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Autonomous Mobile Robot Navigation in Healthcare Facilities using Simultaneous Localization and Mapping

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Abstract
Autonomous mobile robots (AMRs) have become really important in hospital environments. They can do hazardous tasks with less human help. By using these robots in hospitals we can improve things like tracking inventory handling waste delivering medicine and emergency communication. A new simulation model using the Robot Operating System (ROS) and Gazebo is proposed for indoor navigation of wheeled mobile robots. This model is a three-dimensional (3D) robot design with physical and sensor setups for real-world conditions. With LiDAR sensors Inertial Measurement Unit (IMU), path planning, obstacle avoidance and SLAM-based localization, safe and reliable autonomous navigation is achieved in indoor healthcare environments. The robot is designed in such a way that it operates collaboratively alongside humans while positional accuracy and navigation safety is maintained. Within structured indoor environments, real-time mapping, autonomous decision-making, localization, and trajectory planning are enabled by this ROS-based model. As a result of experimental simulation results, improved navigation stability, obstacle avoidance capability, and localization exactness is seen under different indoor conditions. Overall, the proposed simulation 3D model provides a scalable and cost-effective platform for future deployment of autonomous service robots in healthcare buildings and hospitals.

Keywords: Autonomous Mobile Robot, LiDAR, ROS, SLAM, indoor navigation, healthcare navigation, obstacle avoidance, and Raspberry Pi.

Introduction

In recent years, Autonomous Mobile Robots (AMRs) have become increasingly popular because of their flexibility and wide range of practical uses in modern society. The capacity of an independent versatile robot to explore an environment without any outside direction, such as physical or electro-mechanical direction expanded its potential. The early independent route frameworks utilized two-dimensional sensors, such as laser rangefinders, to explore without human intercession. For an independent portable to perform its errands, a huge number of natural sensors are required. These sensors are either joined to the robot or work as outside sensors. [1-2].

The rapid advancement of robotics, Artificial Intelligence (AI), and embedded systems has lead to intelligent robotic platforms which help humans in critical applications. Among the application areas, healthcare is the important one. As healthcare places like hospitals require more attention in patient assistance, waste transportation, medicine delivery, medical supplies, and emergency communication, time consumption and infection risk is seen in case of human deployment. In such cases, the use of AMR robot is recommended as it can reduce direct human interaction, improve safety, and operational efficacy [3-6].

But, several challenges prevail in indoor healthcare environments when it comes to autonomous navigation like dynamic medical staff, visitors, and equipments. So, it is essential that the autonomous robot should possess safe human-robot interaction, effective path planning, obstacle avoidance, and localization abilities. Numerous studies have explored the use of AMRs for automation and healthcare assistance. Yet, they focus primarily on isolated functionalities like monitoring, navigation, and delivery. Also, some of the frameworks are expensive hardware configurations, minimal adaptability issues, and lack localization abilities. So, there remains a need for cost-effective, scalable, and reliable autonomous navigation architecture for healthcare applications [7, 8].

As an attempt to fulfill this need, a 3D autonomous robot with Simultaneous Localization and Mapping (SLAM) techniques is proposed in this paper. SLAM mechanisms play a crucial role in helping robots to build maps of unknown environments and estimating their position in real-time instantly. The collaboration of LiDAR and Inertial Measurement Unit (IMU) results in environmental perception and navigation accuracy in indoor healthcare spaces.

To research work aims to accomplish the following objectives:

- To develop a realistic ROS-Gazebo simulation-based autonomous wheeled mobile robot with SLAM-based localization and mapping techniques.
- To integrate LiDAR and IMU sensors for accurate environmental perception and obstacle avoidance.
- To design an autonomous navigation robotic architecture for indoor healthcare facility operations.
- To evaluate the navigation and localization recital of the proposed robotic system under simulation conditions.

Remaining sections of the paper are organized as follows: Section II reviews various research works related to AMR and healthcare robotics applications. Proposed methodology, sensor integration techniques, and system architecture is described in section III. Section IV discusses the system implementation of the developed AMR-ROS simulation model. Whereas, section V outlines ROS-Gazebo simulation environment, experimental results, and implementation details. Finally, section VI concludes the paper with future research direction outline.

Literature Review

Numerous types of robots, including robots and nanorobots, are used in the healthcare industry for tasks such as diagnostics, inventory monitoring, waste management and hygiene. It is expected that the fourth industrial revolution (4IR) and related developments in manufacturing, referred to as Industry 4.0, will lead to smart factories that operate with little human supervision, autonomously manage products and supplies, and are characterized by increasing machine intelligence, where machines will work autonomously alongside humans [9].

