

# Simultaneous Localization and Mapping for Mobile Robot Using a Single 2D LiDAR Sensor

Herlina Abdul Rahim<sup>1\*</sup>, Kevin Hugh O'Keeffe<sup>1</sup>, Nur Athirah Syafiqah Noramli<sup>2</sup>, Indrabayu<sup>3</sup>, Aisyah Mohd Akram<sup>4</sup>

<sup>1\*</sup>Department of Control and Mechatronics Engineering, Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310 Skudai, Johor, Malaysia

<sup>2</sup>School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia

<sup>3</sup>Department of Informatics, Faculty of Engineering, Hasanuddin University, Makassar, Indonesia

<sup>4</sup>Regional Development & Strategy, Siemens Energy, Cyberjaya, Selangor

Corresponding author\* email: herlina@utm.my

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## ABSTRACT

This paper presents the development and validation of a cost-effective mobile robotic platform that performs Simultaneous Localization and Mapping (SLAM) using a single 2D Light Detection and Ranging (LiDAR) sensor. While traditional SLAM systems often rely on expensive 3D LiDAR or computationally intensive visual sensors, this study proposes a novel approach combining a 2D LiDAR mounted on a servo-controlled gimbal to emulate 3D scanning capabilities. The Robot Operating System (ROS) is employed for modular development, integrating packages such as Gmapping for mapping and the Navigation Stack for autonomous movement. The platform features an omnidirectional base to enhance maneuverability. All experiments are conducted in the STDR simulator, providing a realistic environment to assess SLAM and navigation capabilities. Results demonstrate accurate map generation, reliable path planning via the Time Elastic Band (TEB) planner, and consistent obstacle avoidance. The findings validate the feasibility of using cost-effective hardware for advanced robotic functions, promoting broader adoption in industrial and research domains.

**Keywords:** SLAM, 2D LiDAR, mobile robot, mapping, navigation, servo-controlled gimbal

## 1. Introduction

Industry 4.0 marks a paradigm shift in manufacturing and logistics, with automation technologies playing a crucial role in streamlining operations. Autonomous mobile robots (AMRs) are instrumental in fulfilling this vision by autonomously navigating and transporting goods within dynamic environments. Historically, navigation systems have relied on line-following techniques or embedded physical markers. However, these methods are inflexible, requiring physical modifications to the environment and limiting reusability across different layouts.

Simultaneous Localization and Mapping (SLAM) is a technique that enables a robot to construct or update a map of an unknown environment while simultaneously keeping track of its own location within that map. Among SLAM solutions, LiDAR-based methods offer an effective balance between precision and computational efficiency. However, 3D LiDAR sensors, though accurate, are expensive and energy-intensive. This study introduces a low-cost SLAM implementation using a 2D LiDAR sensor mounted on a gimbal to emulate vertical scanning, combined with ROS-based tools to achieve comprehensive mapping and navigation.

For every type of approach in localization and navigation, there will be bound to be some issues. The widely used line-following method has numerous issues as well. One of the main problems faced when using line-following is that it requires the presence of fixed physical paths either in the form of magnetic tapes or electrical wires. The requirement of a physical paths results in the need to invest both time and resources into the installation of these paths. The installation for these paths might even disrupt the workflow or production of any given site causing the work efficiency to decline as well as money loss. Aside from that, these physical paths are also susceptible to physical damage and environmental influence resulting in the necessity for maintenance and this brings about similar disadvantages as the installation.

Sonar navigation is widely used in underwater localization but when it comes to mobile robot localization on land, there are several disadvantages. These disadvantages include [1],

- (a) slow scanning speed compared to using optical sensors as sound travels slower than light
- (b) unreliable when it comes to sensing smooth-surfaced objects as the scanned objects will be concealed from its detection

- (c) objects that are not present might also be detected with the presence of multiple reflections and beam side-lobes
- (d) inconsistency might be seen during the duration of echo travelling which will cause small variations in the sonar map.

