Development and Implementation of Autonomous Mobile Robots for Warehouse Applications

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***Abstract*—This paper presents the development of an autonomous mobile robot specifically designed for indoor warehouse applications, utilizing advanced Lidar laser sensor technology to detect and avoid obstacles efficiently. By implementing sophisticated navigation algorithms, the robot can autonomously traverse the warehouse environment, minimizing the need for human intervention. A key focus of this research is the creation of a mobile robot model that is not only highly functional but also cost-effective, making it accessible for organizations with budgetary constraints. The robot's capability to localize itself within the indoor environment and generate optimal paths to specified locations enhances its operational efficiency. This blend of cutting-edge sensor technology, intelligent algorithms, and economical design marks a significant step forward in the field of autonomous mobile robotics, particularly in Vietnam's warehouse automation scenarios.**

***Keywords*—autonomous mobile robots, warehouse applications, navigation algorithms**

I. INTRODUCTION

Mobile robots have numerous advantages, one of which is their computer vision skills. Mobile robots use a complex network of sensors to monitor their surroundings, allowing them to correctly observe their surroundings in real-time. This is valuable, especially in industrial settings that are constantly changing and shifting. Mobile robots are devices controlled by software and equipped with sensors to perceive their surroundings, enabling them to move autonomously. This field, a blend of robotics and information engineering, integrates artificial intelligence with physical robot components. There are primarily two types of mobile robots: autonomous robots, which navigate without external guidance and guided robots, which require a framework for navigation. Autonomous mobile robots can operate in uncontrolled environments without the need for physical or electromechanical guidance systems.

Early developments included the creation of autonomous robots like Elma and Elsie, which used light sensors to navigate toward light sources while avoiding obstacles [1]. Mobile robots like the Stanford Cart could navigate obstacles and map their surroundings. Sony's Aibo, a robotic dog, and Boston Dynamics' quadruped robot BigDog were notable milestones [1–2].

Domestic robots like Roomba and advanced robots capable of performing tasks in rugged terrains were presented [3–4]. The rise of e-commerce has accelerated the development of mobile robots, reducing reliance on guidance systems and expanding their use across logistics, service, commerce, and supply chains.

Mobile robots can be classified based on their operational environment, such as unmanned ground vehicles, unmanned aerial vehicles, autonomous underwater vehicles, and polar robots. They can also be categorized by their mobility mechanisms, including legged, wheeled, and tracked robots [5–7].

Despite their numerous advantages, autonomous mobile robots face several limitations. One significant constraint is the size of the load they can carry, which restricts their application in scenarios requiring heavy lifting. Additionally, achieving optimal performance often necessitates a large number of Stock Keeping Units (SKUs), which can be a logistical challenge [8–10]. Furthermore, maintaining reliable wireless connections between the robots and information endpoints remains problematic, leading to potential communication issues that can disrupt operations. These limitations highlight the ongoing need for advancements in technology and infrastructure to fully harness the potential of autonomous mobile robots [11–13].

Several recent studies have focused on improving the autonomous navigation and control performance of mobile robots. Yeom [14] developed a combined kinematic and dynamic controller for car-like mobile robots, emphasizing enhanced stability during autonomous driving. Lin *et al*. [15] proposed a deep learning-based indoor path planning approach, enabling mobile robots to

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navigate complex environments by learning optimal paths from data, which demonstrates the potential of machine learning techniques in mobile robot applications. Farag [16] investigated complex trajectory tracking using Proportional Integral Derivative (PID) control for autonomous vehicles, providing practical insights into achieving precise path following under real-world constraints. In recent years, reinforcement learning has been increasingly applied to enhance mobile robot navigation capabilities. Yeom [17] proposed a Deep Reinforcement Learning (DRL) based architecture for autonomous navigation in unknown environments, achieving collision-free path planning without external supervision. The success of DRL-based approaches in dynamic environments provides inspiration for developing more adaptive and intelligent navigation strategies, complementing the traditional trajectory tracking and obstacle avoidance methods.