Autonomous Mobile Robots in Healthcare Facilities

Given the biohazards associated with manual processes and the ongoing shortage of human labour, the demand for robotic recycling methods is increasing. Robotic waste sorting is crucial for recycling mixed industrial waste on the road to a modern, sustainable civilization [10]. The regular schedule of traditional waste disposal is quite ineffective and expensive. Due to improper recycling practices, the public has also realized the inefficiency of the current recycling package. Classification of waste is now faster and more accurate thanks to advances in deep learning and image processing techniques [11, 12]. Numerous unmanned systems, including unmanned boats, unmanned drones and unmanned vehicles, have made significant use of autonomous navigation technologies [13]. To ensure clarity and allow mission commands to be formatted and modified by human experts without programming skills, Prolog logic programming is utilized [14]. Many path planning algorithms for mobile robots assume the robot can gather all necessary environmental data, but in reality, robots often struggle to fully comprehend complex or crowded settings and cannot obtain complete information about their surroundings [15].

Rapid advances in nanorobotics have opened new possibilities for medical nanoscale robotics in particular [16].

Although professionals have no control over the position, orientation or functions of the capsule, capsule endoscopy is limited to passive monitoring of the gastrointestinal (GI) tract through optical imaging. Mobile medical milli- and micro robots could access intricate and limited areas of the human body as an alternative to currently used tethered medical instruments, such as flexible endoscopes and catheters [17]. Efficient management of hospital supplies through the use of swarm robots, reducing the risk of infection for medical staff. Using the Lora communication protocol, a connection was established that allowed them to transmit commands. The robot successfully used the indoor positioning system to find the location of the stationary garbage can [18, 19]. The researchers tackle the challenge of vehicle teleoperation by introducing a straightforward approach that delivers sensor data to users via mixed reality and visual elements integrated into the user interface. A system for structuring the presentation of information and a collection of visual aids in teleoperation control panels makes this possible [20]. Service robots are basically devices that can perform a variety of tasks. The researchers address the challenge of vehicle teleoperation by developing a straightforward technique that presents sensor information to users using mixed reality and visual supports embedded in the user interface [21].

The heart rate data suggest that a conversation between a robot and a patient can reduce stress. The results show that verbal interactions have a greater impact on trust than gestural ones [22]. Creating a medical aid solution that provides a variety of non-invasive diagnoses performed by an autonomous robot whose mobility can also be controlled manually via a mobile application or voice command [23, 24]. Real-time visual feedback on the outcomes of actions could be used in future safety-critical human-robot interactions, including remote patient examinations. The transfer of human capabilities to robots is a pressing concern for human-cyber robotic systems. The fundamental problem for a mobile medical rescue robot is how to safely transport patients or medical supplies, especially in confined spaces [25-27]. In hospitals, the robot must perform challenging tasks both indoors and outdoors, in addition to some extensive assembly work [28]. Using optical navigation, multi-arm robotic maxillofacial surgery is being introduced as an alternative to conventional manual surgery [29]. There are excellent applications for robotic orthopedic surgery, and the accuracy of the robot is critical to the success of the procedure [30, 31].It was noted that there is a need to support increasing workloads, including inventory monitoring, waste disposal, meal and medication delivery, and emergency communications, including patient emergency communications and medical staff emergency communications [32]. The safety rules for navigation must be followed by both humans and robots working in the same space [33].

Autonomous Mobile Robots for Waste Management in Healthcare Facilities

The transportation and handling of hospital waste is a time-consuming, hazardous and infectious process as staff come into contact with medical and biohazardous waste. The intelligent truck-mounted waste collection robot has a number of sensors and moves along a predetermined path. These robots are specially designed for the transportation of various goods [34]. The COVID-19 pandemic that began in 2019 led to a substantial increase in clinical waste generated by isolation units within hospitals and healthcare centres [35].This suggests that it is understood both in terms of the circumstances that produce it and the contexts to which it belongs. It also implies that waste must be understood in relation to consumption [36]. In circumstances where there is a high need for repetition and risk, automated control of giant industrial cranes is a more efficient option than using human operators [37]. A cost-effective approach to the issue of trajectory optimization and autonomous navigation for MR in field hospitals (FHs) [38].

The advancement of technology has created a complex environment that poses numerous health risks to individuals. The most dangerous and fast-spreading disease is dengue fever, which is spread by mosquitoes. The robotic system must be connected to a control station and be semi-autonomous in order to continuously analyze data [39]. Hospital wards generate waste, which is referred to as biomedical waste. There are different types of biomedical waste, including leftover drugs and cytotoxic drugs, anatomical waste, animal waste and waste from biology and biotechnology [40]. It collects the waste and stores it in its waste container [41]. The storage of highly radioactive waste in central interim storage facilities (CIS) is a process that precedes the permanent storage of waste in geological repositories [42, 43].

Research Gap

By reviewing the above research works, it can be seen that significant advancements are seen in healthcare robotics, SLAM techniques, autonomous navigation, and robotic waste management systems. Yet, main focus on individual functionalities like teleoperation, biomedical waste handling, and so on is only made [44]. Also, only limited research related to SLAM localization, autonomous indoor navigation, and LiDAR-assisted obstacle avoidance is carried out. finally, some of the techniques are hardware-expensive, limited adaptability in dynamic hospital environment, and lacks reliable real-time navigation.