As for localization using radar, it comes with low resolution and relatively easy to be affected by optical effects. Hence, using radar for positioning on a mobile robot is not recommended [2]. Using IMU and encoders data with the help of a well written algorithm can produce accurate and precise positioning but lacks the ability to detect surrounding objects or obstacles. Without the functionality of obstacle detection, the robot will not be able to be fully autonomous in a production line filled with personnel and will prove to be unsafe.

Among all the mentioned methods, Visual SLAM and LiDAR SLAM are the two most frequently used approaches for SLAM applications. Visual SLAM which uses RGB-D camera, a camera that produces images along with depth information, as feedback is more challenging compared to LiDAR SLAM as images contains excessive data and will be troublesome to compute [3]. As for using LiDAR SLAM, there are two approaches that may be taken which are using 3D LiDAR or 2D LiDAR. The feedback obtained from 3D LiDAR is with high accuracy and precision which will be easily utilized to reconstruct a 3D map of the surroundings but with some drawbacks. 3D LiDAR is very costly [4] and since autonomous service robots are price-sensitive, high cost sensors are not favorable [5].

Since low cost sensors are high in demand in the implementation of autonomous robots, 2D LiDAR will be the proposed approach in this paper. The drawback of using a 2D LiDAR is its lack of ability in producing 3D volume data due to being only able to undergo scanning on single horizontal line [4]. This weakness can be overcome with the installation of a gimbal that can determine the pan and tilt of the 2D LiDAR sensor [6].

## 2. Literature Review

To implement an autonomous mobile mapping robot, there will be 3 key roles that will be needed to be fulfilled. The three key roles include: the Simultaneous Localization and Mapping (SLAM) which will provide the robot with the ability to detect obstacles and determine its position while moving, a 3D mapping algorithm to reconstruct a 3D model of the surroundings using sensor data as input, and a navigation algorithm that will allow the robot to move around while avoiding any instantaneous obstacles automatically [6].

Autonomous mobile service robots cannot be without two vital functions which are localization and navigation. A required basis that is known to be a must for this is SLAM. The concept of SLAM is to allow a robot to be aware of its surroundings by using sensors equipped on it while also reconstructing a map of the area and estimating its location and orientation. Two most common approaches taken for practical usages will be LiDAR-SLAM and Visual-SLAM [7]. Regarding mobile robot navigation and localization that utilizes laser-based sensors, 2D LiDAR is one of the conventional choices despite having the drawback of lacking the ability to perform multi line scanning. Using a 3D LiDAR sensor will resolve this issue but also bring about another as 3D LiDAR sensors are costly. Sensor fusion is an effective solution that will overcome the 2D LiDAR's weakness by having the 3D depth point cloud from PCL to act as a secondary source for detecting obstacles.

### 2.1 A Single 2D LiDAR

LiDAR can detect obstacles and its distance from the sensor, and for grid maps construction, there is no better sensor to use. [4] A grid map is representation of structures and obstacles on a plane of robot motion. In the early stages of SLAM, LiDAR was the mostly used sensor. Extended Kalman Filter (EKF) was utilized to approximate the robot pose and it resulted in a less than ideal performance. In certain cases regarding strong nonlinear systems, this approach will bring about more truncation errors, which may cause inaccuracy in positioning and mapping. Aside from EKF, particle filter methods were introduced as they have no issues with non-linear problems, but it has the drawback of increment in the amount of calculation based on the increment of particle number. Next, Gmapping was developed based on improved Rao-Blackwellized particle filter (RBPF). This method shows an increase in accuracy for positioning and a decrease the computational complexity by improving the proposed distribution and adaptive re-sampling technique.