Based on the above analysis, this paper presents autonomous mobile robotics, particularly in the context of indoor warehouse applications. Firstly, it applies advanced Lidar laser sensor technology to enable the mobile robot to detect and avoid obstacles, ensuring safe and efficient navigation. Secondly, it implements sophisticated algorithms that allow the mobile robot to autonomously navigate indoor environments, enhancing its operational autonomy. Thirdly, the research focuses on designing a mobile robot model that is both effective and cost-efficient, making it accessible to organizations with varying financial resources. Finally, the developed mobile robot is equipped with robust localization capabilities, allowing it to determine its position within an indoor environment and generate optimal paths to specified locations. These contributions collectively enhance the functionality, efficiency, and accessibility of autonomous mobile robots in warehouse settings.

II. Design and Calculation

A. Theoretical Calculation

The steering mechanism of mobile robots must be highly accurate and reliable, even when subjected to high-duty cycles. Additionally, these systems need to be rugged, economical, and easy to assemble, operate, and maintain. They must also meet specialized requirements for electric steering systems. Building on the design of a previously manufactured mobile robot, we have developed a system incorporating two castle wheels that can rotate 360 degrees with ease, enhancing the robot's maneuverability and adaptability in various operational environments (Fig. 1). This design ensures that the steering mechanism remains robust and efficient while maintaining simplicity and cost-effectiveness.

The load force which is needed for the motor can be calculated as:

$$F_w = F_{ms} + ma \tag{1}$$

where F_w is the loaded force produced by the moment of the motor. F_{ms} is the friction force between the wheel and the surface. m is the mass of the mobile robot and a is the acceleration. The torque needed to speed up can be estimated as:

$$T_w = F_w r \tag{2}$$

where T_w is the torque of the motor. r is the radius of the wheels. The required power of motor P_m can be estimated as:

$$P_m = F_w T_w \tag{3}$$

The length of the belt can be calculated as:

$$l = 2a + \frac{\pi(d_1+d_2)}{2} + \frac{(d_2-d_1)^2}{4a} \tag{4}$$

where a is the center distance. d_1 and d_2 are the diameters of the pulley.

Eqs. (1)–(4) are derived under the assumptions that the mobile robot moves on a flat and uniform surface, experiences pure rolling without slippage, and operates with constant friction conditions. Rapid angular accelerations and transient external disturbances are neglected to simplify the analysis. These assumptions facilitate the application of a standard unicycle kinematic model, which is suitable for typical warehouse environments but may limit accuracy in more dynamic or irregular scenarios.

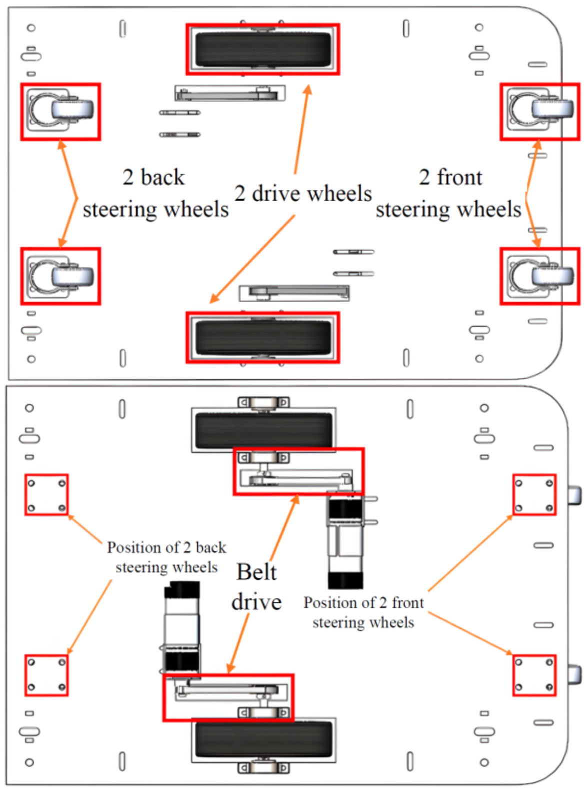

Fig. 1. Completed steering wheels and driving wheels mechanism.

