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ORIGINAL RESEARCH

Localization-based waiter robot for dynamic environment using Internet of Things

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Abstract In response to the growing demand for robotic service providers in the hospitality industry, this work presents a cost-effective IoT-based waiter robot designed to enhance customer experiences and restaurant efficiency. Leveraging an rplidar sensor and encoded DC motors for mapping and navigation, this robot distinguishes itself by its ability to carry heavier loads and navigate to designated tables. Using an herbal lidar map in the Robot Operating System (ROS), the robot efficiently plans paths and navigates within the restaurant environment. The sensor's 360-degree rotation captures environmental data, generating sequential data points for mapping. Through adaptive Monte Carlo localization in ROS, the robot demonstrates autonomous operation and successful route planning. Initial testing confirms its ability to autonomously locate and reach target tables, marking a promising advancement in service robotics.

Keywords RP Lidar · Indoor · Server mobile robot · Localization · Mapping and autonomous · Graph mapping · Robot Operating System (ROS)

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1 Introduction

In recent years, the hospitality industry has undergone a profound transformation with the integration of robotics, reshaping service dynamics and elevating customer experiences. Notably, the deployment of robotic servers in restaurants and cafes has emerged as a pivotal advancement. However, traditional waiter robots have faced limitations primarily rooted in their suitability for static or predictably structured environments, which contrasts with the dynamic and variable nature of real-world restaurants [1, 2].

The challenges posed by dynamic environments, such as those found in bustling restaurants, include navigating through ever-changing layouts, coping with unpredictable human movements, and adapting to varied object placements. These complexities demand a robotic system capable of rapid adaptation, reorientation, and real-time decision-making to ensure operational efficiency and safety [3, 4].

To address these challenges, our approach represents a groundbreaking fusion of IoT (Internet of Things) technology with advanced robotics. Unlike existing systems that predominantly cater to static or minimally dynamic settings, our waiter robot is equipped with a sophisticated rplidar sensor and encoded DC motors. These components enable high-precision mapping and agile navigation, empowering the robot to adeptly respond to dynamic changes in its operating environment. This not only enhances navigational accuracy but also augments the robot's ability to handle heavier loads and execute precise movements.

Furthermore, the integration of IoT technology plays a pivotal role in our design, facilitating seamless real-time data exchange. This integration significantly enhances the robot's responsiveness to environmental shifts and customer interactions, a notable improvement over earlier models that relied primarily on preset routes and displayed limited adaptive capabilities [5, 6]. Leveraging adaptive Monte Carlo localization within the Robot Operating System (ROS), our waiter robot showcases an exceptional level of autonomy, precision, and efficiency, a claim substantiated by extensive real-world testing in restaurant settings.

In the context of comparative advantages and contributions, this paper delves into the technical architecture of our innovative waiter robot, highlighting its superiority over traditional waiter robots in terms of adaptability, efficiency, and customer service quality. We provide evidence of its outstanding performance in dynamic environments, showcasing its ability to swiftly adapt to layout changes and accommodate customer demands. The integration of IoT not only enhances operational efficiency but also opens up new possibilities for enriched customer interactions, a feature notably absent in existing models. Through rigorous comparisons and in-depth analyses, we aim to establish the transformative potential of our waiter robot in modernizing the hospitality industry, marking a significant step forward in redefining the future of service in this sector.

2 Methodology

Localization and Dynamic Environment are critical aspects of mobile robot operation. Localization involves determining the position and orientation of the robot within its Environment, which is essential for navigating and completing tasks. Dynamic environments, such as obstacles moving into the robot's path, refer to environments that change over time. Effective localization in dynamic environments requires sensors such as cameras and lidar, which provide real-time information about the robot's surroundings [7]. Additionally, the robot's control system must be able to adapt to changes in the Environment and adjust its movements accordingly. Effective localization and dynamic environment management are crucial for the success of mobile robots in a wide range of applications, including manufacturing, logistics, and exploration. In this article, we can use adaptive Monte-Carlo localization (AMCL), also referred to as particle clear-out localization. It's far an algorithm for robots to make it localized using a particle clear out. Given a natural map, the algorithm estimates the location and role of the robot as its movements and senses the Environment.

2.1 Particle filter localization (AMCL)

There are two essential situations in which ekf is not an option for robotic behaviour. Every other scenario is that the first region for robots is entirely unknown, regularly referred to as a global area problem. In this example, the area of the robot that wishes to be described using particle interference distribution so that we can reply to the device's preference. In the case of particle filtration (also called the neighbourhood Monte Carlo), alternatively of choosing the area of the robots, a weighted set of space-primarily based robots, known as debris, is used to define the distribution of site for robots. Since the figures are particle-primarily based, and most debris is located in clean-to-robotic environments, particle filters provide an effective alternative to the Markov localization. A set of such speculations describes the excellent to-be-had records, frequently referred to as a delusion, about the exact place of a robot. Inside the case of global layout, the first region for robots is entirely unknown; therefore, a fixed of equilibrium particles flippantly disbursed in the surroundings is used to symbolize the theory of robotics. In the course of the system of localization, this perception is revived as more statistics are acquired through the senses. In the particle filter, on every occasion, fact from the sensors is collected, and the current concept is renewed.

(1) Prediction: By relocating each particle following the dynamic motion model Eq. 2, a new theory is obtained δvk, $\delta\omega k$ when a robot is given motion commands.
(2) Update: The belief is revived using the visual model with the acquisition of new sensory perceptions. Here, the particle weights are adjusted so that physical robots can be brought into proper alignment with them. Radiation from each particle is used to calculate an unexpected value for jth observations using laser range detection. If the dj provides the actual value and the difference between the two is assumed to be zero, then the probability can be determined using a Gaussian distribution.

$$\frac{1}{\sigma_d\sqrt{2\pi}} exp\left\{-\frac{\left(-\hat{d}_j - d_j\right)^2}{2\sigma_d^2}\right\} \tag{1}$$

The likelihood of receiving a sequence of observations is determined similarly, assuming a wide variety of independent spectral perceptions are received by listening. This is a standard method for determining particle weights so long as all particles can be counted.

Resampling. Prevents a scenario where a negligible number of exceptionally massive particles skews the resulting picture. The following is an illustration of an ordinary sampling procedure:

(a) Calculate the approximate number of particles as:

$$n_{eff} = \frac{1}{\sum_{i=1}^{n} w_i^2} \tag{2}$$

(b) If the n_{eff} is less than the upper bound, new particles will be drawn using the present particle's mass as the probability. Swap out the old articles for the new ones. Adjust the mass of each particle to 1 / n.

The particle effect represents a revised theory of robotic space. This process is repeated as new control measures are taken and new findings are made.

2.1.1 Odometry localization

See Fig. 1.

2.1.2 Adaptive Monte-Carlo localization (AMCL):

See Fig. 2.

2.2 LIDAR mapping for environmental assessment

While studying localization, positioning, and automated navigation in robotics, environmental mapping is a crucial part of the research process. Environmental mapping can be used for narrow caves, low-oxygen underground passageways, and unknown environments humans cannot reach. In addition, the number of manufacturing jobs, mining, and industry that are still manually done by humans is very prone to accidents [8]. LIDAR is a remote sensing technology that has the potential to help (map, monitor, and estimate spatial element locations) of many fields/applications related to the provision of geospatial databases. Many researchers reported using laser range finders in their system [9], which uses the RP Lidar sensor to map with a mobile robot. Using particle filters [10], corrected the incorrect poses of mobile robots with the help of laser range finders and a system for guiding self-driving cars around indoor environments using optical sensors [11].

2.3 Robots connected to the Internet of Things

The IoT, or the "Internet of Things," is an upgraded network of interconnected devices. As a result, the Internet is transitioning from a network of computers to an Internet of Things. There is a wide variety of uses for the Internet of Things, including but not limited to traffic monitoring, smart homes, intelligent parking management, car tracking systems, and industrial applications [12, 13]. This paper demonstrates how to utilize the IoT to command a networked robot from afar (from any location), provided the robot is online. In our waiter robot, the communication between Customer-chef and chef-robot is through IOT. When the customer selects their desired dish then, the data (dish name and Table number) will go to the chef's mobile APP through node MCU (Wi-Fi-controller) and in the same way, when the chef prepares food and place it on the robot; he will give directions to the robot through APP which is connected to Robot Node MCU (Wi-Fi-controller).

2.3.1 Block diagram

See Fig. 3.