Optimization-based methods have become popular as the alternative for probabilistic methods. Karto-SLAM is an optimization-based approach that applies sparse pose adjustment to overcome the issue of matrix direct solution in non-linear optimization. Aside from that, Hector-SLAM introduces the use of Gauss-Newton method to tackle the scanning matching problem. The benefit of using this method is that odometer information is not necessary but high precision LiDAR is needed and they are costly. Since 2006, a Google-developed solution known as Cartographer was introduced. [4] The Cartographer applies laser loop closing to both sub-maps and the global map resulting in a reduction in accumulative error. The Cartographer is used [4],[6]. There are multiple possible sensor configuration that can be used to implement a 2D SLAM and 3D mapping mobile robot. A large percentage of sensor configurations uses two sensors: one for 2D SLAM and another to gather 3D data. A 2D plane of data can be translated into a 3D volume of data with the correct rotations and translation of the LiDAR. Hence, a servo-controlled gimbal can be used as the actuator to adjust the pan and tilt of the LiDAR sensor [6]. For mobile robot, LiDAR SLAM is the choice as grid maps are ready for path-planning and motion control [5].

## 2.2 2D LiDAR and RGB-D Camera Fusion

In recent years, laser-vision fusion, which is the integration of both LiDAR SLAM and Visual-SLAM, has become a hot topic regarding SLAM. This is because it can produce a more robust result for practical applications [5]. The issue with using a 2D LiDAR sensor is that it lacks the ability to perform multi line scanning while 3D LiDAR can do so, it is too costly. Hence, an alternative solution will be to use an RGB-D camera which contains depth data. These data will then be handled using OpenNI and Point Cloud Library (PCL). The 3D depth point cloud from PCL will be utilized to overcome the weakness of the 2D LiDAR [4]. 2D LiDAR and RGB-D camera fusion shows better performance as compared to using only a single 2D LiDAR in terms of obstacles detection. The 2D LiDAR will only be able to detect obstacles that are detectable at the height of the horizontal scanning line of the LiDAR whereas with the additional information obtained from the RGB-D camera, it is possible to detect obstacles within the limitations of the camera view. Despite performing better than LiDAR-SLAM, the strain from the extra complexity in computation for laser-vision fusion has cut down the working time of the robot [4].

## 2.3 Visual-SLAM

A known popular method for environment map building for robot navigation is Visual-SLAM. Putting Visual-SLAM and LiDAR-SLAM side-by-side, Visual-SLAM would be the more complex approach as images carry excessive and have difficulties in computing distance. Robot motion estimation by matching taken image features with different position and orientation to create a map is a widely used method for Visual-SLAM.

Many Visual-SLAM are considered to originate from Mono-SLAM which was proposed during 2007. Tracing of sparse feature points in the front-end is done by back-end utilizing the EKF. A probability density function is used to express the uncertainty. The deviation and average of the posterior probability distribution can be obtained from the observation model and recursive calculation. RBPF was also used to implement Visual-SLAM. This approach overcomes the non-linear issue with high precision but has high computational complexity as it demands a large quantity of particles. Parallel Tracking and Mapping (PTAM) proposed an easy and efficient method which is the extraction of key frames, parallel framework of a real-time tracking thread and a non-linear optimization mapping thread. The first separation of front-end and back-end concept to be introduced, the basis of many SLAM methods' structural design.

ORB-SLAM which uses Oriented Fast and Rotated BRIEF (ORB) features and bag-of-words (BOW) model produce feature maps of the surroundings in real-time for numerous cases. An amazing contribution of this method is the loop detection and closing done by BOW. It avoids cumulative error and can be retrieved with ease when the tracking is lost.

Among the many Visual-SLAM approaches, some were direct methods which estimates the motion of robot using pixel value directly. Dense image alignment according to each pixel from images can create a simple 3D map of the surroundings. A semi-dense map can be constructed by approximating the depth values of pixels in an image that has a large gradient. Semi-Direct Monocular Visual Odometry (SVO) is a combination of feature points and direct methods to locate key points such as corners and then undergoes camera position and motion approximation based on data regarding the key points.