B. Controller Design

The electronic design of the mobile robot is illustrated in Fig. 2, encompassing a sophisticated integration of various components to ensure seamless operation. This design includes the power supply, controller, and sensor system, all of which are crucial for executing the control and navigation algorithms that run on the hardware. The power system is divided into two main sources: a rechargeable battery that powers the modules, and a lithium battery that specifically powers the embedded board. This dual-battery setup ensures that the robot has a reliable and consistent power supply, which is critical for maintaining performance during extended operations.

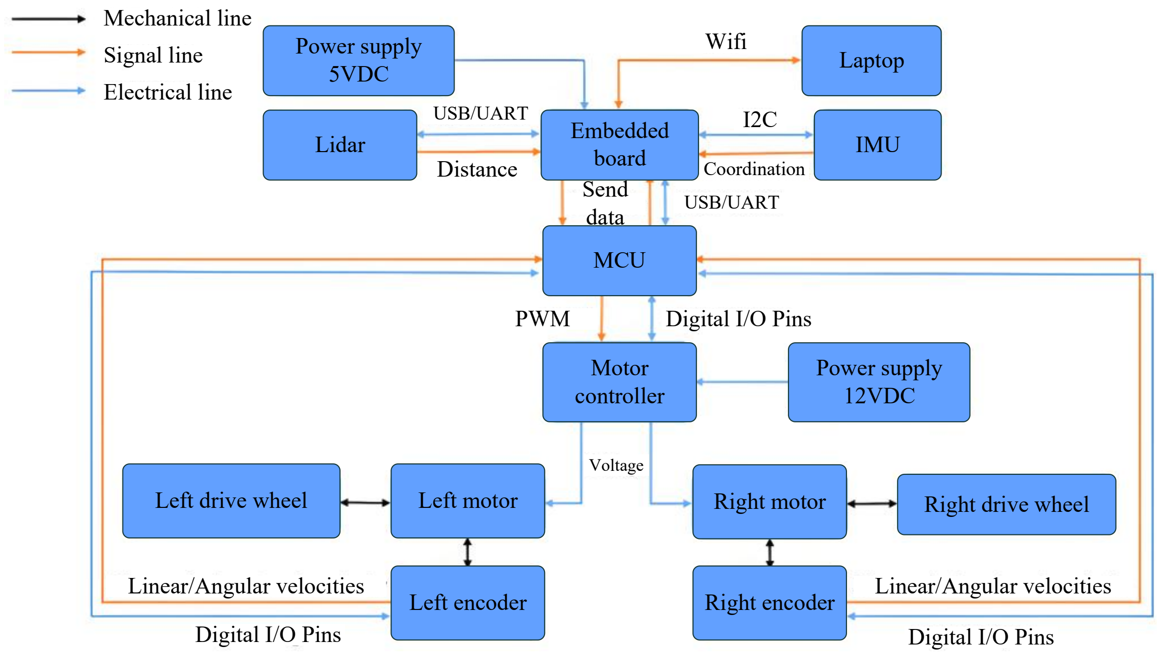

Fig. 2. Scheme of electronic design of the mobile robot.

For the control system, a laptop is utilized as a monitoring and control interface for the embedded board. This setup leverages a WiFi connection for communication between the laptop and the embedded board, eliminating the need for a separate screen and thus reducing complexity and cost. The communication between the embedded board and the microcontroller is managed through a serial connection using the Universal Asynchronous Receiver-Transmitter (UART)/ Universal Serial Bus (USB) protocol. This protocol is chosen for its reliability and efficiency in data transmission.

The microcontroller plays a pivotal role in the system, being responsible for controlling the two motors via a motor controller. This control is essential for the movement and maneuverability of the robot. The Lidar sensor data, which is crucial for obstacle detection and environment mapping, is sent directly to the embedded board. Concurrently, the parameters from two encoders, which are connected to the shafts of the two motors, are sent to the embedded board by the microcontroller. These encoders provide precise rotation data that is vital for accurate speed control and directional changes of the motors.

The embedded board uses the Lidar sensor data to create a detailed 2D map of the indoor environment. This map is then utilized to navigate the robot based on pre-programmed navigation algorithms. These algorithms enable the robot to move autonomously, avoiding obstacles and reaching designated locations efficiently. Additionally, the encoders help in pulse control, which regulates the speed and direction of the motors, ensuring smooth and precise movement.