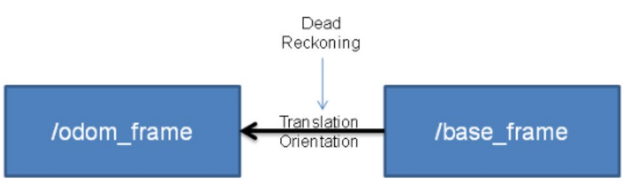


Fig. 1 Odometry Localization

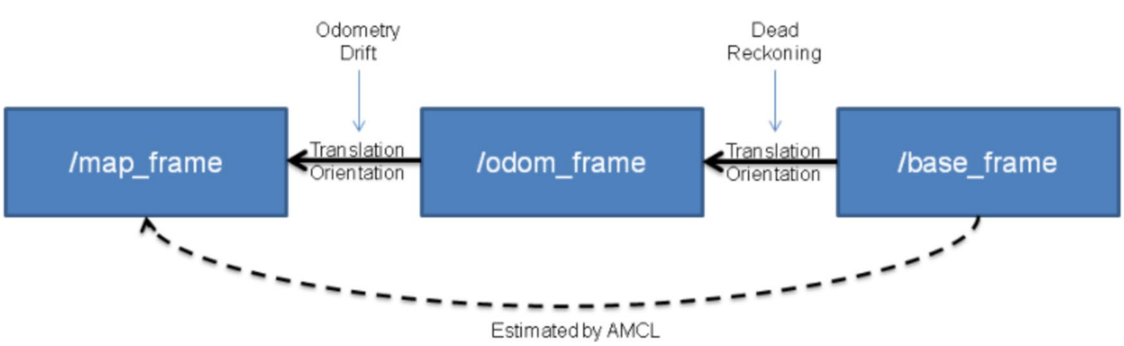


Fig. 2 AMCL Map Localization

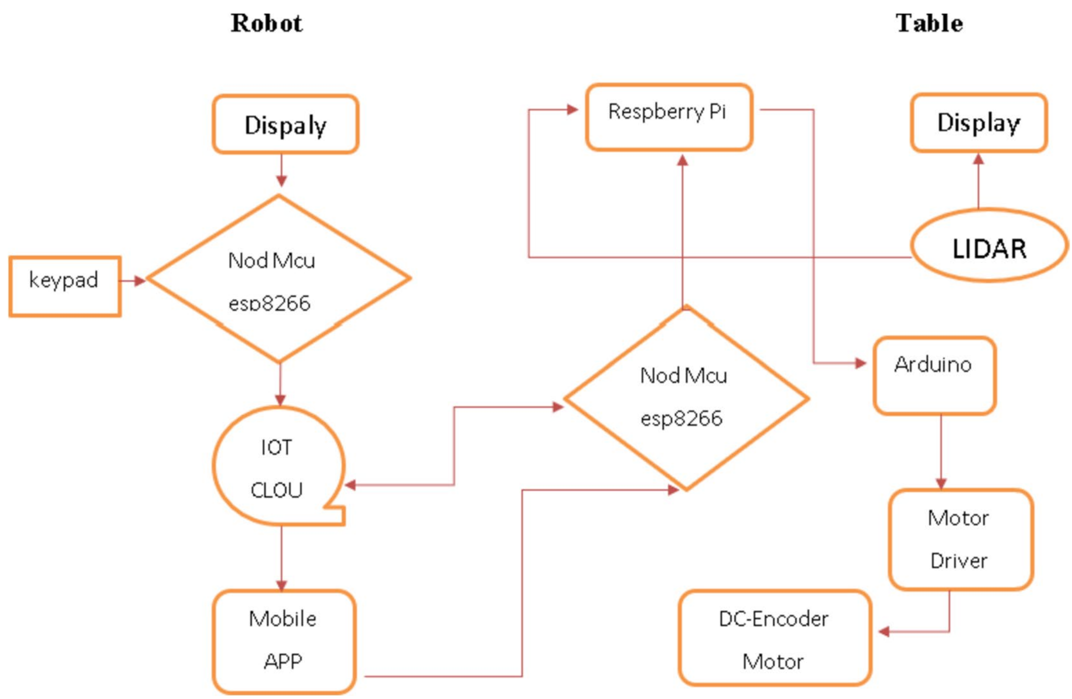


Fig. 3 Framework of the Mobile Robot

2.3.2 Flow chart

See Fig. 4.

2.4 Long-term mapping

When considering the temporal nature of environmental change, conventional approaches seem inadequate. A robot exploring a broad area will find its way around and return to previously explored areas at various times. Infrequently moving things that don't maintain a steady path present a significant challenge for the robot [14]. The robot needs to be able to recognize environmental shifts so it may adjust its map accordingly. Scanning the same room a second time may produce somewhat different findings if, for example, furniture has been relocated—the dynamic nature of the setting results from both the people and the Table in motion.

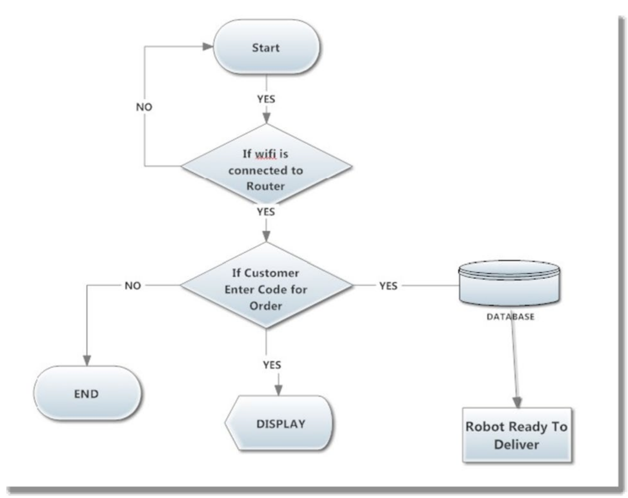


Fig. 4 Mobile Robot Process Flow Diagram

2.5 The ROS system and related components

The Robot Operating System (ROS) is cutting-edge software that can assist in accomplishing numerous goals in robotics by combining the collaboration of algorithms and sensor data [15]. Our method is based on the ROS Melodic framework [16], which provides many algorithm-specific libraries. Mecanum wheels, encoded dc motors (encoders for feedback signals), a micro-controller like an Arduino 2560, a raspberry pi module for the display, and a lithium-ion battery with a capacity of 3000mAh are all present in the waiter robot shown in this paper's hardware.

2.6 Structured algorithmic outline of the methodology

(1) Initialize Robot Localization (See Fig. 5):
- Start with the Adaptive Monte-Carlo Localization (AMCL) algorithm.
- Generate a set of initial position hypotheses (particles).

(2) Environmental Mapping with LIDAR:
- Deploy LIDAR sensors to map the environment.

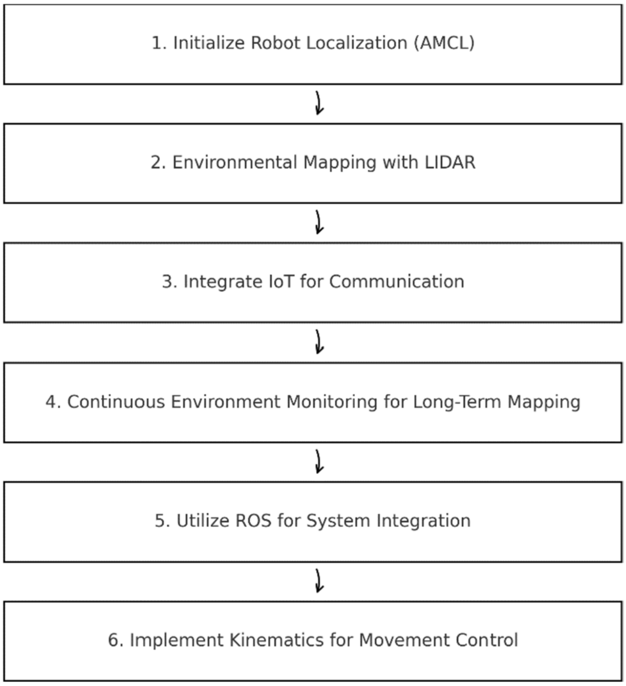


Fig. 5 Algorithmic representation of the methodology

- Update the robot's internal map to reflect changes.

(3) Integrate IoT for Communication:

- Connect the robot to IoT for remote control and data exchange.
- Implement real-time response mechanisms.

(4) Continuous Environment Monitoring for Long-Term Mapping:

- Regularly update the environmental map to account for dynamic changes.
- Adapt robot navigation strategies based on updated maps.

(5) Utilize ROS for System Integration:

- Implement various algorithms and sensor integrations using ROS.
- Ensure smooth data flow and processing.

(6) Implement Kinematics for Movement Control:

- Apply mathematical models for forward and inverse kinematics.
- Control and predict robot movements accurately.

3 Background studies

This section introduces the background knowledge of the development of waiter robots and the various localization methodologies.

3.1 Origins and development: the quest for early efficiency

The genesis and evolution of waiter robots are deeply intertwined with the broader narrative of automation in the service industry. Initially conceptualized as a means to enhance efficiency and productivity, these robots have undergone significant transformations over the years. The early prototypes, often simplistic in design and functionality, primarily focused on basic tasks such as carrying and delivering orders to tables. However, with advancements in robotics and AI, modern waiter robots have become far more sophisticated. They now integrate complex technologies such as artificial intelligence, machine learning, and advanced sensor arrays, allowing for nuanced interactions with the environment and customers [17, 18].

A pivotal aspect of their development has been the incorporation of software systems that allow for real-time updates and interaction with kitchen databases. For instance, in a study [19] by Sakari Pieska, Juhana Jauhiainen, Markus Liuska, and Antti Auno, it was highlighted how an Android tablet could be used in conjunction with these robots to improve customer experience by providing updated menus and facilitating order placement. This software sophistication extends to features like an "urgent button" for immediate server attention, streamlining the customer service process.

Additionally, innovative contributions in this field [20], such as those by Tan-hsu Tan, Chung-Su Chang, and Yung-Fu Chen, have led to the development of robots that not only serve food but also enhance the overall dining experience through customizable menu options and online booking systems. The integration of RFID technology for customer recognition and the strategic placement of lights for robot navigation further exemplify the technological ingenuity at play.

The design elements of these robots are also noteworthy. The utilization of Arduino technology for controlling lighting and movement paths, as discussed in [21] works by Rupali Sapli, Ketaki Zujarrao, Siddhi Patil, and Ketan Deshmukh, showcases the blend of electronic and mechanical engineering in creating efficient and responsive waiter robots. The robots' navigation systems, often based on following designated paths marked by lines or LEDs, represent a blend of simplicity and efficiency.

Moreover, the adaptability of these robots to different restaurant layouts and their ability to interact seamlessly with kitchen staff and cashiers illustrate the multifaceted nature of their design and operation. The backend systems that these robots integrate with, such as kitchen boards and cashier systems, allow for a seamless flow of information, ensuring that orders are processed accurately and efficiently [22].

The evolution of waiter robots reflects a journey of technological advancement and innovation. From basic task-oriented machines to sophisticated, interactive service robots, their development mirrors broader trends in robotics and AI, offering a glimpse into the future of automation in the service industry. This evolution is not just a testament to technological progress but also to the changing dynamics of customer service, where efficiency, personalization, and experience are paramount.

