essential to enable autonomous behavior, especially in dynamic and non-structured environments. This module translates sensor data to create spatial awareness and match the robot to the features of the environment needed for accurate mapping. In this framework, the velocity vectors are calculated on the basis of motion inputs, and the position estimation is done by SLAM integrated with LiDAR. The SLAM method improves global consistency by correcting the drift inherent in odometry methods. The combination of the speed data and the corrected positional estimates provides a solid and reliable basis for the AWMR to perform localization and mapping efficiently. The AWMR model is a mobile robot model with two wheels, consisting of a kinematic model and a dynamic model, where the dynamic model has been described in (1), with the kinematic model described in the equation.

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos(\theta) & 0 \\ \sin(\theta) & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix} \tag{1}$$

Here, v is the translational speed of the robot and ω is the rotational speed. x, y denote the Cartesian coordinates of the robot in the global reference frame. θ is the robot's orientation angle with respect to the global frame. $\dot{x}, \dot{y}, \dot{\theta}$ represent the time derivatives of the robot's position and orientation, i.e., its velocity components in the global frame. Equation (1) describes how the robot's pose changes over time in response to its control inputs, v and w. By transforming the robot's local frame-where velocities are defined-to the global frame, the matrix on the right-hand side makes sure that the motion respects the robot's current orientation, θ. For high-level path planning and control in structured environments, this model is perfect because it assumes non-slipping and pure rolling conditions.

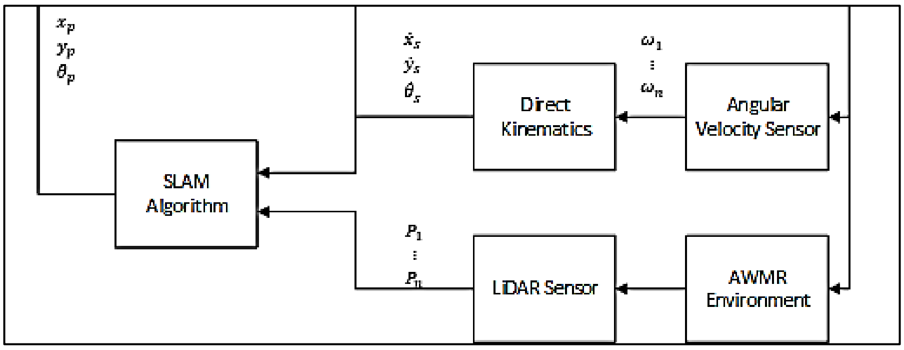


Figure 1. AWMR navigation scheme

2.1. Google cartographer SLAM

The cartographer system consists of two parts: local optimization and global optimization. The local optimization runs the appropriate part of the LiDAR scan frame and its submaps, after which the submap is optimized [8], [15]. Meanwhile, global optimization performs global map optimization according to the positional relationship between frame scans after finding a closed loop frame scan. Local optimization is the process of matching LiDAR frame scans to submaps, and iteratively aligning LiDAR frame scans and references from submap frames to create submaps. Multiple iterations of the frame scan create a grid submap of probability resolution r, with each system grid point determining the corresponding pixel. Each time a new scan is entered into the probability grid, a set of hit or miss grid points is calculated. Before sending a map scan to a submap, the position of the scan frame is optimized by the ceres application in the current submap, and the scan point mapping is superimposed by nonlinear least squares optimization, and the total value of the scan reaches the hit value. After changing the position and pairing with the probability values in the submap, every place that matches the view should have a high probability of being hit. Since the least squares problem is a local optimization problem, a good initial value will have a large influence on the solution. Therefore, the use of IMU [18] or odometry can be used to provide a variable rotation or position matching scan for the initial initialization value.