Furthermore, the robot incorporates an Inertial Measurement Unit (IMU), which includes an accelerometer and a gyroscope. The IMU provides odometry data that is essential for tracking the robot's position and movement over time. This combination of sensors and control systems ensures that the robot can navigate complex environments accurately and reliably, making it a robust solution for various applications.

In summary, the electronic design of the mobile robot integrates multiple advanced technologies to create a reliable and efficient system. The use of a rechargeable and lithium battery setup, a laptop for control interface, microcontroller-driven motor control, direct Lidar data processing, encoder feedback, and IMU-based odometry collectively contributes to the robot's capability to perform autonomous navigation and obstacle avoidance in indoor environments.

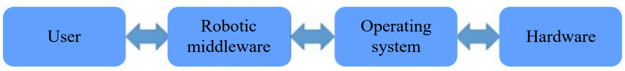

Fig. 3. Operator and hardware interaction.

From the above scheme of electronic design, a diagram representing the interaction between the operator and the mobile robot is provided (depicted in Fig. 3). During the operation process, the mobile robot cannot move immediately upon power-up; it requires commands from the user, which are sent to the embedded board from a laptop. The robot is configured with two operating modes: manual mode and automatic mode.

In manual mode, the robot is used for 2D mapping. A Lidar laser sensor collects obstacle data, which is sent to the Jetson Nano. The robot is then controlled to move around the indoor environment using a mobile app or keyboard to create a 2D map. Once the 2D map is created, it is saved for the robot model to use in navigation planning.

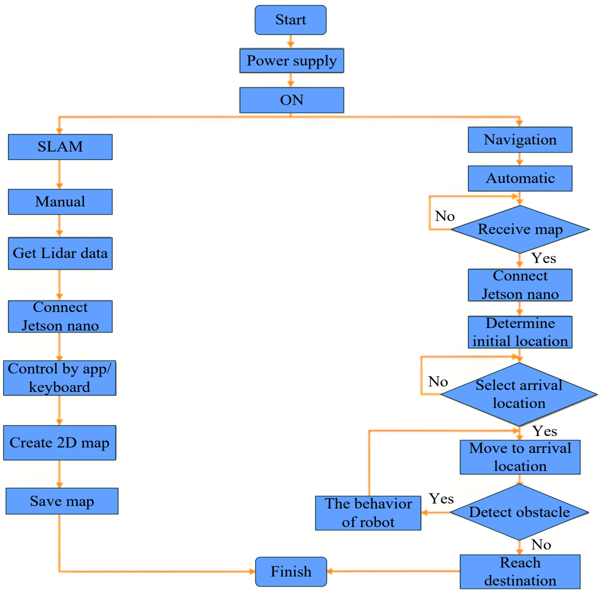

Fig. 4. Flowchart of mobile robot.

In automatic mode, the robot utilizes the 2D map for navigation. It receives the map and moves from its current location to the destination location indoors. After receiving navigation and run commands, the robot starts moving and continuously updates the map to find the shortest path. If an obstacle is detected, the robot replans and finds an alternative route to continue moving. Upon reaching the preset position, the robot stops and informs the control software that it has arrived (shown in Fig. 4).

III. Results

A. Experimental Mobile Robot

After thorough research and calculation, a robot was designed with dimensions of 605×450×209 mm (as in Fig. 5). The bottom plate, which bears the total weight of the robot and the goods, is made of SS400 steel. This material was chosen for its characteristics similar to C45 steel, which is widely used in mechanical applications.

Aluminum profiles with dimensions of 40×40 mm are used to construct the robot frame, allowing it to support a load weight of up to 40 kg. However, to avoid damaging the gearboxes of the two motors, a safe load weight of 20 kg to 30 kg is recommended. During the construction of the mobile robot's hardware, unexpected issues arose, such as the tolerance of manufactured components like the bottom plate or the two side plates. These tolerances caused misalignment between the screw holes and the aluminum profiles. Additionally, the caster wheels do not maintain a flat position, resulting in one of the four steering wheels not making contact with the surface. This misalignment causes the robot to deviate from a straight path, leading to unintended rotations before correcting itself to move straight again.