3.2 Advanced localization techniques: navigating a dynamic landscape

The origin and evolution of waiter robots, a critical innovation in the service industry, intertwine with advances in localization technologies and probabilistic frameworks. These robots emerged from a need to enhance efficiency and productivity, using technologies like Android tablets for menu synchronization and RFID for customer identification. Their development has been heavily influenced by SLAM (Simultaneous Localization and Mapping) techniques [23, 24], essential for robotic navigation in dynamic environments like restaurants and service areas. Over the past 15 years, robust approaches to SLAM have evolved, particularly in function-based settings. These involve using EKF (Extended Kalman Filters) and nonlinear least-squares optimization [25–28], proving reliable in most cases. The integration of advanced sensors like cameras, which are crucial for navigation due to their low cost and efficacy in extracting information, has been a game-changer. Vision-based navigation and real-time solutions to robot area estimation in unknown environments have been greatly enhanced by these technologies.

Moreover, the introduction of the probabilistic framework [29] by Thrun in 2016 marked a significant advancement. This framework addresses the uncertainty in robot localization by storing the robot's position and orientation in a state variable, and mapping the environment in an 'm' variable, which could be a feature-based map, a volume-based map, etc. This approach uses idiothetic data, like velocity commands and wheel encoders, for the robot's estimated motion, and allothetic data, which involves external environmental information, for relative stance inference. The robot then computes a conditional probability function to effectively map and localize its surroundings. This framework has made significant contributions to addressing the challenges in dynamic environments where waiter robots operate. It accounts for the complexities of continually predicting a robotic location within an unknown environment over a lengthy duration, a crucial factor in ensuring seamless service in the ever-changing layouts of restaurants and service areas.

The combination of these advanced localization techniques with the ongoing development of waiter robots represents a synergy of robotics and environmental awareness, leading to more efficient, adaptable, and intelligent service solutions in the industry. This evolution not only exemplifies technological progress but also highlights the importance of adaptive and intelligent systems in dynamic and human-centric environments.

3.3 Robotic navigation advancements: the fusion of IoT and sensor innovations

In the realm of robotic navigation and localization, the challenges posed by dynamic environments are significant, particularly when considering the integration of Internet of Things (IoT) technologies and advanced mapping techniques [30]. Dynamic environments, such as shopping centers, hospitals, and industrial settings, constantly evolve, necessitating robots to have a flexible and up-to-date understanding of their surroundings [31, 32]. This is where IoT plays a crucial role, offering a network of interconnected devices that assist in the real-time control and operation of robots. Traditional static maps, often created using LiDAR technology, quickly become outdated in such settings, rendering them less effective for ongoing navigation and localization tasks [33].

Addressing these challenges, the Graph SLAM (Simultaneous Localization and Mapping) technique [34, 35] emerges as a pivotal solution. Unlike conventional SLAM methods, Graph SLAM is adept at managing dynamic changes in the environment. It represents the environment in local maps comprising 2D point clouds, where the connections between these maps are defined as constraints or edges. This approach allows for continual updates to the environmental data, maintaining accuracy despite changes in the surroundings.

A key component of Graph SLAM is the Iterative Closest Point (ICP) algorithm [36, 37], essential for aligning and merging point clouds to keep the local maps up-to-date. ICP handles the transformation (translation and rotation) between sensor scans, enabling the robot to accurately determine its location and orientation. This process is critical in dynamic settings where minor environmental changes are frequent.

The selection of sensors for G-Mapping in these scenarios is crucial [38, 39]. While early approaches relied on monocular cameras for 3D environmental data, their high cost led to the exploration of alternative sensors, such as sonar and ultrasonic sensors. However, these alternatives had limitations, like inefficiency in high-light conditions. A breakthrough came with the introduction of the RP Lidar sensor, a state-of-the-art method that uses pulsed laser beams for distance measurement. The accuracy of RP Lidar in generating detailed 2D point clouds, combined with its ability to swiftly adapt to environmental changes, makes it an ideal choice for dynamic SLAM applications. This sensor technology not only captures the distance to various surfaces but also integrates this data to form a coherent and updated representation of the environment.

The dynamic environment SLAM problem necessitates a sophisticated interplay of advanced mapping techniques, IoT integration, and the judicious selection of sensors. Together, these components enable robots to operate effectively in ever-changing environments, ensuring accurate localization and navigation even in the most complex and unpredictable settings.

3.4 Table of systematic literature review: evaluating technological progressions in IoT-enabled waiter robots for dynamic service environments

Study References	Key findings	Methodology	Outcomes/Implications
Lin and Mattila [17]	Explores the value of service robots in hotels from guests' perspectives	Mixed-method approach	Highlights guest preferences and perceptions towards service robots in hospitality
Sinha et al. [18]	Examines acceptance of robotics at the workplace using Twitter analytics and SEM	Integrated Twitter analytics – SEM approach	Provides insights into behavioral intentions towards accepting robots at the workplace
Cheong et al. [23]	Details the development of a robotic waiter system	Experimental design and development	Shows the practical application and challenges in developing robotic waiters
Wan et al. [24]	Studies the implementation of waiter bots in casual restaurants	Case study analysis	Evaluates the effectiveness and adaptability of waiter bots in casual dining settings
Sun et al. [25]	Designs a low-cost indoor navigation system for food delivery robots	Multi-sensor information fusion technique	Offers a cost-effective solution for robotic indoor navigation
Cerbaro et al. [31]	Compares fuzzy logic approaches for obstacle avoidance in waiter robots	Analysis of LiDAR-based obstacle avoidance systems	Provides insights into efficient navigation methods in dynamic environments
Garcia-Haro et al. [32]	Reviews the application of service robots in catering	Comprehensive literature review	Discusses challenges and future directions in the use of service robots in catering
Waqas et al. [33]	Focuses on the development of a localization-based waiter robot using RP-LIDAR	Experimental design using RP-LIDAR technology	Demonstrates the efficacy of RP-LIDAR in robot localization and navigation
Chen et al. [34]	Explores the development of non-contact service robots in fast-food restaurants	Case study in fast-food restaurant settings	Evaluates the performance and customer acceptance of non-contact service robots
Qasim et al. [35]	Discusses AI-based smart robots for restaurant serving applications	Analysis of AI integration in service robots	Showcases advancements in AI for enhancing restaurant service robots
Niloy et al. [36]	Reviews design and control issues of indoor autonomous mobile robots	Literature review focusing on design and control	Provides comprehensive insights into challenges and solutions in robot mobility
Kang and Teng [37]	Studies intelligent control system design for IoT mobile robots	Analysis of ring light control via IoT in robots	Offers innovative approaches to control systems in robotic applications
Teoh et al. [38]	Examines reinforcement learning for mobile robot environment exploration	Study on the application of reinforcement learning	Highlights the potential of learning algorithms in robotic navigation
Naik et al. [39]	Provides a review on automated waiters	Literature review on automated waiter systems	Summarizes the current state and future prospects of automated waiter technology

3.5 Gap Identification

(1) Integration of IoT with Robotic Waiters: While several studies like [23] and [24, 24] have explored the implementation of waiter robots in restaurants, the specific integration of IoT for enhanced connectivity and real-time data processing remains less explored.

(2) Advanced Navigation in Dynamic Environments [25]: and [31] focus on indoor navigation and obstacle avoidance. However, there is a gap in applying these technologies in highly dynamic and unpredictable environments like busy restaurants.

(3) Customer Interaction and Service Enhancement [17]: and [31] discuss the perception and application of service robots in hospitality. The opportunity lies in enhancing customer interaction using advanced AI and machine learning techniques, which is not deeply explored in current literature.

(4) Cost-Effective and Efficient Design: While the study by [25] mentions low-cost navigation systems, there is a need for comprehensive research on developing cost-effective yet efficient waiter robots suitable for varied restaurant settings.

3.6 Proposed work

(1) Innovative IoT Integration: Develop a waiter robot that seamlessly integrates IoT for real-time data processing

and connectivity, enabling it to respond dynamically to the restaurant environment.

(2) Advanced Localization and Navigation Techniques: Utilize technologies like RP-LIDAR (as in [33]) and AI-based navigation systems to enable precise and adaptive navigation in dynamic and crowded restaurant settings.

(3) Enhancing Customer-Robot Interaction: Incorporate AI-driven communication and interaction modules to improve the customer experience, taking cues from studies on customer perceptions and service enhancements.

(4) Design Optimization for Cost and Efficiency: Focus on developing a design that balances cost-effectiveness with high operational efficiency, making the technology accessible for a wide range of restaurants.

4 Kinematics of the robot

In the first part of this section, the forward and inverse Kinematics of the robot is discussed.

4.1 Forward kinematics

Specifies the integrated parameters and includes the configuration of the series. In serial manipulators, this is achieved by directly inserting the parameters included in the previous kinematics calculations of the sequence series. The same tricksters insert boundary parameters in kinematics calculations that require the arrangement of multiple polynomial limits to determine the layout of areas that may have the final effect.

4.2 Inverse kinematics

Reverse Kinematics identifies the location of the final result and analyzes the combined points. For successive regulators, this requires the arrangement of multiple polynomials that have been detected in Kinematics and produce different sequence formations. An example of a standard 6R sequence control (a series of six revolving joints) shows sixteen other kinematics arrangements and sixteen-degree polynomial systems. For equal controllers, in particular, the final result's location improves the Kinematics conditions, reflecting the equilibrium of the combined parameters.

We assume the following to solve the Kinematics of a robot with Omni-directional wheels:

(1) First, let's pretend the entire mobile robot is rigid, particularly the wheels (Fig. 6).

(2) Every possible motion happens in only two dimensions (ignoring rough ground).

(3) The roller's point of contact with the ground is precisely below the wheel's centre.

- α = offset angle
- β = steering angle
- γ = roller's angle w.r.t wheel
- l = offset length
- $\alpha + \beta = 0$

Equation of rolling constrain:

$$[\cos(\alpha+\beta+\gamma)\sin(\alpha+\beta+\gamma)\imath\sin(\beta+\gamma)]R(\theta)\xi_I - R\varphi\sin\gamma - \dot{r}_{sw}\dot{\varphi}_{sw} = 0 \tag{3}$$

Equation of sliding constrain:

$$[\sin(\alpha+\beta+\gamma) - \cos(\alpha+\beta+\gamma)(-\imath)\cos(\beta+\gamma)]R(\theta)\xi_I - r\varphi\cos y = 0 \tag{4}$$

Now for forward and Inverse Kinematics:

Given a set of wheels' speeds, determine robot velocity in the global reference frame. We were given robot orientation θ, wheel radius, wheel distance ***l***, from P, and spinning wheel speed θ1 and θ2.

