Intelligent Enhanced Mobile Robotics Navigation: Integrating Neural Networks with Type-2 Fuzzy Logic for Dynamic Environments

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Abstract

Intelligent mobile robots move on uncertain grounds, thus requiring good navigation strategies for things like path tracking and obstacle avoidance. This research uses an Omni-drive mobile robot to autonomously approach given objectives in different situations encountered in static and dynamic environments. The paper compares two distinct controllers – fuzzy logic controller and neural network controller- that lead the mobile robot towards its destination without hitting obstacles. These are responsible for adjusting the linear and angular velocities of a mobile robot which makes adaptive navigation possible during real-time. The experimental results have depicted the adaptability of each controller as well as its efficiency especially when dealing with uncertainties involved with the mobile robot navigation system. By systematically evaluating and contrasting them, this study brings out the best performance between Fuzzy Logic and Neural Network Controllers regarding enhancing the autonomy and robustness of Mobile Robots. This research helps to advance knowledge in autonomous systems for practical applications, which will give rise to more efficient navigational techniques for mobile robots; thus, efficient systems that are autonomous become more reliable today. The results show that these controllers are effective in safely steering the robot from its starting point to a specified destination without hitting obstacles.

Keywords: Omni-drive robot; collision environment; neural network controller; type2 fuzzy logic controller.

1. Introduction

In the modern world, robots have become a part of everyday life. There are numerous applications where robots can be used due to their mobility such as healthcare, entertainment, hospitality, and military operations. Mobile robotics is one of the most rapidly developing areas of scientific investigation while acting as a driver of human civilization in general [1]. These devices have shown great efficiency in supplementing or completely replacing people from many activities; thus high- performance applications might be foreseen [1]. The need to avoid obstacles is an important function in mobile robots and thus ensures that they reach their goal without colliding with obstacles. This means they should be enabled to make decisions by autonomously planning their paths to possible hazards that prevent their progress. So, this becomes progressively difficult using only classical control approaches operating within unknown environments, leading to intelligent control techniques [1]. Likewise, some intelligent control methods struggle with the vast uncertainties involved in sensor readings, actuator responses and environmental conditions [2]. The author has developed a strong controller using type-2 fuzzy logic controllers (FLCs) [6]. The simulation results of obstacle avoidance showed that this algorithm provided the shortest path in comparison to other algorithms. To conquer these uncertainties, Chiu and Santiago [7] used nine sonar sensors for independent obstacle evasion as well as tracking along walls with period type-2 FLC and PID controllers. Their approach succeeded in navigating through unknown environments while maintaining constant wall-following

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behaviour. This paper explored different kinds of fuzzy logic controllers used for robot obstacle avoidance as compared to Type 1isms through twelve Infrared sensors (IR) which demonstrated similar characteristics over various scenarios [8]. Nevertheless, when uncertainty increases, type-2 FLC proves superior to both systems in terms of precision and speed. As an example, reference [9] was utilized to build a mobile robot using the type-2 FLC as the controller.

To track its movement within unfamiliar environments, three sensors were installed on its left front and right sides whose orientation angle measurements were employed by the linear angular velocity response of the controller therefore, the outcome was that the controller during the direction changes to the target exhibited dexterity in carrying out seamless manoeuvres through smoothly controlling accelerations and decelerations. To avoid such obstacles, they proposed a hybrid system of type-2 FLC and optical flow using image processing based on camera inputs for environmental cue extraction [10]. Simulation results indicate that this approach is effective in terms of obstacle avoidance. This paper [11] presents interval type-2 fuzzy logic controllers (IT2FLC) and type-1 fuzzy logic controllers (T1FLCs) developed for Swarm Robotics. They used the X-Bee communication and distance sensors. The simulation results demonstrated the effectiveness of type2 fuzzy logic controller, which models complex problems, and outperformed type-1 FL. Ruqayah et al. [12] investigated the efficacy of the adaptive FLC in navigating through unstructured surroundings. Meanwhile, Guo et al. [13] formulated an FLC-based step by step optimal path-planning reaching to spherical robots to navigate through unfamiliar and unstructured environments. Kumar et al. [14] presented a hybrid fuzzy strategy crafted to enable the smooth and obstacle-free mobility of various humanoid robots across intricate terrains, effectively tackling diverse and challenging scenarios.