Methodology

This research proposes a ROS-based AMR framework designed for indoor healthcare applications. This section details on modules used in the robotic model and other computation details. An autonomous mobile robot can be tailored in healthcare facilities and utilizes LiDAR technology and the computing capabilities of a Raspberry Pi. The robot is designed to operate autonomously in indoor environment while ensuring safe navigation in spaces shared with humans. Sensor fusion and ROS-based communication is employed to achieve reliable localization, mapping, and obstacle avoidance.

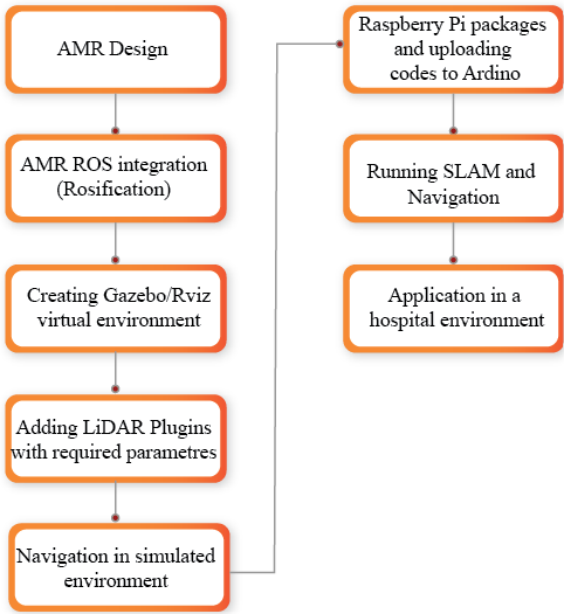


Fig. 1. Proposed ROS-based AMR development and navigation workflow

Figure 1 illustrates the overall AMR setup and integration workflow adopted in the study. The workflow begins with mechanical design of the AMR followed by ROS integration. Further, a Gazebo/Rviz virtual environmental configuration is created. Next, LiDAR plugins with required parameters are added. It is then followed by a sequence of operations like navigation testing in simulation, Raspberry Pi package configuration, code upload to Arduino, and running SLAM autonomous navigation algorithms. At last, the developed robot module is deployed within a healthcare environment premises. A detailed architecture of the proposed ROS-AMR system is given in Figure 2.

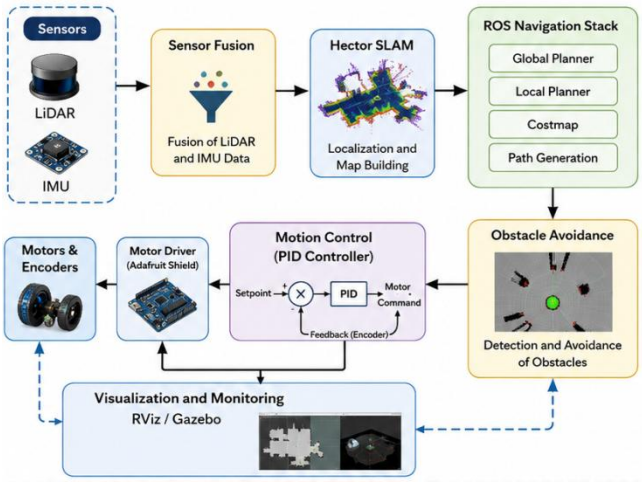


Fig. 2. Detailed architecture of the ROS-based AMR system

SLAM-based Navigation

Simultaneous Localization and Mapping is a technique that simultaneously estimates a robot's state—such as its position, orientation, velocity, and sensor calibration—and builds a map of its surrounding environment using data gathered from the robot's sensors [45-50]. The SLAM problem involves determining if an autonomous vehicle can begin in an unknown location within an unfamiliar environment, incrementally build a map of that environment, and use the map concurrently to estimate its own precise position [51]. Theoretical validation of SLAM's feasibility was demonstrated in , showing that the estimated map steadily converges toward an accurate relative map [52].Today, the SLAM technique plays a growing and crucial role in enabling indoor navigation for mobile robotic systems [53-55].

In this research, the Hector SLAM algorithm is selected as it has the ability to offer accurate localization without depending on wheel encoder odometry [56]. Similar to conventional laser-based SLAM techniques, Hector SLAM uses high-frequency LiDAR scan matching mechanism on occupancy grid maps directly. This makes the model suitable for indoor environments with limited computational resources.

The primary advantage of using Hector SLAM is that, unlike laser SLAM which struggles to accurately determine the mobile robot's position during scan matching, Hector SLAM effectively projects scan data onto a grid map for improved localization. SLAM involves three fundamental operations performed repeatedly as the robot moves to new viewpoints. However, unavoidable noise and errors during movement increase uncertainty in the robot's localization. Addressing this challenge requires a mathematical model to provide an automated solution.

The SLAM module comprises of three major stages:

1. Sensor data acquisition from LiDAR and IMU sensors.
2. Occupancy grid map generation and scan matching.
3. Robot pose estimation and autonomous navigation.