For Visual-SLAM, the most reliable camera to be used will be the RGB-D camera which can capture color images with depth information. An example of a RGBD camera is Kinect. Hence, the Kinect fusion is introduced. It uses the depth images retrieved from Kinect to compute the minimum distance of each pixel in each frame, followed by fusing all the images to produce global map information. The position and orientation of the camera can be determined by minimizing the error function that is constructed using photo-metric and geometric data from image pixels. The issue of Visual-SLAM is that a large percentage of its approaches generate feature maps which are reliable for determining the position of the robot but is not recommended for path-planning. RGB-D cameras makes 3D scene mapping possible but is not recommended due to high cost in calculation or foundation [5]. RGB-DSLAM is to be avoided due to calculation time [4].

## 2.5 Comparison between SLAM Approaches

Table 1 shows the difference between the many SLAM approaches in terms of cost, mapping type, advantages, weakness and hardware used. Since autonomous navigation will play a major role in this project, the decision was made to use a single 2D LiDAR as the sensor. By using a 2D LiDAR sensor, a grid map, which is suitable for path-planning and navigation control [5], can be built. There is still the option of using 3D LiDAR sensor but it is very expensive and due to mobile service robots being price sensitive, the cheaper 2D LiDAR sensor will be the better choice.

**Table 1.** Comparison between SLAM Approaches

Approach	Single 2D LiDAR	3D LiDAR	Visual-SLAM	Laser and Vision Fusion
Cost	Cheap	Expensive	Moderate	Slightly above moderate
Map type	Grid map	3D mapping	Feature map	Grid map
Advantages	Good for path planning and navigation control	Does not require any additional sensors or mechanism to produce 3D volume of data	Can obtain extra data from images that LiDAR sensors are unable to retrieve	Cost effective, good for path-planning and navigation control without 2D LiDAR limitation
Weakness	Only produces a plane of 2D data but can be overcome with a servo-controlled gimbal	Expensive	Higher complexity	Reduces total working time of robot due to higher complexity for fusion
Hardware	2D LiDAR mounted on a servo-controlled gimbal	A single 3D LiDAR sensor	Single RGB-D camera	A 2D LiDAR sensor with a RGB-D camera

### 3. Methodology

#### 3.1 Hardware Architecture

The robotic system is composed of an omnidirectional base with four Mecanum wheels, allowing it to move in any direction without changing its orientation as shown in Figure 1. This base supports high maneuverability essential for navigating narrow and cluttered environments. The locomotion system is powered by DC motors controlled by H-bridge drivers, while wheel encoders provide feedback for velocity control.



**Figure 1.** An image of an actual omni wheel

The core sensing module is a TF-mini 2D LiDAR sensor, chosen for its compact size, reliability, and low cost. To compensate for the sensor's single-plane scanning limitation, it is mounted on a servo-controlled gimbal. The gimbal consists of two digital servos as shown in Figure 2, that provide pitch and yaw motion, allowing the system to scan vertically and horizontally. This mechanical augmentation simulates multi-plane scanning to collect richer spatial data.



**Figure 2.** SOLIDWORK drawing of the servo-controlled gimbal with TF-mini LiDAR sensor

### 3.2 Motion Control and Feedback System

Each motor is governed by a PID controller implemented in the embedded software. The PID controller continuously adjusts motor outputs based on error signals derived from velocity setpoints and encoder feedback. The formula used is:

$$PID = (K_p * e) + (K_i * e_{sum}) + (K_d * de) \quad (1)$$

where  $e$ : the error,  $e_{sum}$ : accumulated error,  $de$ : rate of change in rate and  $K_p$ ,  $K_i$ ,  $K_d$ : proportional, integral, and derivative gains respectively

These parameters are manually tuned through empirical testing. An MPU6050 IMU provides orientation data, enhancing the robot's ability to correct yaw deviations and maintain stability during turns.