Global optimization is achieved through closed loop detection. Because each LiDAR frame scan only matches the submap that contains the most recent frame scan, errors build up slowly. To eliminate accumulated errors, the sparse pose adjustment (SPA) method was used to optimize all scan positions and submaps [11]. The positions of the LiDAR scan frames entered in the submap are stored in memory. When a submap is created, frame scans and corresponding submaps are calculated for closed loop detection. All matching scans are performed on the back end, and once a good closed-loop match is found, it is added to the global optimization [19]. The algorithm flow of the mapping system method is illustrated in Figure 2. The environmental map model, on the environmental map, is modeled with dots on the occupation grid, with the actual map originating from the UMM's hospital. Navigation design, in this section, designs the SLAM algorithm which utilizes the data model from LiDAR and the designed environment model, which is a map of several rooms of UMM's hospital.

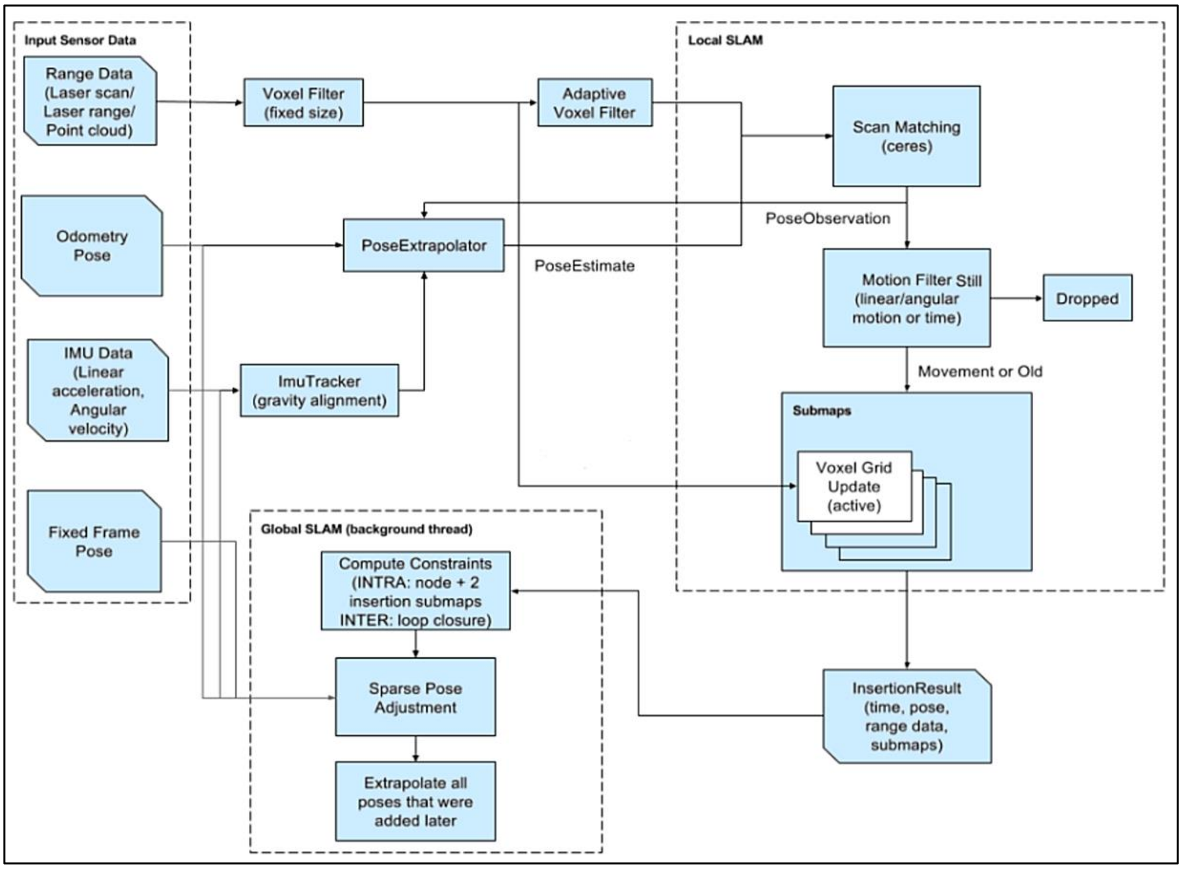


Figure 2. Google cartographer scheme

3. RESULTS AND DISCUSSION