The generated occupancy grid map enables the robot in identifying free space, navigable pathways, and obstacles in real-time. This information is further utilized by the ROS navigation block for supporting path planning and obstacle avoidance during autonomous operation.

LiDAR

LiDAR is a widely used sensor in autonomous vehicles for tasks like navigation, mapping, environment sensing, and localization [57]. It produces 3D point cloud data, which is then processed through point cloud registration to build a detailed three-dimensional map of the surroundings.

The goal of point cloud registration is to bring different groups of points from various coordinate systems into alignment. By determining the precise transformation between the locations, the drift error in matching can be avoided.
By extracting the feature and comparing the current LiDAR frame to the cloud map and can produce the map [58].

A 2D LiDAR sensor uses laser technology to measure the distance to objects around it in a single horizontal plane [59].

LiDAR sensors work by sending out laser beams and calculating the time it takes for them to bounce back. This creates a 2D map of the environment. This technology is widely used in robotics, self-driving cars and industrial automation for mapping detecting obstacles and guiding navigation [60].

The LiDAR sensor in our mobile robot provides a 360-degree view of the environment. This helps the robot monitor obstacles and dynamic objects. The LiDAR data is processed in the Robot Operating System to support real-time SLAM, collision avoidance and autonomous navigation. Using a 2D LiDAR is a cost- solution for indoor healthcare environments where horizontal spatial perception is sufficient for navigation tasks.

The benefits of LiDAR sensors include coverage, quick data collection and excellent accuracy. Generally 2D LiDARs are less expensive. Have a simpler design than 3D LiDAR sensors. This makes them suitable for applications that only require spatial information [61, 62].

Map Gradient Computation

To estimate changes and improve scan alignment accuracy during robot movement the SLAM algorithm uses gradient computation. This leads to localization precision and more stable occupancy grid mapping. Algorithm 1 shows the map gradient computation process used during localization and scan matching.

Algorithm 1. Map Gradient Computation

Input: Sensor data (z_t), initial map (M), robot pose(x, y, θ), and Kalman Filter estimates.
Output: Map Gradient ∇M (P_m) at map point P_m.
Step 1: Acquire sensor measurements z_t from LiDAR and IMU.
Step 2: Update the robot state estimate using the Kalman filter prediction and covariance matrix.
Step 3: Determine the map point P_m = (x, y) in the occupancy grid, M.
Step 4: Compute the gradient of occupancy map at P_m.

$$\nabla M(Pm) = \left(\frac{\partial x}{\partial M}(Pm), \frac{\partial y}{\partial M}(Pm)\right) \quad (1)$$

Step 5: Approximate the partial derivate along the x-direction using central difference method:

$$\frac{\partial M}{\partial x}(Pm) \approx \frac{M(x+\Delta x,y)-M(x-\Delta x,y)}{2\Delta x} \quad (2)$$

Step 6: Approximate the partial derivate along the y-direction using central difference method:

$$\frac{\partial M}{\partial y}(Pm) \approx \frac{M(x,y+\Delta y)-M(x,y-\Delta y)}{2\Delta y} \quad (3)$$

Step 7: Frame the map gradient vector.
Step 8: Return the computed map gradient.

End

System Implementation

Ros And Pc Hardware

RViz is a 3D visualization tool in the Robot Operating System. It helps with real-time visualization and analysis of robot data [63]. Its modular design is vital for robotics researchers and developers. It allows the integration and display of data types including sensor outputs, robot models and coordinate transformations.

RViz supports real-time viewing and interpretation of robot data. Its flexible modular structure is valuable for developers and researchers. It enables the display of data types such, as sensor information, robot models and spatial transformations. In short RViz is a visualization tool used for real-time robot data display and analysis. It's flexible architecture allows robotics researchers and developers to visualize multiple types of data, including sensor readings, robot models, and coordinate transformations.

RViz facilitates an intuitive comprehension of a robot's perception and interaction with its surroundings by displaying data from several sensors, including LiDAR, cameras, and depth sensors. Furthermore, it makes it easier to debug and validate the kinematic relationships of robotic systems by supporting the display of coordinate frames and transformations (TF).

Where real-time response is crucial in tasks such as motion planning, autonomous navigation, and SLAM, it becomes highly necessary. RViz significantly reduces the time spent in the development of complex robotic systems because of its seamless integration of ROS topics and services. This results in a coherent picture being provided of the activities performed by the robot. Its flexible adaptation to robotics tasks in both academic research and industrial processes is ensured by its extensible ability due to plugins and customization [64].The Raspberry Pi 3 single board has the ROS and Yd LiDAR drivers installed.

The URDF (Unified Robot Description Format) is an XML standard for the specification of a robot's physical structure and joint properties within ROS [65]. URDF is a well-defined language that makes it easier to represent the physical structure of a robot for purposes such as simulation, visualization, and control. URDF files facilitate the smooth incorporation of different ROS modules, including motion planning and sensory simulation. The use of URDF in modeling the robot ensures the ease of integration into other ROS tools [66].