The rolling constraint of the four-wheel omnidirectional robot could be calculated by putting the alpha-beta gamma values in the below equation.

$$\begin{bmatrix} sin(\alpha+\beta+\gamma) - cos(\alpha+\beta+\gamma) - lcos(\beta+\gamma) \\ sin(\alpha+\beta+\gamma) - cos(\alpha+\beta+\gamma) - lcos(\beta+\gamma) \\ sin(\alpha+\beta+\gamma) - cos(\alpha+\beta+\gamma3) - lcos(\beta+\gamma) \\ sin(\alpha+\beta+\gamma) - cos(\alpha+\beta+\gamma) - lcos(\beta+\gamma) \end{bmatrix} \begin{bmatrix} R \\ P \\ Q \end{bmatrix} \tag{5}$$

$$\begin{bmatrix} r & 0 & 0 & 0 \\ 0 & r & 0 & 0 \\ 0 & 0 & r & 0 \\ 0 & 0 & 0 & r \end{bmatrix} \varnothing cosY = 0 \tag{6}$$

Values of parameters estimated by proper measurement:

$\alpha = \beta = \alpha = \beta = 0$, $y_1 = y_2 = y_3 = y_4 = 45°$

$\alpha = \beta = \alpha = \beta = 180°$, $r_1 = r_2 = r_3 = r_4 = 6.4$

$l_1 + l_2 = l = 20.5$ cm

By putting these values into sliding constraint equation, we get

$$\begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & -\frac{20.5}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & \frac{20.5}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & -\frac{20.5}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & \frac{20.5}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} R \\ R \\ \varphi \end{bmatrix} - \begin{bmatrix} 6.4 & 0 & 0 & 0 \\ 0 & 6.4 & 0 & 0 \\ 0 & 0 & 6.4 & 0 \\ 0 & 0 & 0 & 6.4 \end{bmatrix} \varnothing 1/\sqrt{2} = 0 \tag{7}$$

$$\Rightarrow 1/\left(2\begin{bmatrix}1 & -1 & -20.5\\ 1 & -1 & 20.5\\ 1 & -1 & -20.5\\ 1 & -1 & 20.5\end{bmatrix}\begin{bmatrix}R\\ R\\ \varphi\end{bmatrix}\right)-6.4\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&0&1&0\\0&0&0&1\end{bmatrix}=0 \tag{8}$$

The above equation is for the sliding constraint of the robot.

By putting values in the sliding constraint equation for four wheels (Eq.4), the sliding constraint of all wheels could be calculated.

$$\begin{bmatrix}\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{20.5}{\sqrt{2}}\\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{20.5}{\sqrt{2}}\\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{20.5}{\sqrt{2}}\end{bmatrix}\begin{bmatrix}R\\ R\\ \varphi\end{bmatrix}-6.4/\sqrt{2}\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&0&1&0\\0&0&0&1\end{bmatrix}-1.28\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&0&1&0\\0&0&0&1\end{bmatrix}\emptyset\omega=0 \tag{9}$$

$$1/\sqrt{2}\begin{vmatrix}1&1&20.5\\1&1&20.5\\1&1&20.5\\1&1&20.5\end{vmatrix}\begin{bmatrix}R\\ R\\ \varphi\end{bmatrix}-6.4/\sqrt{2}\begin{vmatrix}1&0&0&0\\0&1&0&0\\0&0&1&0\\0&0&0&1\end{vmatrix}$$
$$-1.28\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&0&1&0\\0&0&0&1\end{bmatrix}\emptyset_S\omega=0 \tag{10}$$

The above equation is for the sliding constraint of the robot.

Now for the Forward Kinematics:

$$\Rightarrow\left(\frac{6.4}{\sqrt{2}}\begin{bmatrix}1 & -1 & -20.5\\ 1 & -1 & 20.5\\ 1 & -1 & -20.5\\ 1 & -1 & 20.5\end{bmatrix}\begin{bmatrix}Rx\\ Ry\\ \varphi\end{bmatrix}\right)=$$

Now for the Inverse Kinematics:

$$\begin{bmatrix}0.22 & -0.22 & -4.55\\ 0.22 & -0.22 & 4.55\\ 0.22 & -0.22 & -4.55\\ 0.22 & -0.22 & 4.55\end{bmatrix}\begin{bmatrix}R_x\\ R_y\\ \varnothing\end{bmatrix}=\begin{bmatrix}\omega_{w1}\\ \omega_{w2}\\ \omega_{w2}\\ \omega_{w2}\end{bmatrix} \tag{11}$$

To get the position vector by velocities of tires:

$$\begin{bmatrix}0.22 & -0.22 & -4.55\\ 0.22 & -0.22 & 4.55\\ 0.22 & -0.22 & -4.55\\ 0.22 & -0.22 & 4.55\end{bmatrix}^{(-1)}\begin{bmatrix}\omega_{w1}\\ \omega_{w2}\\ \omega_{w2}\\ \omega_{w2}\end{bmatrix}=\begin{bmatrix}R_x\\ R_y\\ \varnothing\end{bmatrix} \tag{12}$$

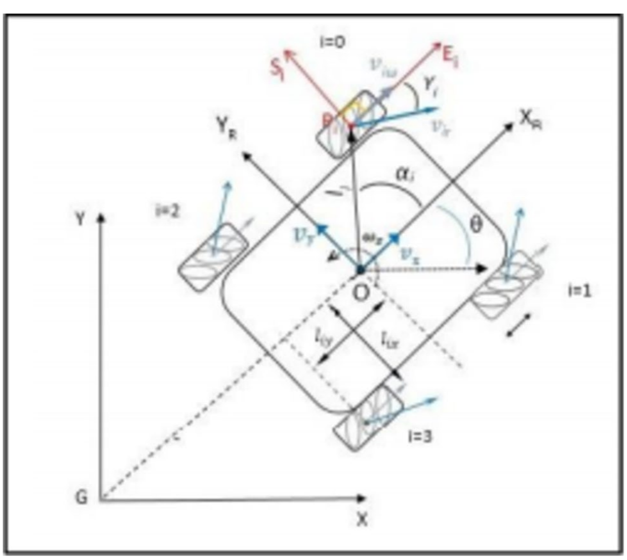


Fig. 6 Mobile Robot with Rigid Wheels

5 Hardware and CAD model of the robotic system

In this section of the paper, the 3D CAD and Hardware model of the mobile robot is presented, together with the model's specifications**.**

5.1 CAD model

See Fig. 7.

5.2 CAD model design specifications

(a) Length of the model = 25 cm

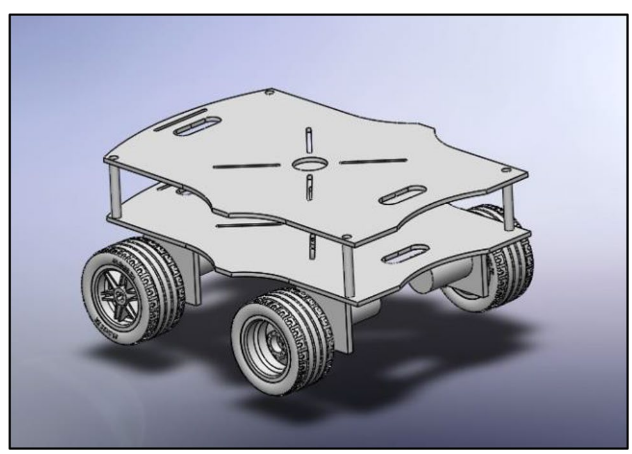


Fig. 7 The 3D CAD Prototype for use in Testing

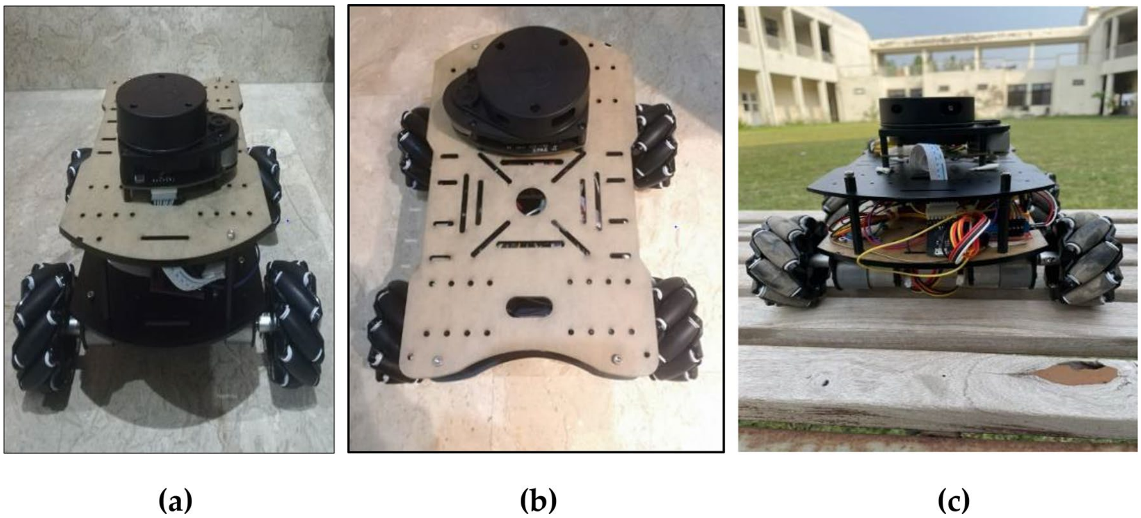


Fig. 8 Model of Hardware along with an RP Lidar Sensor (a,b & c)