This research was carried out with three types of tests, such as testing object detection around LiDAR to determine the distance of objects that can be detected by LiDAR. The next test is making a map and positioning/localization accuracy in one test room. Positioning testing includes position and orientation tests. Tests were carried out with RP-LiDAR A1 hardware with a range of 12 meters and 360 degrees. SLAM processing is carried out using an Nvidia Jetson Nano Mini PC with a 1.45 GHz Nvidia Tegra processor and a 128-core GPU. Hardware connections are shown in Figure 3.

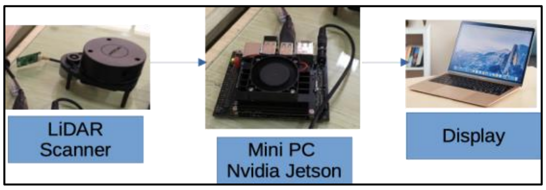
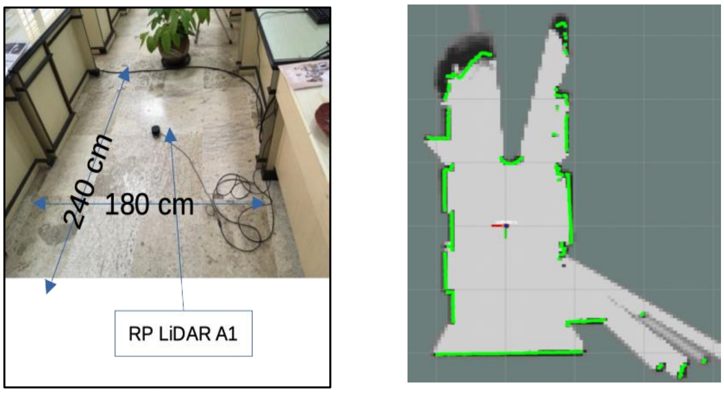


Figure 3. Test-bed rig

To estimate the robot's pose and create environmental maps in autonomous navigation, dead reckoning and SLAM are frequently employed techniques. SLAM combines sensor data to track the robot's location and produce a consistent map of an unfamiliar environment. On the other hand, dead reckoning estimates displacement over time using incremental motion data, usually obtained from inertial sensors or wheel encoders. Dead reckoning is vulnerable to cumulative drift, despite SLAM's superior global consistency. To prevent duplication and guarantee clarity, the current study compiles the theoretical underpinnings of these methods into a single, dedicated section, concentrating later references on their particular application or relative influence on the experimental results.