Universal Robotic Description Format help with simulation and visualization tools. Universal Robotic Description Format tells us about the robots dynamics. This includes things like mass and friction. It also tells us what the robot looks like in simulation environments like Gazebo. This information is necessary for physics simulations [67]. We need these simulations to test things like motion planning algorithms. We also need them to evaluate sensor data before we use the robot in the world.

Universal Robotic Description Format files are also used by tools like RViz. These tools show us the robots configuration and sensor information in time. This is really helpful, for developers. They can see what is going on with the robot and its environment. This makes it easier for them to find problems when they are developing the robot. By looking at the robot and its sensor data at the time engineers can make sure the robot model is accurate. They can also make sure that all the parts are working like they should [68].

Real-time feedback is needed for timely detection and fixing errors that may appear when operating robots. It provides instant feedback about how changes in the control design influence the performance of systems and enables constant monitoring to ensure consistent performance of robots in a dynamic environment [69]. As a result, it makes robot operation safer and more reliable.

In our study, different resources are used for different purposes depending on tasks that have to be performed within the ROS environment. For instance, the Graphical Processing Unit (GPU) is mainly responsible for visualization and simulation tools such as RViz and Gazebo as well as LiDAR sensors. At the same time, the Central Processing Unit (CPU) operates critical functions such as path planning and localization because they involve complex computational algorithms and require making decisions. This way, we ensure that GPU will not interfere in computational tasks because they require logical thinking.

ROS communication is managed using the ros.h library, which plays a pivotal role in receiving velocity commands (cmd_vel) and publishing odometry data for feedback control. The robot relies on encoder feedback from its motors to achieve accurate motion control. The motor speeds are regulated through Proportional-Integral-Derivative (PID) controllers, which adjust the power input to the motors to maintain the desired velocity [70]. This closed-loop control system continuously corrects deviations between the actual and target wheel speeds to ensure smooth and precise movements.

Motion control hardware includes two motors governed by an Adafruit Motor Shield, which interfaces the control signals from the microcontroller to the physical motors. The encoder feedback signals are processed to measure the actual speed of each wheel, enabling the PID controller to compute the necessary adjustments. An overview of the AMR setup and integration process is depicted in Figure 1, illustrating the hardware connection and software configuration steps.

For basic navigation commands, the robot interprets ROS cmd_vel messages to perform simple maneuvers such as moving forward, reversing, and turning left or right. In this initial control mode, the commands directly map to motor actions through the Adafruit Motor Shield library without engaging the PID control loop. This approach allows straightforward testing and movement verification of the robot but lacks the precision offered by closed-loop PID control.

The PID parameters for both motors are initially set to Kp=0Kp=0, Ki=0Ki=0, and Kd=0.1Kd=0.1. These initial values are placeholders and require empirical tuning to suit the dynamic characteristics of the robot, including motor response, friction, and load conditions. Proper tuning of these parameters is essential for achieving stable, responsive, and accurate motion control. The control loop runs at a recurring interval defined by LOOPTIME, set to 100 milliseconds. This timing governs the frequency at which sensor feedback is processed and motor commands are updated. Should PID calculations or other routine tasks exceed this time budget, LOOPTIME may need adjustment or code optimizations must be implemented to maintain timely control loop execution without delay, ensuring reliable robot performance.

Overall, this architecture successfully combines GPU-accelerated visualization and sensor processing with CPU-based control logic and closed-loop motion control to facilitate efficient and accurate robot navigation and operation. The modular integration of hardware and software components, along with the use of ROS communication protocols and PID control, provides a robust foundation for further development and refinement of autonomous mobile robots.

Amr Design

For this study, a custom AMR model was developed using the SolidWorks CAD software [71]. The model was then converted into a URDF file through SolidWorks' export capabilities, enabling seamless integration of the designed AMR within the ROS framework.



Fig. 3. Autonomous Mobile Robot Design

Figure 3 presents the detailed design of the AMR, featuring a differential drive mechanism and several onboard sensors. The robot's dimensions are 339 mm in length, 279 mm in width, and 220 mm in height, making it compact and suitable for indoor navigation tasks. The differential drive configuration enables smooth rotational movement and enhanced maneuverability within narrow hospital corridors and confined indoor environments. This compact mechanical structure helps in stabilizing motion and effective sensor integration.

Table. 1. Materials and weight

Component	**Specification / Function**	**Weight**
Raspberry Pi 4	Main processing unit	200 g
Yd LiDAR	Environment sensing and mapping	180 g
MPU-6050	Orientation and motion sensing	5 g
DC Motor	Differential drive locomotion	400 g
Arduino Uno	Motor control interface	50 g
L293D Motor Driver	Motor actuation control	50 g
Battery	Power supply	2.25 kg
Chassis	Structural framework	3 kg
Total Weight	—	6.59 kg

In order to ensure all-round environmental awareness, a LiDAR sensor is attached to the robot's upper side to guarantee the maximum coverage. On the other hand, the IMU sensor is attached to the middle level of the chassis to detect the position and orientation of the robot. Below is the list of materials used in making the AMR together with their weights in table 1.