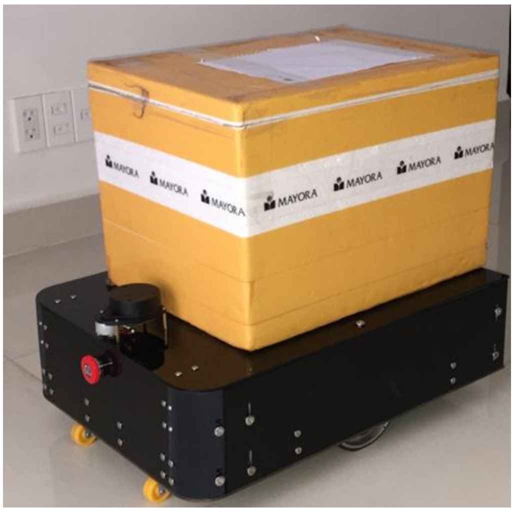

Fig. 5. Experimental mobile robot.

B. Navigation Experiment

The mobile robot was tested in an indoor environment simulating a warehouse, with an approximate area of 8 meters by 4 meters (Fig. 6). Obstacles included cardboard boxes, mock walls, and stationary barriers to replicate real-world warehouse challenges (Fig. 7). The robot was tasked with autonomously navigating to specified target locations while avoiding collisions and optimizing its travel path. The mobile robot was able to autonomously navigate to the intended location (Fig. 8), recognizing obstacles and creating new paths to avoid them (Fig. 9). However, the robot's operation is not entirely stable; it sometimes takes longer to reach the specified position, and the deviation from the target position remains quite high.

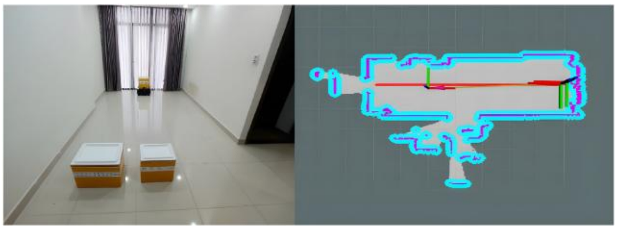

Fig. 6. Robot routed the shortest way to a specified location.

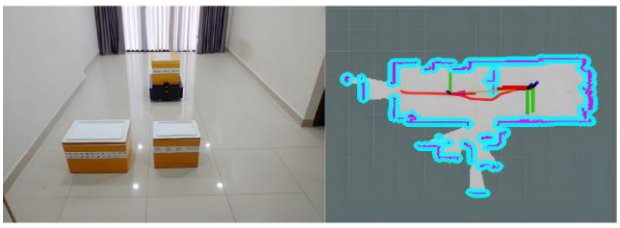

Fig. 7. Robot found a new way to avoid collision with the obstacle.

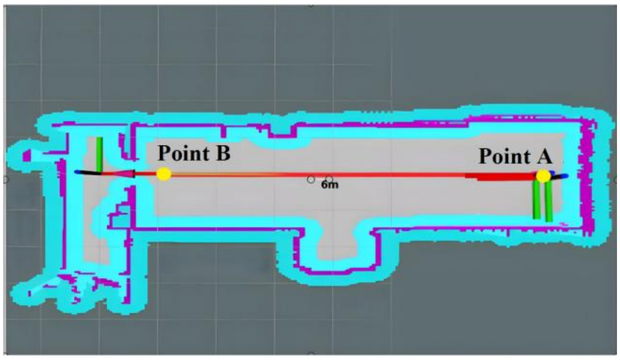

Fig. 8. Robot was at the beginning of the journey.

In the first experiment, the robot moved from point A to point B and back to point A with loads of 0 kg, 10 kg, and 22 kg, respectively. Ten measurements were taken to determine the time required for the robot to complete the distance and to assess the position error relative to the initial starting position. The results obtained were then compared.