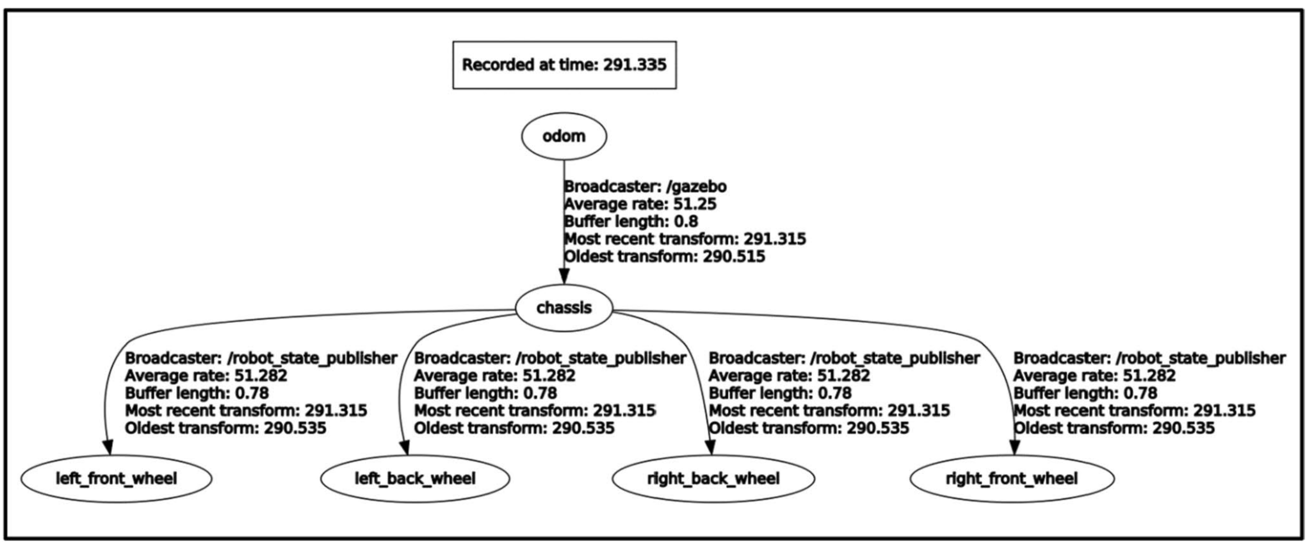


Fig. 9 Flow Chart

(b) Width of the model = 20.5 cm
(c) Height to the first plate = 7 cm
(d) Space b/w plates = 5 cm
(e) Diameter of tyre = 8 cm
(f) Thickness of plates = 2
(g) Material: Acrylic Sheet

5.3 Hardware model

See Fig. 8.

6 Simulation and experimental results

Here we present the results of our ROS and Real-World Environment simulations and experiments with a mobile robot.

6.1 Testing of mobile robot

There are a variety of environments and indoor settings in which robot motion errors might arise. The most common mistake is that the robot's wheels are not correctly

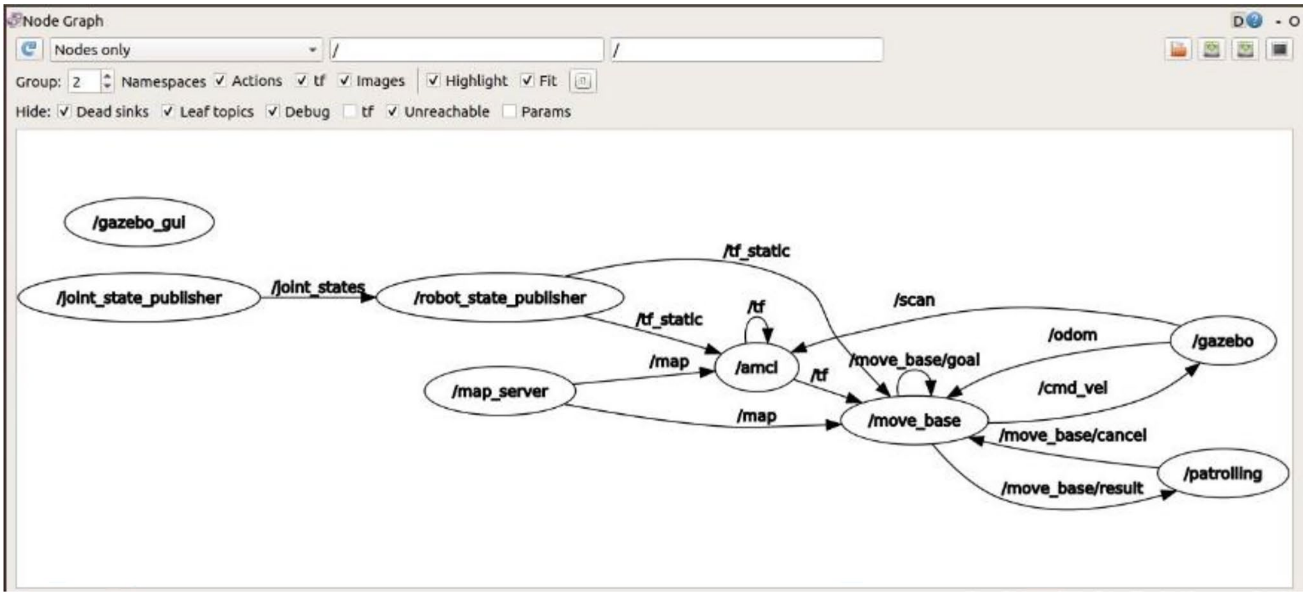


Fig. 10 TF-Tree for Nodes

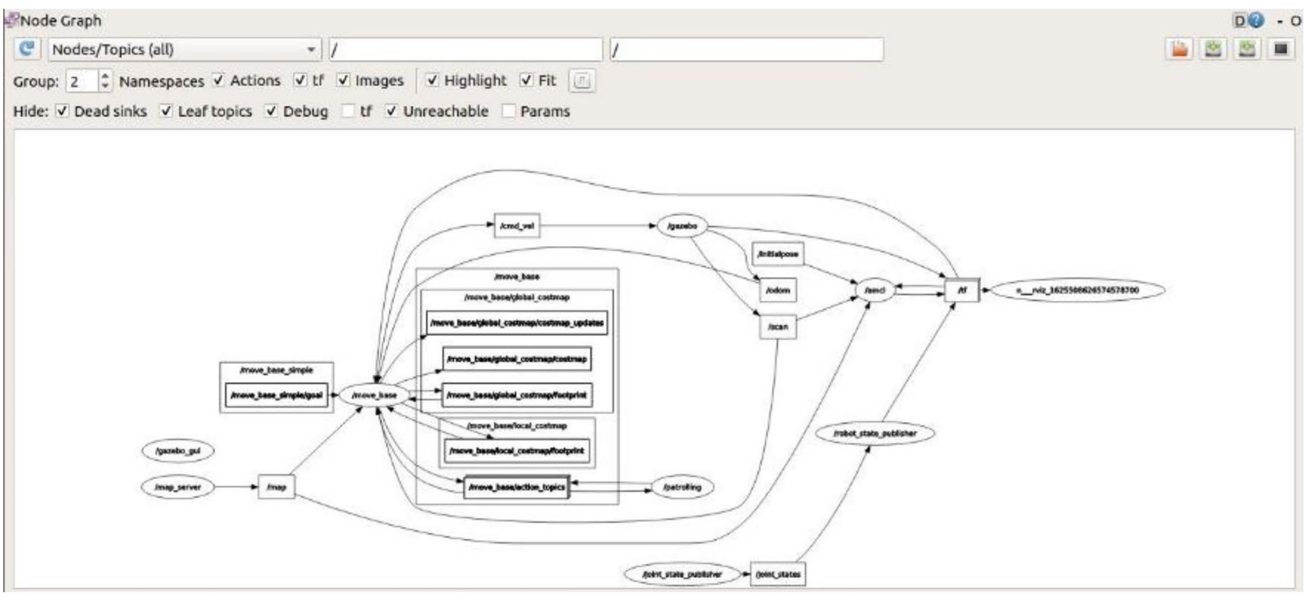


Fig. 11 TF-Tree for Nodes/Topics All

balanced on the floor. We used a PID controller to manage the Robot Motors. Figure 9 is a flowchart depicting how our robot controls its motors.

To regulate the movement of the robot's wheels, our technology uses a PID algorithm that is fed data via encoder sensors. The robot's angular velocity and speed are independent of one another. The robot strays because of the disparity in linear and rotational acceleration (Figs. 10, 11, 12).