The wheels of the AMR are located at the center of the chassis, making it easy to rotate the robot around its vertical axis. Figure 4 illustrates how the AMR operates in the ROS visualization utility known as RViz where it shows the current position and orientation in relation to its location in the mapped environment. The fact that it correctly represents the position and orientation of the robot in the physical world means that the robot's state is accurately represented in the virtual environment.

The integration of accurate sensor data with the robot's mechanical design ensures reliable perception of its surroundings, which is essential for safe navigation. The use of a differential driving system provides stability and flexibility, allowing the AMR to perform complex maneuvers efficiently. Furthermore, the URDF model

facilitates smooth communication and control within the ROS framework, streamlining the development and testing processes.

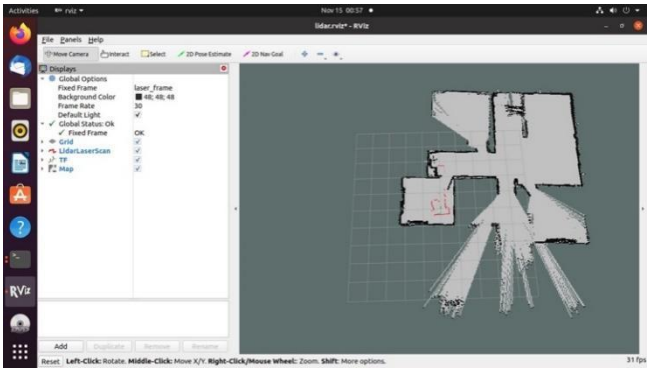


Fig. 4.RViz Environment using Hector SLAM

Experimental Design

Integration of the data from sensors into the design of a mechanical robot allows for successful perception of the environment and, therefore, guarantees safety in navigation. Implementation of the mechanism with differential drives offers stability and versatility of movement for the robot that is crucial for successful execution of sophisticated operations. Moreover, the URDF model allows for a streamlined work of the robot in the ROS environment.

All the experiments were performed in a virtual environment due to the need to implement several local planners in the control system of a ROS-based AMR. As opposed to other studies where the control algorithms of robots like the Turtlebot are implemented, this one focused on using a custom-built AMR and experimenting on it.

The virtual space was designed in Pavilion software that provided a realistic environment for experimentation with the robot. In order to perform all tasks, the robot was teleoperated manually so that a map of the environment could be generated based on the data received by the robot from its sensors.

In this stage, manual control played a key role in ensuring accurate motion and thorough exploration of the environment in order to build the initial map.

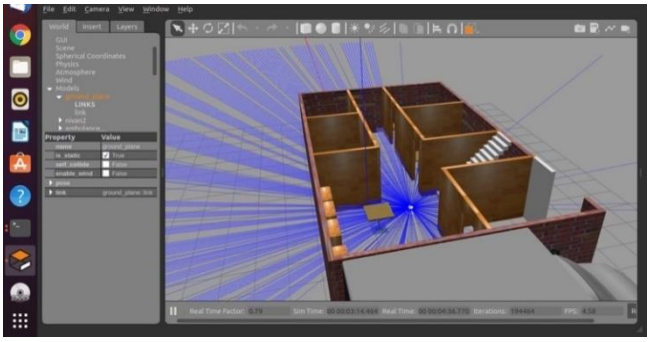


Fig. 5. Virtual environment for navigation

Manual teleoperation of the robot during the mapping stage ensures full exploration of the environment and accurate map building prior to autonomous navigation and other experiments such as localization and obstacle avoidance.

The figure 5 shows the virtual environment used in this experiment. It represents the kind of environment where the experiments have been conducted and the nature of spatial challenge presented in the experiment. The simulated environment was designed in line with real-life environments that may pose difficulties to the robot's ability to navigate. In this way, mapping the environment using data obtained through sensors during manual navigation contributed to the creation of efficient autonomous navigation algorithms and path planning mechanisms.

Using the customized AMR model for this experiment meant that different local planners could be tested within the same experimental setup without varying factors such as robot platform. Utilization of the ROS framework in this experiment made it easier to connect all software modules including the hardware abstraction layer and the planner modules together.

Conducting experiments in a setting with a well designed Autonomous Mobility Robotics model is really useful. This setup is flexible and efficient for testing and refining autonomous mobility strategies. It helps to make robotic systems more practical.

Result and Analysis

First, it is important to analyze the hospital setting in order to get more insights into the aspects of human resource management and use of autonomous technologies contributing to the safety and security in this environment, which are of vital importance in healthcare organizations. It is obvious that design improvement for the future uses and management of automated logistics with Automated Guided Vehicle (AGV) systems will imply anticipation of new knowledge and experience acquired through practice [72].

The results of this research can be seen in Figure 6 and 7. The URDF file of the robot model is added into the Gazebo environment by means of a special URDF spawner. In the Gazebo simulation, the LiDAR is a plug-in working just like a real LiDAR and creating scan lines of lasers to detect the environment and create its maps [73-75]. This figure shows Gazebo simulation from the perspective of the robot equipped with the sensor.