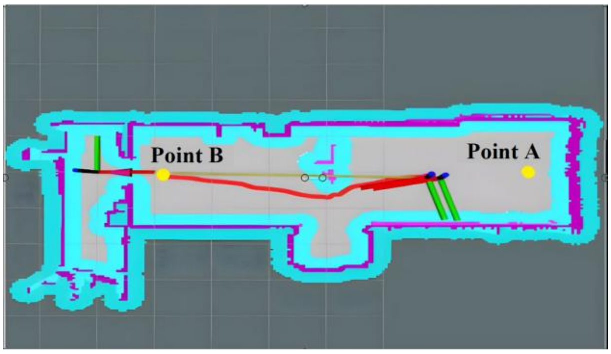

Fig. 9. Robot found another way to avoid collision with the obstacle.

C. *Actual Experiment Results*

1) *The first experiment without avoiding obstacles*

In the first experiment, after running the robot 10 times with each different load on the same path, it was observed that increasing the load resulted in a tendency for both deviation and time to complete the distance to increase (Tables I–III). At the highest load level of 22 kg, the motor's rotational speed was significantly reduced, causing the robot to stagnate. This increased the time required to complete the distance and resulted in a notable increase in position deviation under heavy loads.

TABLE I. ROBOT WITHOUT LOAD TO COMPLETE ITS MOVING PROCESS

Order	Road completion time (s)	Deviation in the X-axis (m)	Deviation in the Y-axis (m)	Deviation (m)
1	38	0.05	0.04	0.064
2	42	0.05	0.05	0.071
3	44	0.06	0.06	0.085
4	37	0.04	0.02	0.045
5	41	0.06	0.04	0.072
6	38	0.03	0.05	0.058
7	36	0.04	0.04	0.057
8	40	0.05	0.03	0.058
9	45	0.04	0.06	0.072
10	36	0.05	0.04	0.064
Average	39.70	0.047	0.043	0.065

TABLE II. ROBOT WITH A LOAD OF 10 KG TO COMPLETE ITS MOVING PROCESS

Order	Road completion time (s)	Deviation in the X-axis (m)	Deviation in the Y-axis (m)	Deviation (m)
1	44.5	0.04	0.03	0.050
2	45.4	0.06	0.04	0.072
3	46.3	0.04	0.07	0.081
4	45.7	0.08	0.05	0.094
5	47.5	0.02	0.06	0.063
6	46.2	0.03	0.03	0.042
7	46.9	0.05	0.05	0.071
8	47.3	0.04	0.05	0.064
9	43.5	0.05	0.03	0.058
10	44.9	0.06	0.04	0.072
Average	45.82	0.047	0.045	0.067

TABLE III. ROBOT WITH A LOAD OF 22 KG TO COMPLETE ITS MOVING PROCESS

Order	Road completion time (s)	Deviation in the X-axis (m)	Deviation in the Y-axis (m)	Deviation (m)
1	53.2	0.05	0.04	0.064
2	54.6	0.06	0.07	0.092
3	55	0.04	0.06	0.072
4	56.5	0.05	0.06	0.078
5	52.3	0.07	0.05	0.086
6	54.5	0.05	0.06	0.078
7	51.2	0.04	0.07	0.081
8	50.8	0.05	0.08	0.094
9	52.6	0.05	0.06	0.078
10	57.3	0.04	0.08	0.089
Average	53.80	0.050	0.063	0.081

Fig. 10 is a column chart comparing the results of the first experiment. The experimental results were statistically analyzed. The mean and Standard Deviation (SD) of the road completion time and the positional deviation under different load conditions were computed as follows:

Road Completion Time:

- No load (0 kg): Mean = 39.70 s, SD = 3.068 s
- Load of 10 kg: Mean = 45.82 s, SD = 1.213 s
- Load of 22 kg: Mean = 53.80 s, SD = 2.047 s

Positional Deviation:

- No load (0 kg): Mean = 0.0646 m, SD = 0.0105 m
- Load of 10 kg: Mean = 0.0667 m, SD = 0.0142 m
- Load of 22 kg: Mean = 0.0812 m, SD = 0.0088 m