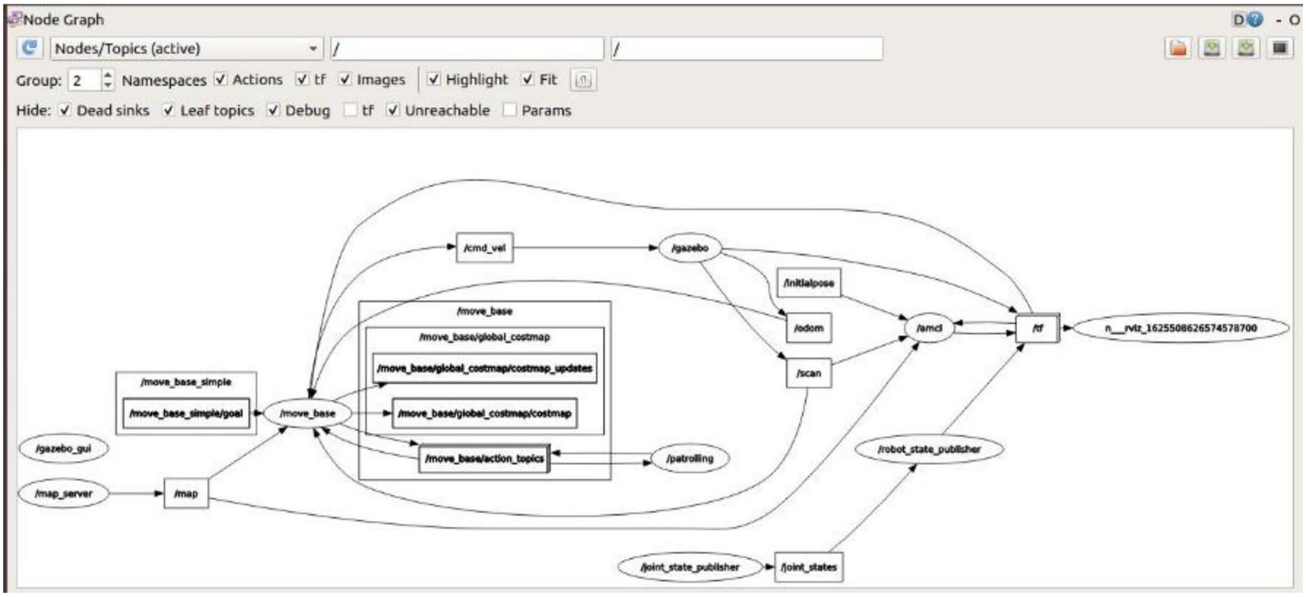


Fig. 12 TF-Tree for Nodes/Topics Active

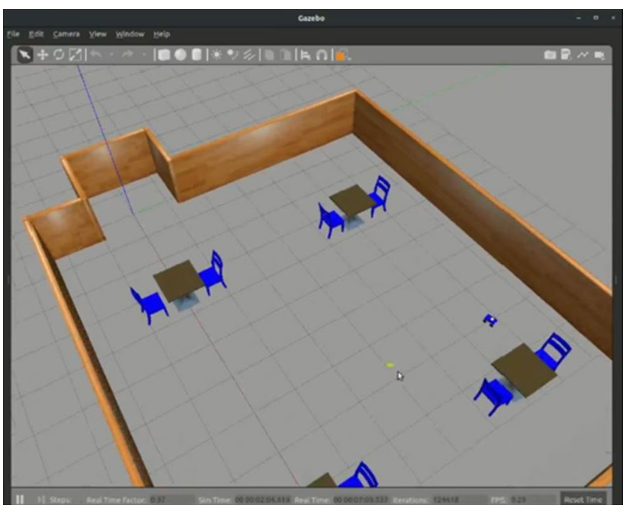


Fig. 13 Environment in ROS

6.2 Environment in ROS

It is the Environment which we create on ROS, as we have to use our robot in a Restaurant so its Restaurant like Environment in which four tables along with chair and Mecanum wheel mobile robot is present (Fig. 13).

6.3 Localization of Waiter Robot in ROS

When the customer order food, chef placed the order on robot and our waiter robot will reach to specific Table then it will localize its pose and there will be a message shown on screen that specific e.g. (1st Table reached). Here is the picture for all the four Table where robot localize its pose along with specific Table reached message (Figs. 14, 15, 16, 17).

6.4 Map representation in RVIZ

Using odometry data from the wheels, we plot data from a LIDAR sensor and study the results on an RVIZ, representing a wide range of ways to create maps (Fig. 18, 19).

6.5 Hardware interfacing with ROS

See Figs. 20, 21, 22, 23, 24.

6.6 Dynamic and long-term mapping

This is a simulated robot experiment. Bag files of the dynamic Environment were utilized for testing the project. We began the simulation by having the robot collect node and edge data from the indoor Environment. After the map

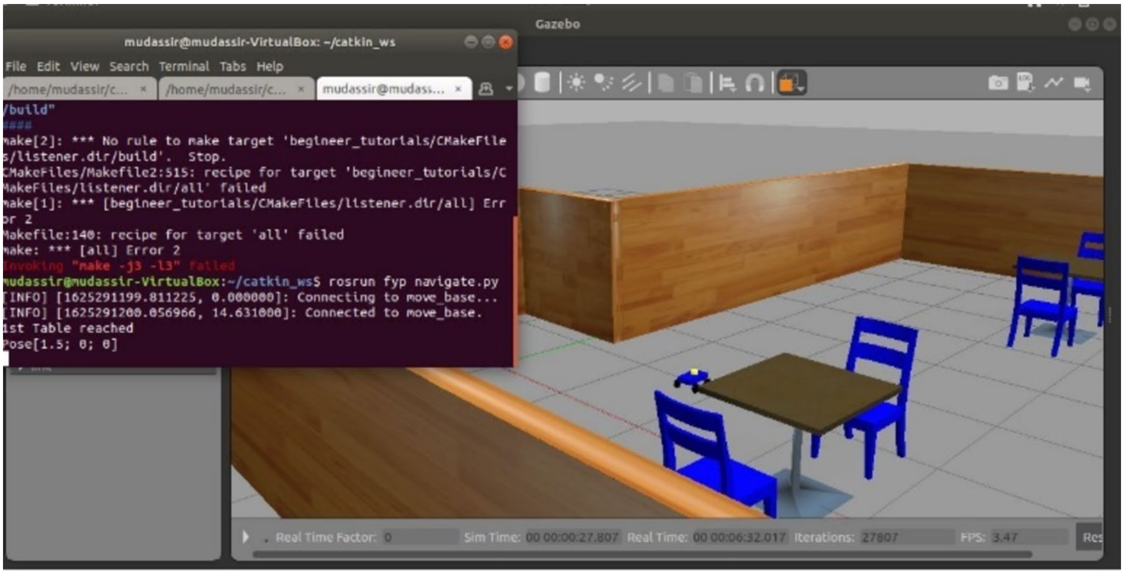


Fig. 14 Localization of First Table

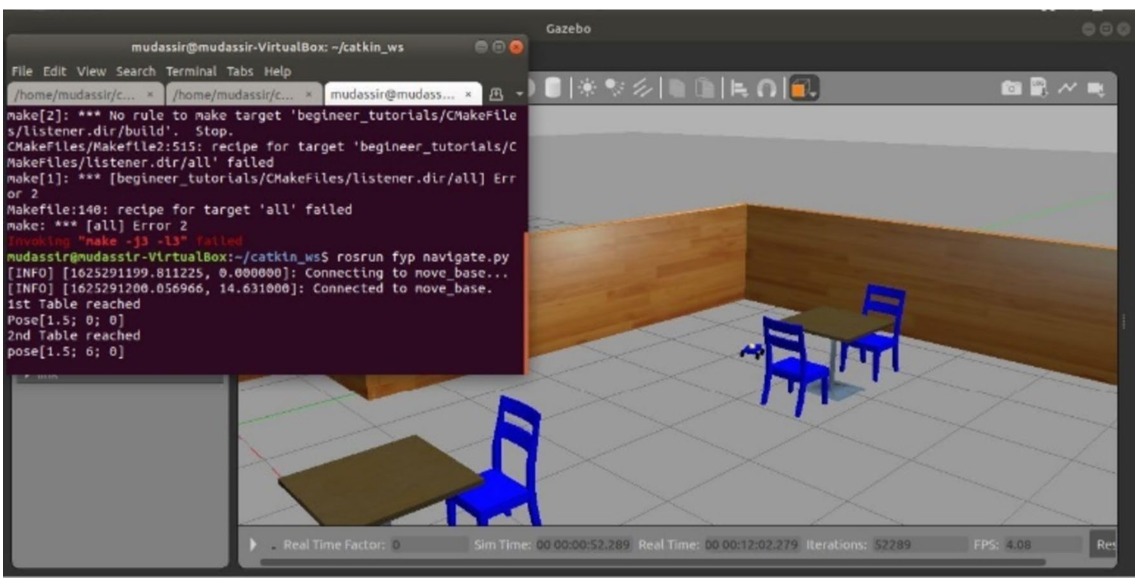


Fig. 15 Localization of Second Table

was made, the robot's path was displayed. By reloading the old map and running the bag files through their paces again, the old map is refreshed, and the highly non-static obstacles are removed. Figures 25a, b, 26, and 27 display the obtained results.

7 Conclusion

This study successfully demonstrated the development and application of an innovative IoT-based waiter robot, designed to operate efficiently in dynamic restaurant