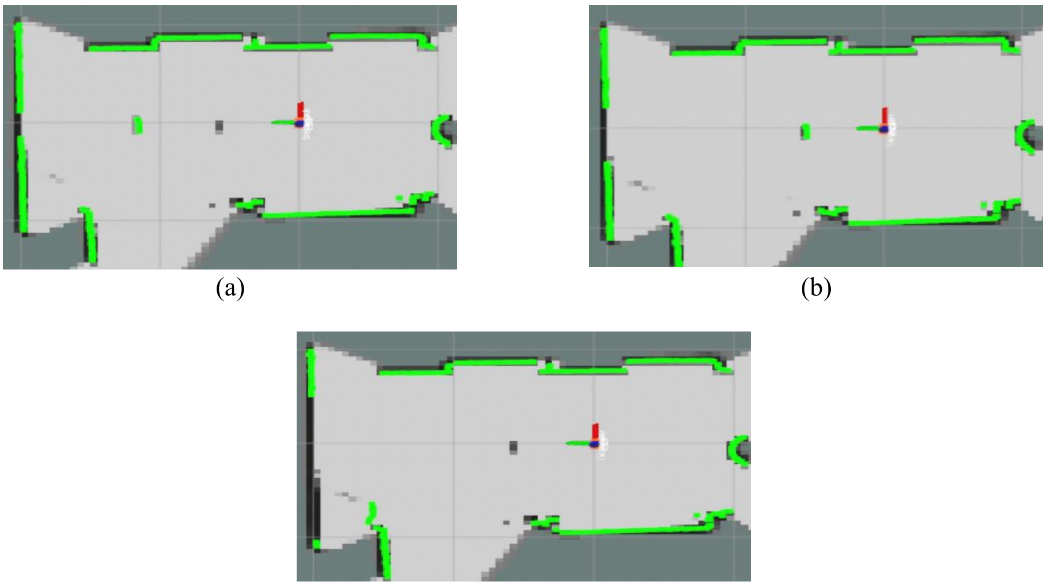
3.1. Mapping accuracy

Figure 4 shows the space for testing and mapping results using the SLAM Cartographer. Figure 4(a) shows the SLAM test, and Figure 4(b) shows that the results of the mapping are in accordance with the test room, where the black dots are the obstacle or wall hypotheses that has been determined by the SLAM algorithm as an obstacle, while the green dot is LiDAR RP data displayed on the map. The map in Figure 5 is a 2D horizontal LiDAR measurement result map, so the displayed map is 2D. Furthermore, the green dots indicate the LiDAR return points (RP) data, which is superimposed on the created map. These points act as real-time localization markers, indicating where the LiDAR sensor identifies things relative to its location [20]. The congruence of the mapped barriers with the physical test environment demonstrates the SLAM process's ability to recognize spatial elements accurately [21].



(a) (b)

Figure 4. Testing and mapping results of (a) SLAM test and (b) SLAM cartographer



(a) (b)

(c)

Figure 5. Placing object test result of the objects in (a) 90 cm, (b) 60 cm, and (c) 30 cm

Furthermore, the map in Figure 5 shows the results of 2D horizontal LiDAR readings. Because the LiDAR system operates on a horizontal plane, the resulting map is purely two-dimensional, providing a flat, top-down picture of the scanned area. This 2D mapping is important for navigation and localization in robotics applications, but it does not retain vertical information such as height differences. Figures 5(a), 5(b), and 5(c) show the results of the test by placing objects at a distance of 90 cm, 60 cm, and 30 cm, respectively. This test was carried out because the specifications for RP LiDAR A1 include a maximum range of 12 meters, but do not show a minimum range. The test results show that RP LiDAR A1 can detect objects that are > 30 cm away, as shown in Figures 5(a) and 5(b). RP LiDAR A1 is unable to detect objects that are less than 30 cm, as shown in Figure 5(c).

3.2. Positioning/localization error

The placement or localization test is carried out by moving the LiDAR sensor to various points distant from its starting location. The major goal of this test is to determine the accuracy of LiDAR in tracking displacement, which is critical for its use in navigation applications [22]. The test checks whether the LiDAR detects and records location changes consistently by measuring its positional shift. To provide a thorough evaluation, three forms of displacement are tested: movement along the x-axis, movement along the y-axis, and movement along a diagonal path (simultaneous displacement along both the x and y axes). These diverse displacement situations aid in determining the consistency and precision of the LiDAR system across multiple movement directions.

The accuracy and dependability of LiDAR-based localization under various movement conditions are assessed in controlled experiments shown in Figures 6 to 8. Figure 6 confirms the high horizontal resolution and sensitivity of the LiDAR by showing the robot moving along the x-axis, with a trajectory that closely resembles the reference path. Figure 7, which focuses on y-axis movement, shows similarly accurate tracking with little drift, indicating balanced performance in both vertical and horizontal directions. This is crucial for tasks like navigating a corridor. In Figure 8, diagonal motion, where both x and y components are combined, is examined. A smooth trajectory that closely resembles the intended course is the result, demonstrating how well the LiDAR manages coupled directional movement with little error accumulation. Collectively, these tests confirm LiDAR's accuracy and reliability in linear and combined motions, bolstering its applicability as a key sensor for autonomous navigation and real-time SLAM [23].