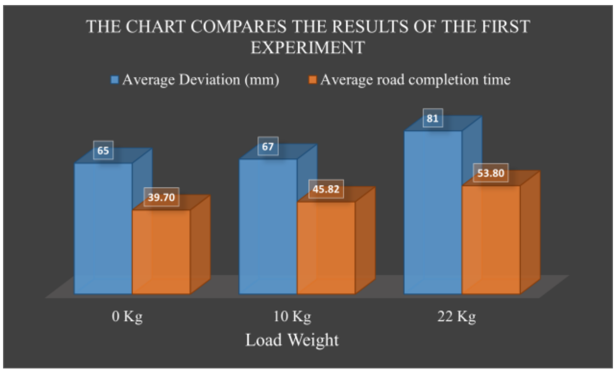

Fig. 10. Results of the first experiment in robot operation with different loads.

The relatively low standard deviations demonstrate that the robot's navigation was consistent and stable across repeated trials, particularly under no-load and moderate-load conditions. These statistical analyses provide a clearer and more quantitative assessment of the robot's autonomous navigation performance.

2) The second experiment with avoiding obstacles

In the second experiment, the robot was tasked with moving to a target position while avoiding simple obstacles with a load of 16 kg (Table IV). Experimentally, it was observed that the robot's obstacle avoidance capabilities functioned well; however, the stability was still lacking. The robot frequently stalled before overcoming obstacles, and the deviation from the target point remained quite high. In addition to the previous statistical analyses, we have also analyzed the second experiment where the robot was tasked with obstacle avoidance under a 16 kg load. The statistical results are summarized as follows:

Road Completion Time:

- Mean = 31.35 s
- Standard Deviation = 2.415 s

Positional Deviation:

- Mean = 0.0764 m
- Standard Deviation = 0.0134 m

These results confirm that even under dynamic obstacle-avoidance conditions, the robot maintained high stability and accuracy during its operation. The relatively low standard deviations demonstrate the consistency of the robot's autonomous behavior.

After the two experiments, it was demonstrated that the mobile robot model could move reasonably stably to the specified position and was capable of avoiding obstacles along its path. However, several disadvantages were revealed. The robot did not operate as stably as expected, with a high position deviation from the target. Additionally, it sometimes encountered issues such as loss of position and self-stopping errors. These problems likely stem from inadequacies in the motor control code, which significantly reduces the motor's rotational speed as the load increases, occasionally causing the robot to stop. Furthermore, when the load is too heavy, belt slippage occurs, which significantly increases the deviation from its intended position.

TABLE IV. ROBOT MOVED WHILE AVOIDING OBSTACLES AND A LOAD OF 16 KG

Order	Road completion time (s)	Deviation in the X-axis (m)	Deviation in the Y-axis (m)	Deviation (m)
1	30.5	0.08	0.05	0.094
2	34.6	0.06	0.04	0.072
3	29.2	0.09	0.03	0.095
4	35.1	0.05	0.04	0.064
5	28.3	0.04	0.06	0.072
6	27.6	0.05	0.03	0.058
7	31	0.03	0.05	0.058
8	31.7	0.07	0.06	0.092
9	33.4	0.06	0.05	0.078
10	32.1	0.07	0.04	0.081
Average	31.35	0.060	0.045	0.077

IV. CONCLUSION

The development of our mobile robot showcases significant advancements in autonomous navigation and obstacle avoidance within indoor environments. Utilizing a 2D map created with the Simultaneous Localization and Mapping (SLAM) algorithm and Lidar laser sensor data, the robot effectively plans and follows optimal routes to user-defined locations. The integration of algorithms from the Robot Operating System (ROS) navigation stack enhances its ability to dynamically reroute when encountering obstacles, ensuring safe and efficient travel. Despite its successes, the project highlighted several areas for improvement, particularly in mechanical design and system stability under computational load. Future enhancements aim to address these issues by refining the robot's navigation controls, improving wheel selection for better stability, and incorporating additional features such as automatic return to charging stations and advanced manipulation capabilities for handling goods. These improvements will broaden the robot's practical applications and reliability in real-world scenarios.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

TCD and TDD conceptualization and methodology; TCD wrote the manuscript; TDD writing, review and editing; and TDD supervised; TDD project administration; all authors had approved the final version.