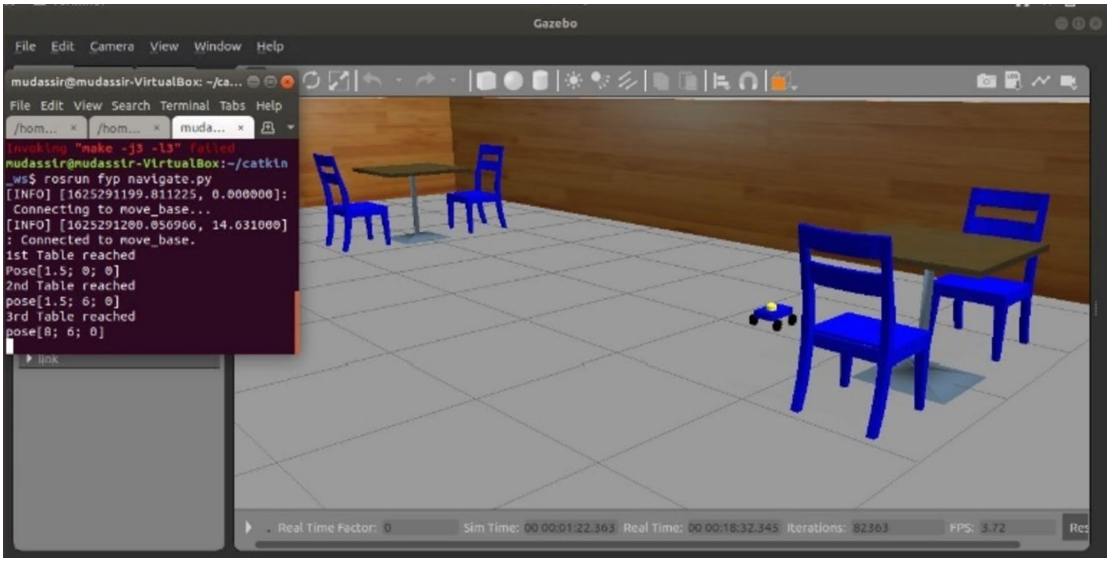


Fig. 16 Localization of Third Table

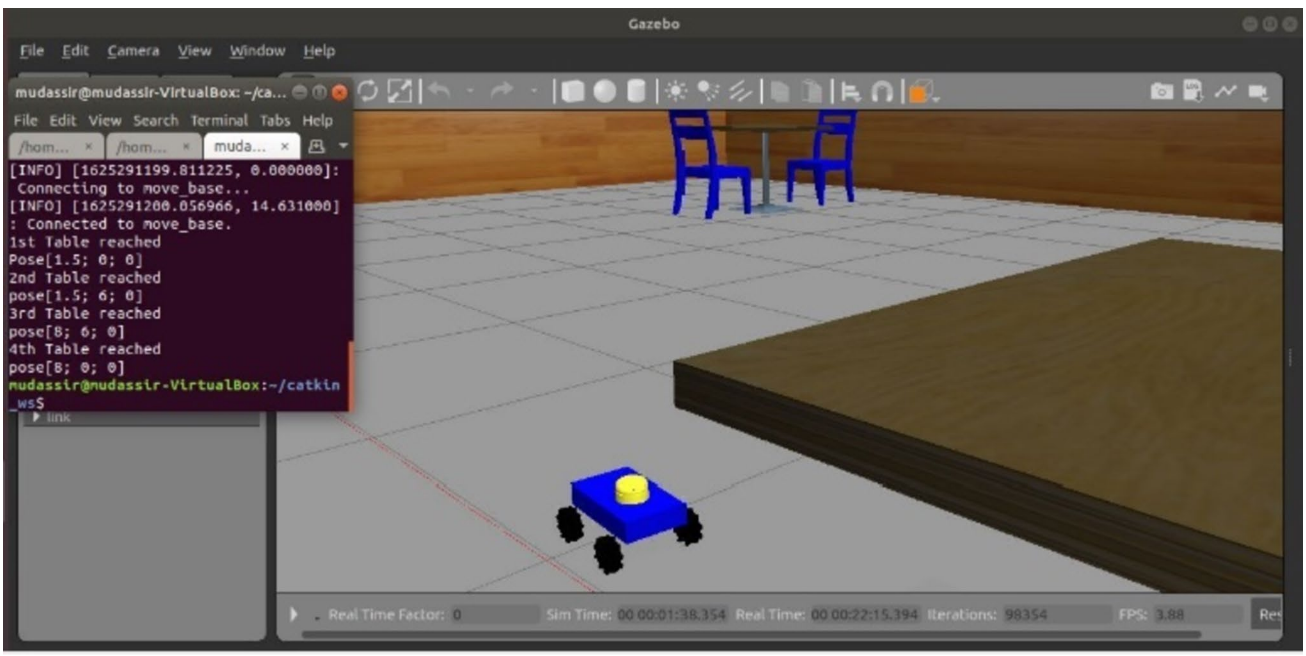


Fig. 17 Localization of Fourth Table

settings. Its unique integration of an rplidar sensor and encoded DC motors allows for advanced mapping and agile navigation, enabling the robot to adapt to changes in its environment effectively. The use of adaptive Monte Carlo localization within the Robot Operating System (ROS) has resulted in a high level of autonomy and precision in navigation, as evidenced by rigorous testing in real-world restaurant scenarios. This project contributes

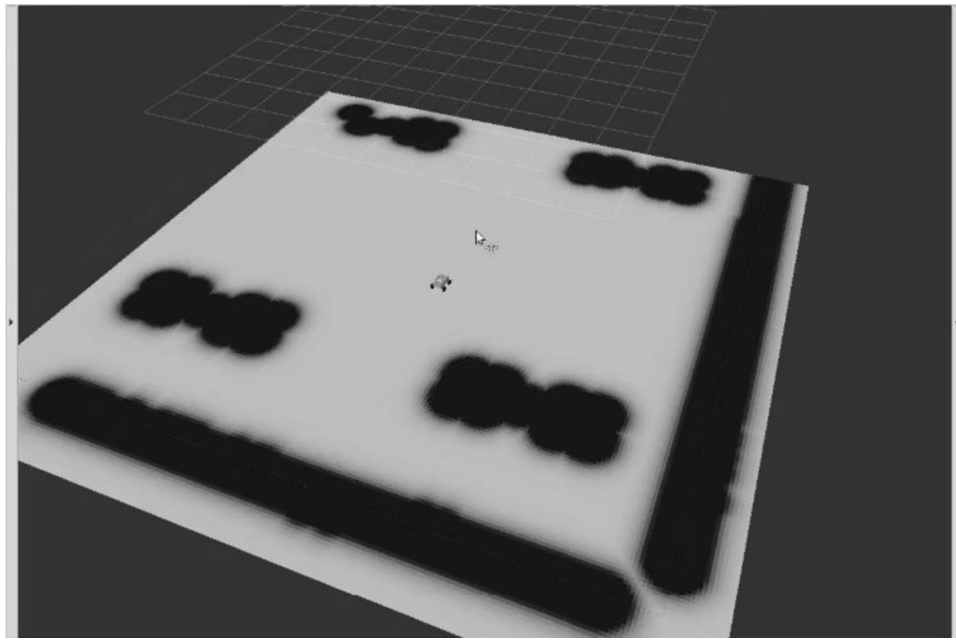


Fig. 18 MAP on RVIZ

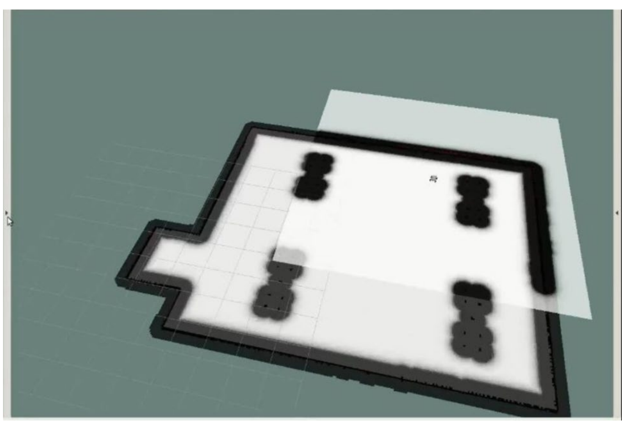


Fig. 19 MAP on RVIZ

significantly to the field of service robotics, offering a promising solution to enhance customer experiences and operational efficiency in the hospitality industry.

8 Future scope

The scope for future work includes enhancing the robot's interactive capabilities for a more personalized customer experience, integrating machine learning algorithms for better environmental adaptation and decision-making, and exploring the use of more advanced sensors for improved mapping accuracy. Additionally, expanding the application of this technology to other service sectors such as health-care and retail can be explored. Research into reducing the

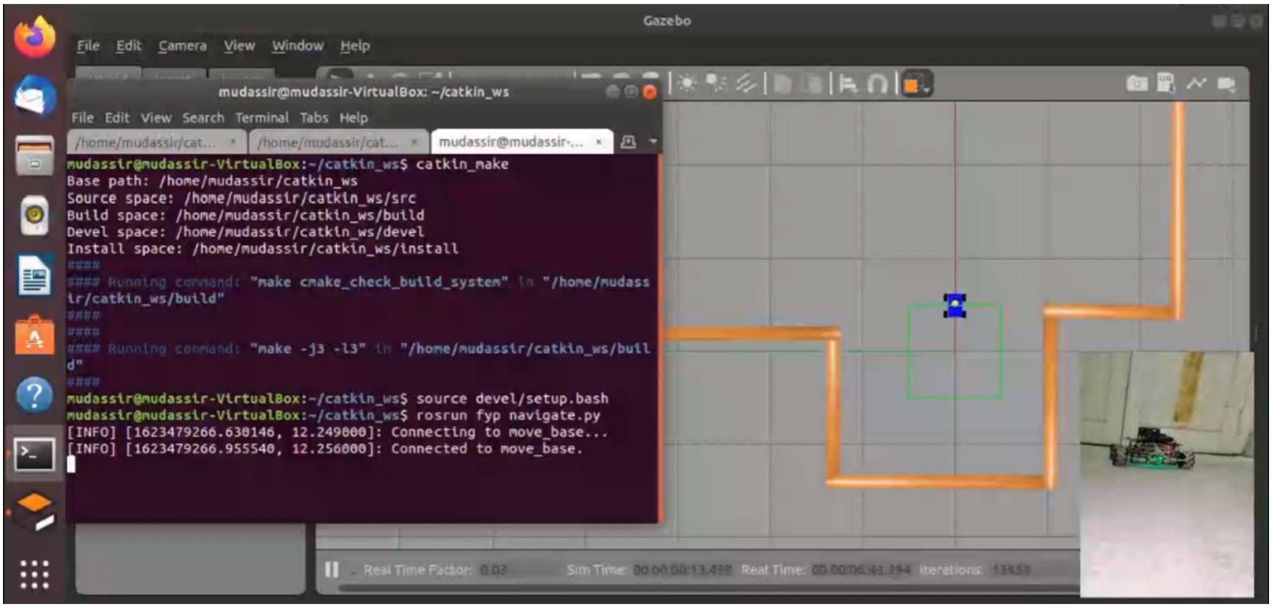
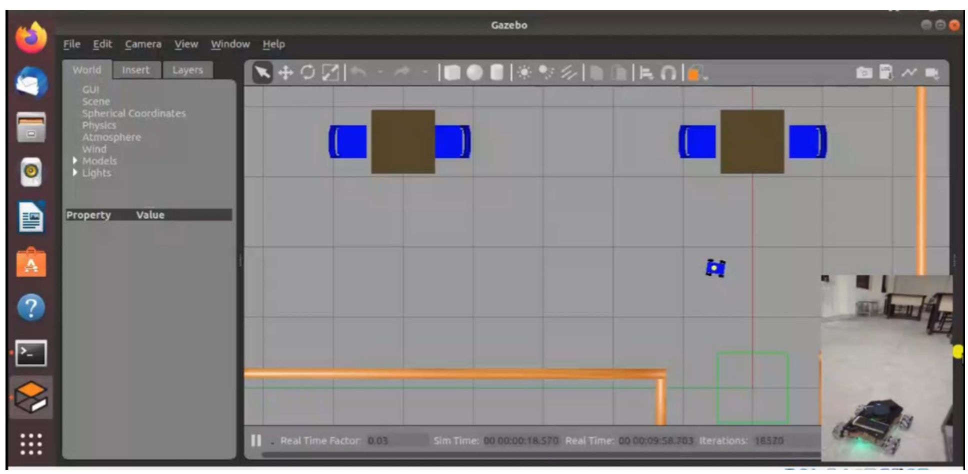