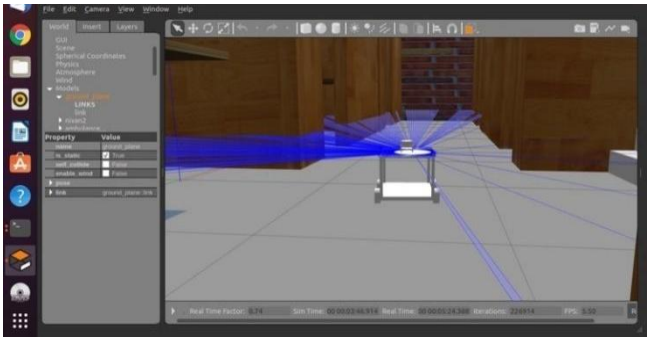


Fig. 6. Gazebo simulation for BOT view

Figure 7 shows where the robot plans its path and navigates within RViz. A bunch of points near the robot shows where it thinks it is after checking sensor data. This helps us see how the robot moves and makes sure its planned route works well. These tools help us test if a robot can work on its own in places like hospitals.

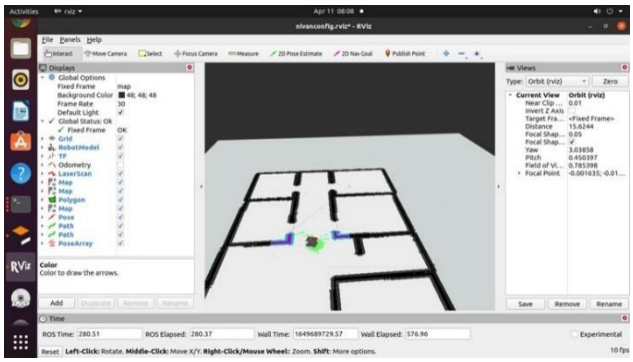


Fig. 7. RViz path plan and navigation

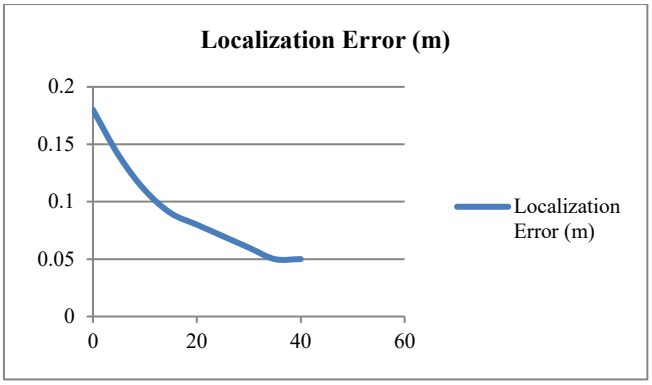


Fig. 8. Localization error during autonomous navigation

Figure 8 shows the observed error instance where the developed robot misses a path in hospital environment. We can see that these mistakes get smaller as the robot uses a method called Hector SLAM to improve its idea of where it's. This happens because the robot matches what its LiDAR sees with its map and updates its grid. This shows that our way of helping the robot find its way works indoors.

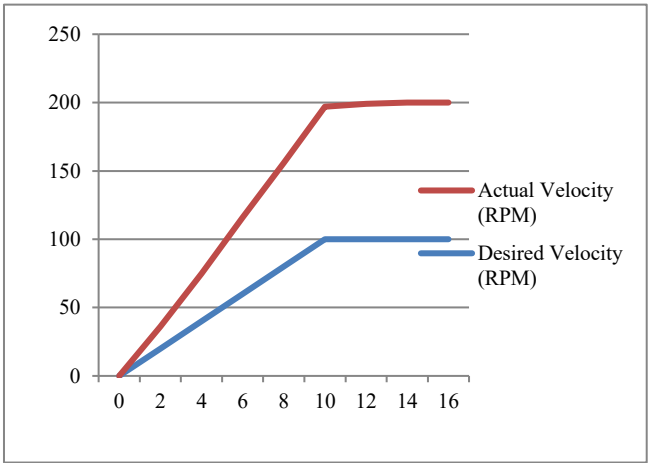


Fig. 9. PID controller Wheel Velocity Response

Figure 9 shows how the robot wheels respond when controlled by a PID system. The wheel speed gets closer and closer to what we want it to be with little error. This proves that the PID controller is good at making the wheels move smoothly and steadily.

The robots path in a simulated space is shown in Figure 10. The robot follows its path avoids things in the way and stays on track. This shows that our navigation system and way of helping the robot find its way work well.