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REFERENCES

[1] A. Loganathan and N. S. Ahmad, "A systematic review on recent advances in autonomous mobile robot navigation," *Eng. Sci. Technol., Int. J.*, vol. 40, 101343, 2023.

[2] G. Fragapane, R. De Koster, F. Sgarbossa, and J. O. Strandhagen, "Planning and control of autonomous mobile robots for intralogistics: Literature review and research agenda," *Eur. J. Oper. Res.*, vol. 294, no. 2, pp. 405–426, 2021.

[3] D. McNulty, A. Hennessy, M. Li, E. Armstrong, and K. M. Ryan, "A review of Li-ion batteries for autonomous mobile robots: Perspectives and outlook for the future," *J. Power Sources*, vol. 545, 231943, 2022.

[4] S. Cebollada, L. Payá, M. Flores, A. Peidró, and O. Reinoso, "A state-of-the-art review on mobile robotics tasks using artificial intelligence and visual data," *Expert Syst. Appl.*, vol. 167, 114195, 2021.

[5] J. Z. Nash, J. Bond, M. Case, I. McCarthy, R. Mowat, I. Pierce, and W. Teahan, "Tracking the fine scale movements of fish using autonomous maritime robotics: A systematic state of the art review," *Ocean Eng.*, vol. 229, 108650, 2021.

[6] H. Liu, W. Dong, Z. Zhang, C. Wang, R. Li, and Y. Gao, "Optimization-based local planner for a nonholonomic autonomous mobile robot in semi-structured environments," *Robot. Auton. Syst.*, vol. 171, 104565, 2024.
[7] M. Eyuboglu and G. Atali, "A novel collaborative path planning algorithm for 3-wheel omnidirectional autonomous mobile robot," *Robot. Auton. Syst.*, vol. 169, 104527, 2023.
[8] N. Promkaew, S. Thammawiset, P. Srisan, P. Sanitchon, T. Tummawai, and S. Sukpancharoen, "Development of metaheuristic algorithms for efficient path planning of autonomous mobile robots in indoor environments," *Results Eng.*, 102280, 2024.
[9] S. V. Manko, V. M. Lokhin, S. A. Diane, and A. S. Panin, "Autonomous mobile robot self-learning in motion planning problem," *Int. J. Mech. Eng. Robot. Res.*, vol. 4, no. 3, pp. 238–244, 2015.
[10] J. H. Teo, A. Loganathan, P. Goh, and N. S. Ahmad, "Autonomous mobile robot navigation via RFID signal strength sensing," *Int. J. Mech. Eng. Robot. Res.*, vol. 9, no. 8, pp. 1140–1144, 2020.
[11] Y. Yin, Z. Chen, G. Liu, J. Yin, and J. Guo, "Autonomous navigation of mobile robots in unknown environments using off-policy reinforcement learning with curriculum learning," *Expert Syst. Appl.*, vol. 247, 123202, 2024.
[12] S. Pecolt, A. Błażejewski, T. Królikowski, P. Z. Trzebiatowski, and B. Schulz, "Autonomous control of a mobile robot to explore areas with difficult terrain," *Procedia Comput. Sci.*, vol. 192, pp. 3467–3476, 2021.
[13] X. Zhang, Y. Huang, S. Wang, L. Jiang, G. Li, and Y. Xie, "Hierarchical autonomous switching control of a multi-modes omnidirectional mobile robot," *Mechatronics*, vol. 80, 102692, 2021.
[14] K. W. Yeom, "Kinematic and dynamic controller design for autonomous driving of car-like mobile robot," *Int. J. Mech. Eng. Robot. Res.*, 2018.
[15] Z. Lin, Y. J. Zhang, and Y. F. Li, "Path planning for indoor mobile robot based on deep learning," *Optik*, vol. 219, 165096, 2020.
[16] W. Farag, "Complex trajectory tracking using PID control for autonomous driving," *Int. J. ITS Res.*, vol. 18, pp. 356–366, 2020.
[17] K. Yeom, "Deep reinforcement learning based autonomous driving with collision free for mobile robots," *Int. J. Mech. Eng. Robot. Res.*, vol. 11, no. 5, pp. 338–344, 2022.