Fig. 20 Hardware Movement w.r.t Software Simulation

Fig. 21 Localization of First Table



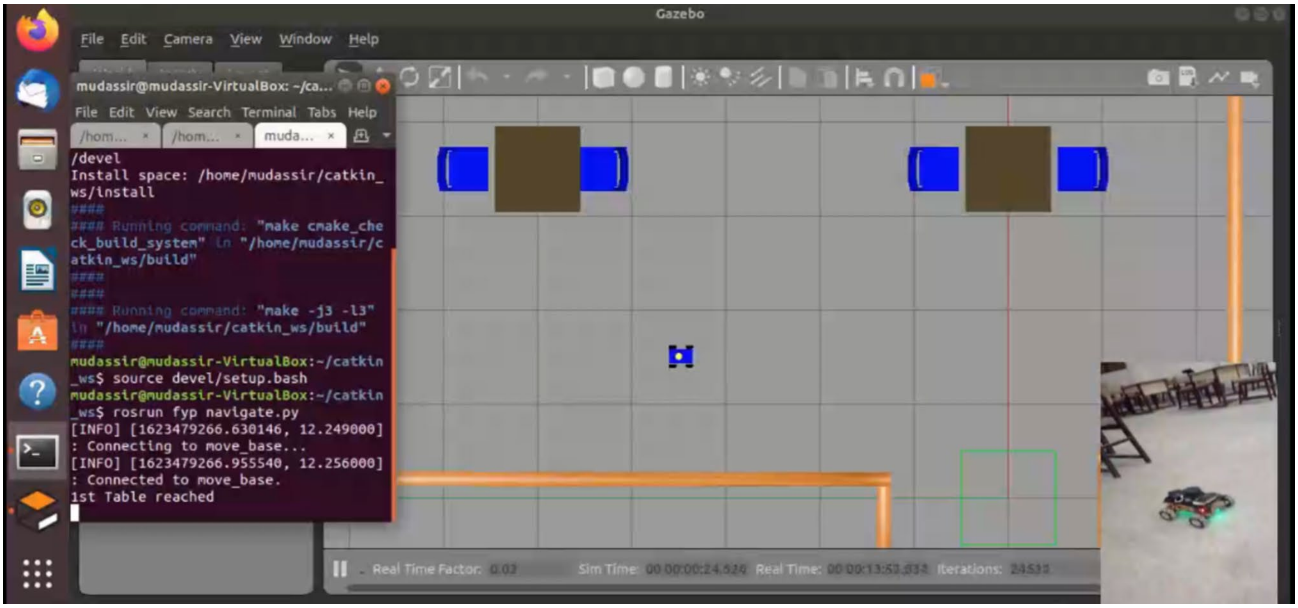


Fig. 22 Hardware moving towards the second Table

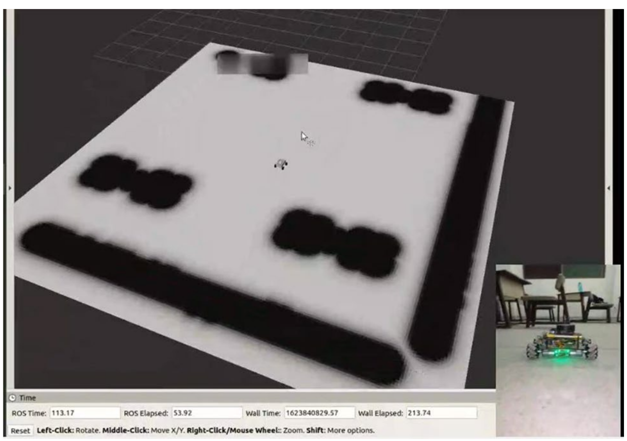
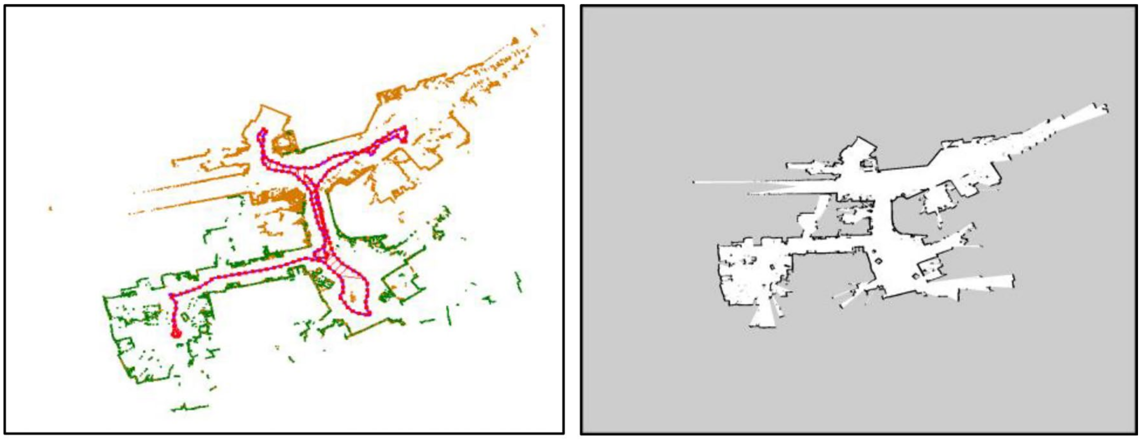


Fig. 23 Hardware moving towards the third Table

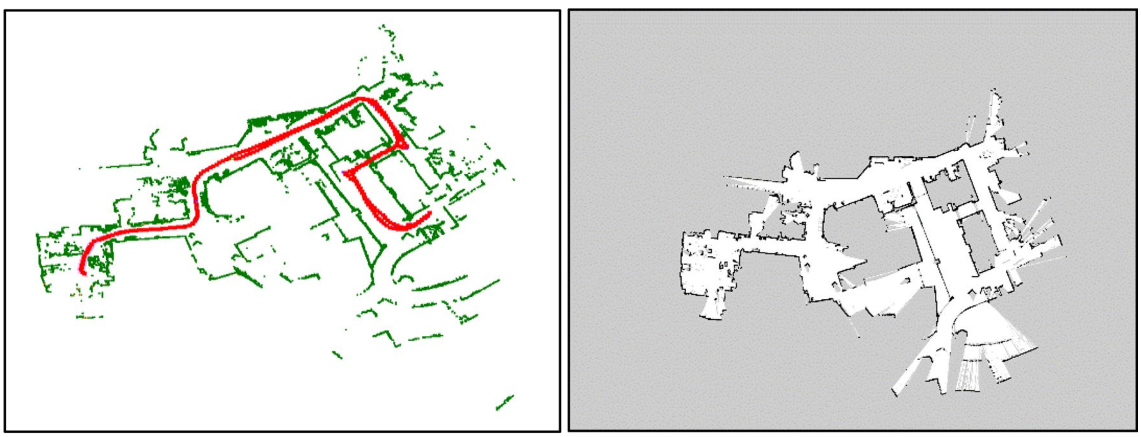
(a) (b)

Fig. 24 Third Table Reached (**a**) Fourth Table Reached (**b**)



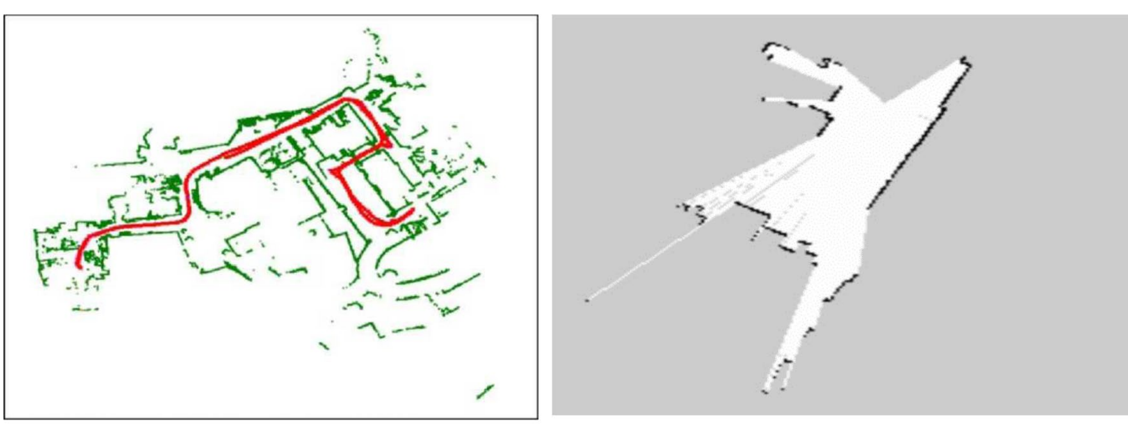
(a) (b)

Fig. 25 The Maps are created with the help of a laser scan



(a) (b)

Fig. 26 Updated map with error minimization and long-term map maintenance



(a) (b)

Fig. 27 Map generated by using G-mapping in static Environment (**a**) Map generated in semi-dynamic Environment with noise (**b**) cost of production and improving the energy efficiency of the robot would make it more accessible and sustainable for widespread use. Continuous software updates and hardware improvements based on user feedback and technological advancements will ensure the robot remains relevant and effective in a rapidly evolving service industry.

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Declarations

Conflicts of Interest The author declare no conflict of interest.

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