### 3.3. Software Stack and Integration

The Robot Operating System (ROS) Melodic distribution is employed for system integration. Core packages include:

- (a) `slam_gmapping`: Implements Rao-Blackwellized Particle Filters for map creation.
- (b) `ROS Navigation Stack`: Provides autonomous goal-directed movement.
- (c) `TEB Local Planner`: Computes time-efficient trajectories accounting for velocity and acceleration constraints.
- (d) `rviz`: A 3D visualization tool to observe mapping and navigation performance.

Simulation is performed using the STDR Simulator, a 2D ROS-compatible platform capable of replicating real-world robotic motion and sensor feedback. This allows comprehensive testing prior to physical deployment.

### 3.4. Mapping and Navigation Workflow

Mapping is initiated with the robot exploring the virtual environment using a simple obstacle avoidance script. LiDAR scans are processed in real-time to build an occupancy grid map using Gmapping. The system stores probabilistic estimates of occupied and free spaces.

Navigation is executed by assigning a target pose in rviz. The Navigation Stack calculates a global path using Dijkstra's algorithm and refines it locally using the TEB planner. This planner accounts for obstacles in the local costmap, robot kinematics, and configured safety margins. The local costmap dynamically updates as new obstacles are detected.

## 4. Results and Discussion

### 4.1 Simulated Motion Accuracy

Initial tests involved navigating to static coordinates (1.5, 1.5) and (3.0, 0.0). Position tracking in Simulink confirmed that the PID controllers maintained precise control over motor velocities, achieving minimal steady-state error. Trajectories closely followed reference lines with minor deviations. The Figure 3 shows the omnidirectional base that was used in generating the real-time result where the position of robot and the velocity of each motor were recorded.

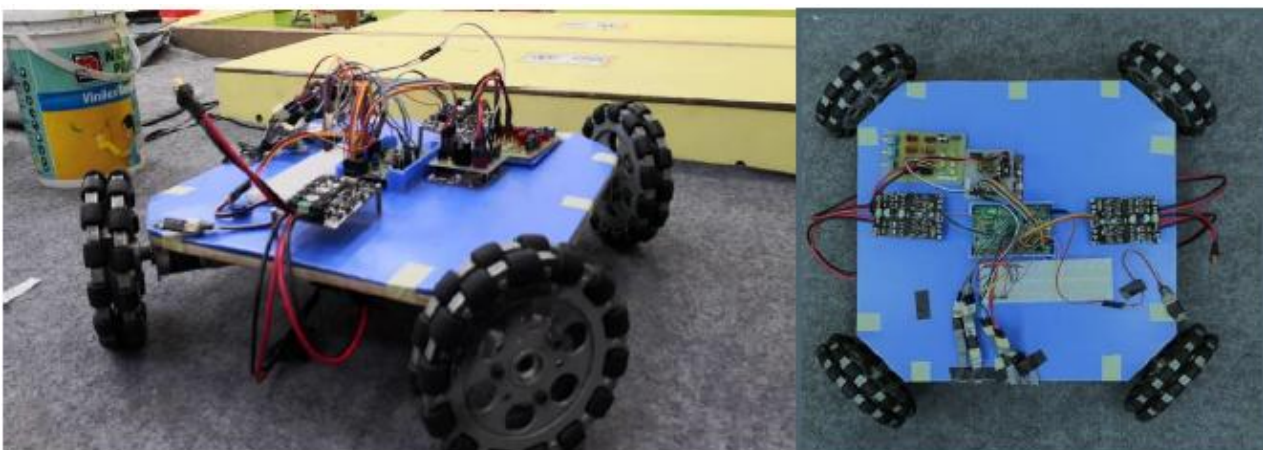


Figure 3. Actual image of the prototype robot

### 4.2 Speed Control and Response Characteristics

Motor velocity plots showed alignment between reference and actual speeds. The PID system effectively compensated for disturbances, particularly during directional changes. The omnidirectional base enabled smooth lateral transitions without needing to reorient the robot.

Figure 4 shows that the velocity control using a PID controller can be observed where the blue line is the reference velocity, and the orange line is the real-time velocity. It can be seen that the reference velocity of the motors is constant for a short time and decreases gradually as it approaches the desired position.