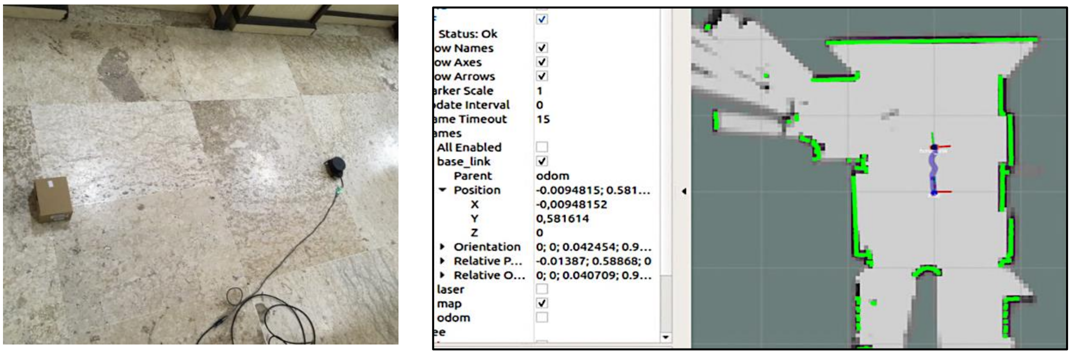


Figure 6. Trajectory tracking with the X axis moves

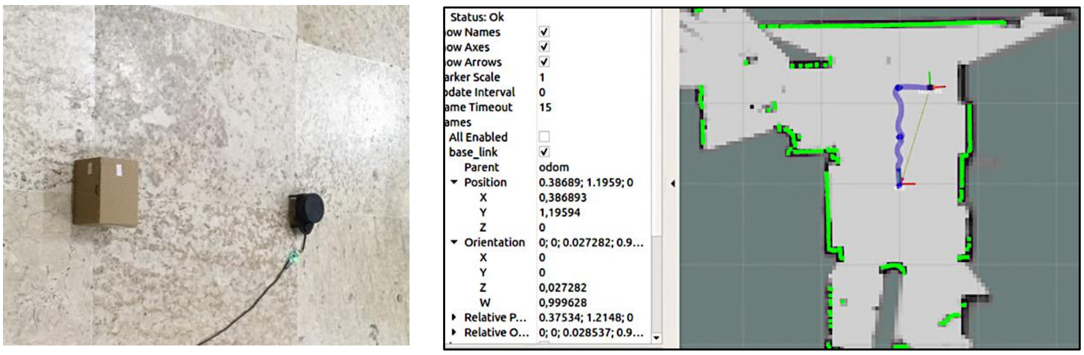


Figure 7. Trajectory tracking with the Y axis moves

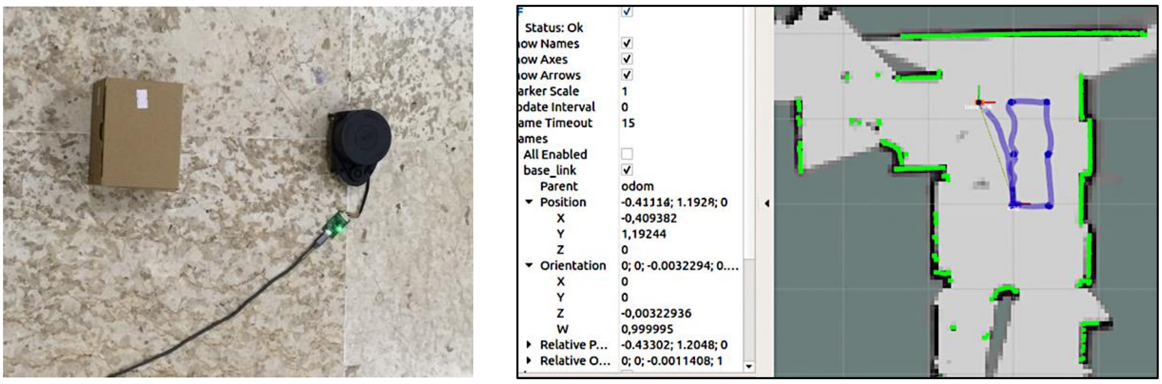


Figure 8. Trajectory tracking with the X and Y axis move

Table 1 shows the accuracy performance of the SLAM Cartographer system using RP-LiDAR. The findings show that the system has an average accuracy of 1.4 cm, with the highest accuracy recorded at 0.26 cm and the largest observed inaccuracy at 3.16 cm. These results indicate that the SLAM method, when paired with LiDAR, may provide accurate localization data with a minimal margin of error. The lowest accuracy was obtained during y-axis displacement, especially when the LiDAR moved from y = 60 cm to y = 120 cm while keeping a constant x position. The accuracy in this scenario dropped, with the highest error value reaching 2.77 cm while going in the opposite direction (from y = 120 cm to y = 60 cm).

These data show that positional accuracy is marginally less dependable in vertical movements than in horizontal or diagonal motions [24]. Despite the variances in precision, the results are still well within acceptable bounds for indoor positioning applications. In situations with localization tolerances of 3 to 5 cm, the SLAM Cartographer system with RP-LiDAR provides enough precision for navigation and mapping applications. This shows that it has practical uses in robotic navigation, autonomous vehicle localization, and indoor mapping [25].

Table 1. Results of X and Y localization

No	Real Position (cm)		SLAM cartographer (cm)		Error (cm)	
	x	y	x	y	x	y
1	0	0	1.7	0.2	1.7	0.2
2	0	60	0.948	58.16	0.948	1.84
3	0	120	3.16	119.66	3.16	0.34
4	40	120	38.68	119.59	1.42	0.41
5	40	60	39.58	57.23	0.42	2.77
6	40	0	40.26	2.61	0.26	2.61
7	-40	120	-40.93	119.24	0.93	0.76
8	-40	0	40.14	2.35	0.14	2.35
				Mean error	1.12	1.41
				Mean square error	0.401	

4. CONCLUSION