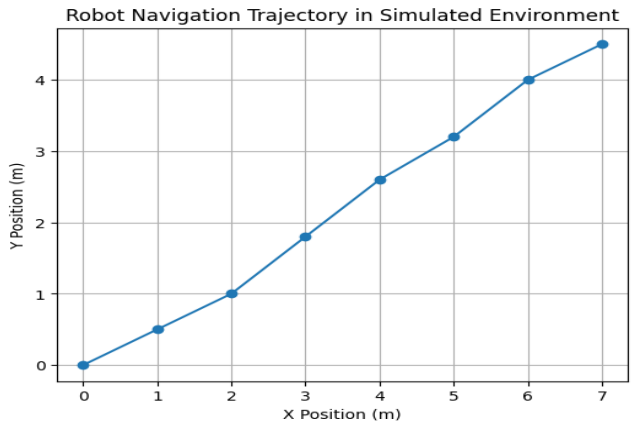


Fig. 10. Robot Navigation Trajectory Plot

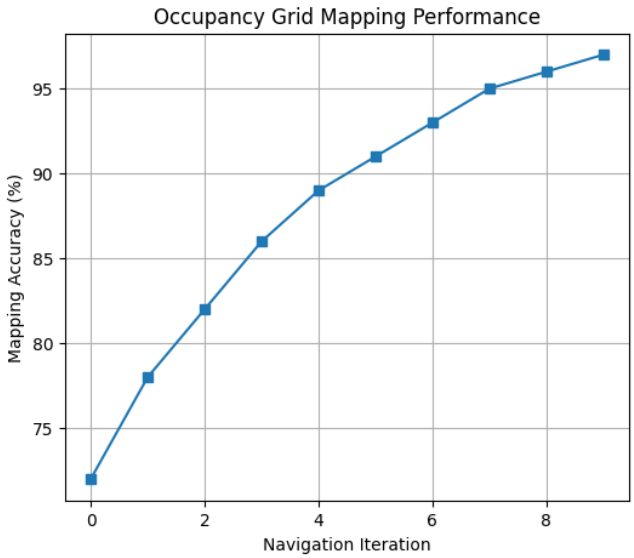


Fig. 11. Occupancy grid mapping performance

Similarly, Figure 11 represents the occupancy grid map created using Hector SLAM and LiDAR sensors' information. The output map presents the indoor hospital environment with identification of walls, paths, and objects. Through LiDAR scan matching and pose estimation algorithms, continuous updating of maps is performed. The resultant occupancy grid map shows least localization errors with the help of which task has been accomplished successfully. Moreover, static objects and boundaries of the environment are well-represented in the resultant map. Enhanced map creation consistency is achieved through LiDAR and IMU data.

The developed AMR framework is presented in Table 2 by comparing it with other models found in the literature. The proposed framework outperforms all other approaches in localization error, mapping, object detection, and navigation capabilities. With 96% accuracy and 0.05 localization error, the proposed modular approach embedded in ROS facilitates reliable indoor navigation for healthcare AMR. Then follows the second best approach, i.e., the LiDAR SLAM framework by Misha et al. [67] with 95% object detection accuracy and 0.05 localization error.

Table. 2. Comparison Of AMR-ROS With Existing Methods

Method	**Localization Error (m)**	**Mapping Capability**	**Obstacle Detection Accuracy (%)**	**Real-Time Navigation**
Teoh et al. [4]	0.25	Partial	85%	No
Gopika et al. [6]	0.21	Moderate	88%	Partial
Abdelhakim et al. [38]	0.15	Good	90%	Yes
Iman et al. [66]	0.1	High	93%	Yes
Misha et al. [67]	0.08	High	95%	Yes
Proposed Work	0.05	High	96%	Yes

Conclusion and Future work

A custom design is developed specifically to optimize AMR tracking and management operations. The new design is efficient and capable of managing all ROS communications processes in the background, which helps to simplify monitoring and navigating the robot in question. The robot was driven through the mapped environment, proving the performance of the navigation system.

This system consists of several parts: ROS messaging protocol that communicates with the robot and encoders, which help to precisely manage its motor movements. The odometry publisher provides real-time information about the robot's current state and helps monitor its motion status. Meanwhile, the PID controller helps to control the speed of wheels and motor output to match target velocities.

All these systems help establish an effective link between hardware and high-level robotic operations by combining ROS communication with sensor feedback and precise motor management. Thus, the described system allows one to develop a solid foundation for autonomous motion and future improvement of the AMR's functions.

The experimental results attained from the Gazebo and RViz environments demonstrated the effectiveness of the proposed ROS-based AMR system for indoor healthcare navigation applications. The fusion of Hector SLAM, LiDAR sensing, and PID-based motion control enabled stable localization and autonomous path planning abilities. As a result of analysis based on localization error, object detection accuracy, and occupancy grid mapping, the proposed approach excelled with 0.05m and 96% accuracy.

Future work can be focused on the following such as,

1. Integrating advanced sensor fusion techniques like depth cameras to enhance localization and mapping capabilities for advanced localization.
2. Adding ultrasonic or infrared sensors for enhanced real-time obstacle detection and dynamic obstacle avoidance.
3. Incorporating artificial intelligence and machine learning techniques for intelligent task prioritization and adaptive robot behavior..

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