The front left motor and back right motor have higher contribution in the robot motion when traveling to the first destination indicating that the robot moves in a diagonal fashion, whereas when the base moves from the first destination to the second destination, the front right motor and back left motor have higher contribution in the robot motion. This observation can be used to conclude that the omnidirectional motion control algorithm used is working as intended.

All four motors are able to reach the reference value due to the control of PID system of motors. The value of PID control was tuned several times by using the method of try-and-error to get the correct value.

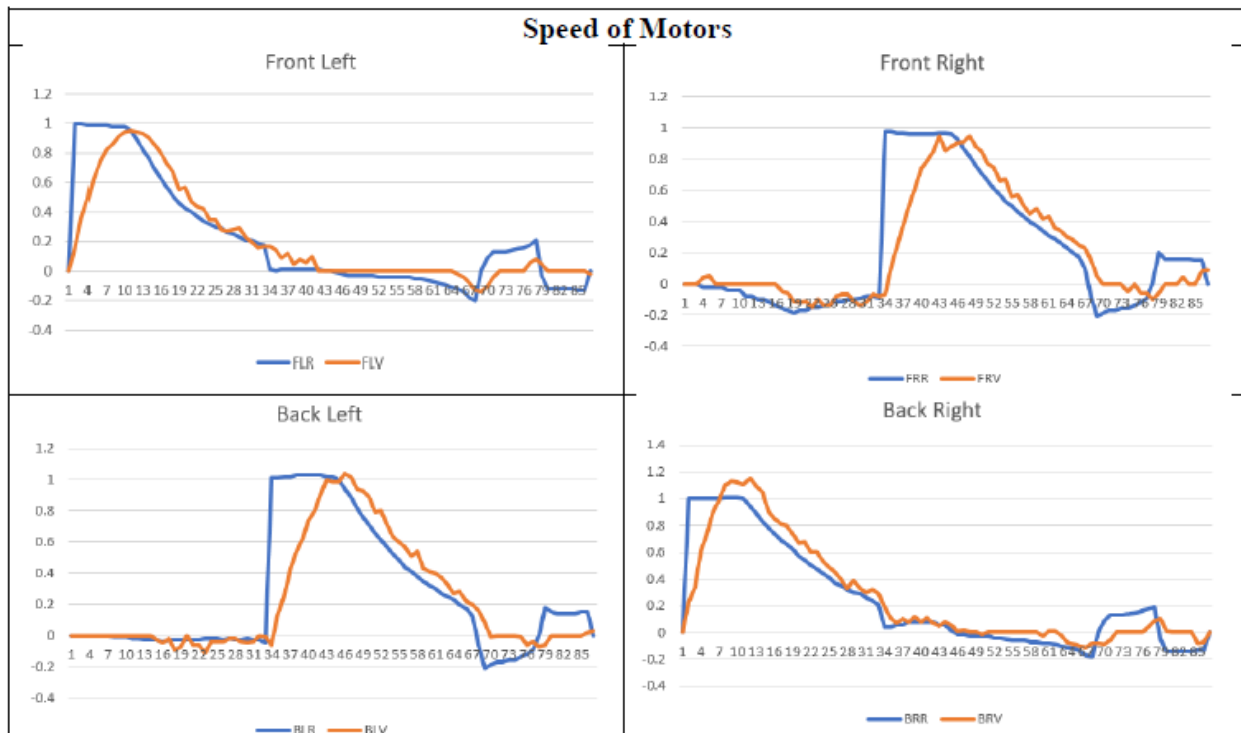


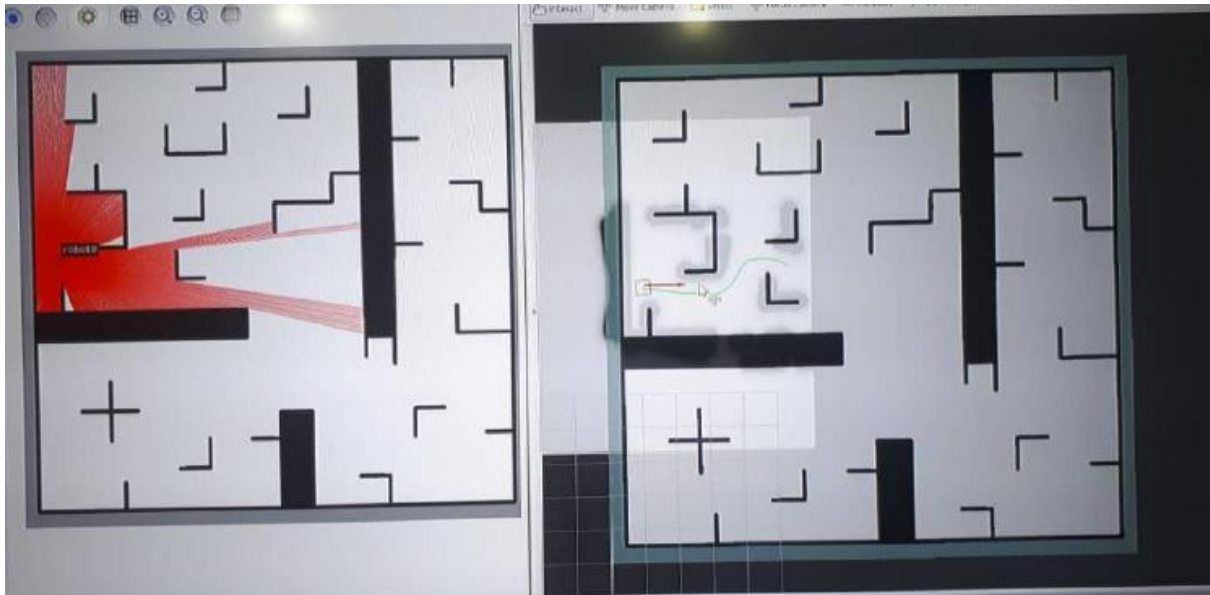
Figure 4. Real time velocity vs velocity reference of the four motors

### 4.3 Mapping Quality

As the robot explored the maze environment, LiDAR scans accumulated into a coherent grid map. Gmapping produced consistent wall structures with low localization drift. The resulting map revealed corridors and obstacles accurately, validating the gimbal's contribution to spatial coverage.

### 4.4 Goal-Based Navigation and Replanning

Goal points placed in rviz triggered the Navigation Stack to initiate path planning. The TEB planner dynamically adjusted trajectories in response to newly detected obstacles. For narrow passages, the robot initially pursued the shortest path but rerouted upon detecting insufficient clearance due to inflation radius. This behavior demonstrated the planner's adaptive capabilities. Figure 5 shows the robot in both STDR and rviz has successfully reached the second goal pose without any collision as the TEB planner has chosen the safest route.



**Figure 5.** Side by side comparison of the STDR simulator and rviz for second goal pose

#### 4.5 Overall System Performance

- (a) Mapping Accuracy: High fidelity with minimal distortion.
- (b) Navigation Robustness: Reliable goal reaching with dynamic replanning.
- (c) Control Precision: Effective PID response across all motors.
- (d) Cost Efficiency: Achieved SLAM functionality with budget hardware.

#### 5. Conclusion and Future Work

This research confirms the potential of a single 2D LiDAR mounted on a gimbal for reliable SLAM operations in indoor settings. By leveraging ROS tools and an omnidirectional base, the system achieves high accuracy in mapping and robust autonomous navigation at a fraction of the cost of 3D LiDAR solutions.

Future work includes transitioning to real-world implementation, optimizing the gimbal scanning strategy for better resolution, and integrating deep learning-based obstacle classification to enhance semantic mapping. Further efforts will also focus on multi-robot coordination for collaborative SLAM.

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