The Google cartographer SLAM algorithm has been successfully implemented in this study for real-time mapping and localization in an AWMR. By combining wheel odometry and LiDAR sensor data within a SLAM framework, the main goal—accurate positioning and environmental mapping—was accomplished. Systematic experimentation has confirmed that the cartographer can both localize the robot and create a consistent map of the surrounding area. The outcomes demonstrate that Cartographer SLAM provides high-precision localization, allowing the robot to function efficiently in indoor settings. Even when moving continuously along linear, rotational, and diagonal paths, the algorithm retains spatial accuracy with little drift. The system's ability to adjust to dynamic changes and maintain accurate state estimation in real time is ascribed to the effective fusion of odometry and laser scan data. Moreover, the tests verify that the system can manage intricate navigational tasks without the need for external positioning tools like GPS. Applications involving indoor robotics, like service robotics, warehouse automation, and search-and-rescue situations, benefit greatly from this autonomy. In addition to being a scalable and well-established solution for facilitating autonomous mobility, the study emphasizes that SLAM Cartographer can be used as a basis for future advancements in autonomous decision-making, multi-robot coordination, and semantic mapping.

Although the results obtained in this study are promising, there is still room for further improvement. Future research can focus on enhancing the system's robustness in dynamic environments, investigating alternative sensor configurations, and exploring ways to optimize computational resources for real-time implementation. In this study, it was found that improvements were still needed regarding localization using LiDAR, using an orientation sensor to obtain position and orientation precision.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Novendra Setyawan	✓	✓	✓	✓					✓		✓			
Amrul Faruq					✓		✓	✓		✓	✓		✓	
Muhammad Irfan								✓				✓	✓	✓
Nur Kasan								✓		✓		✓		
Fitri Yakub					✓					✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

The data will be made available on request.

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