In contrast, Rath et al. [15] spearheaded the development of intelligent fuzzy methodologies specifically designed to ensure the smooth or uninterrupted and effective traversal of humanoid robots through environments abundant with obstacles. In a complementary vein, Muni et al. [16] introduced an effective motion planning approach for legged robots suitable for dynamic environments, harnessing the capabilities of Sugeno FLC. Al-Dahhan et al. [17] introduced a method utilizing two FLC to navigate through straightforward-shaped obstacles. Additionally, Pham et al. However, in [18], the focus shifts to planning the safest and shortest path in a static environment with the hurdle of different shapes using the A* algorithm. Although the path generated by A* ensures safety with ample distance from obstacles, it can lead to sharp corners, hindering smooth turns for the robot. In [19] and [20], FLCs were deployed to determine the safest and shortest path and navigate through unknown environments containing static and dynamic obstacles. However, the robots used in these studies possessed constraints, particularly in manoeuvrability, due to limitations in rotation angles. Researchers have addressed this issue by incorporating non-holonomic robots in their work, as seen in [20] and [21] where a neuro-fuzzy logic approach integrated with a safe boundary algorithm for navigating non-holonomic robots safely is proposed. [21] and [22] introduce FL methods for planning a path, employing the non-holonomic robot.

The work by [23] combines swarm optimization with FL to improve navigation performance for non-holonomic robots. This approach focuses on controlling trajectory and minimizing travel time to reach predefined targets. With advancements in autonomous systems and robotics, numerous researchers continue to explore innovative techniques and methodologies to enhance navigation capabilities in mobile robotics [24]. In contemporary times, neural networks (NNs) have become widely employed in various areas like artificial intelligence and machine learning (ML) [25]. Unlike traditional path-planning approaches, NN algorithms excel in improving the accuracy and effectiveness of pathfinding in complex and dynamic environments through learning and optimization processes. Their superiority lies in their ability to extract crucial information from diverse incorporating inputs such as maps, sensor data, robot status, and mission requirements, along with other multidimensional data. Via training and deep-learning, NNs autonomously recognize and understand this information, seamlessly integrating it into the path-planning process to yield more intelligent and adaptable outcomes [26].

However, it is essential to recognize that NN also has limitations, particularly when traversing through unstructured and intricate environments. Despite this, specific types of robots can leverage it to gain insights into optimal paths in such intricate terrains [27]. For example, Chen and Zhao [28] proposed a motion planning methodology utilizing radial basis function NNs, guiding automated vehicles to extract navigable areas, extracting information from perceptual grid maps in unstructured environments, resulting in flexible, smooth, and safe paths that can adapt to different road configurations. In [29], FLC type-2 was utilized for the Omni-robot with the aim of obtaining a safe obstacle-free path as the robot moved from the starting point to the endpoint. Experimental results elucidated the effectiveness of the control in navigating past both static and dynamic obstacles and safely reaching the destination. However, a real-time obstacle avoidance strategy is proposed for mobile robots equipped with monocular cameras in [30]. This approach utilizes the binary semantic segmentation FCN-VGG-16 to extract features from images captured by the monocular camera and estimate the position and distance of obstacles in the robot's environment.

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The purpose of the research in [31] is to conduct an experimental investigation into the performance of the adaptive Mamdani Fuzzy Controller (AMFC) implemented in LabVIEW, which has been designed and applied to the second-order dominant nonlinear Dual-Input Tank System (DITS) and the Single-Input Tank System (SITS).

The literature review highlights the existing control techniques employed for obstacle avoidance. This study enhances the current literature by developing a straightforward control algorithm capable of guiding a mobile robot safely and obstacles-free to its predetermined final goal point.

The structure of this article follows is as: Section two introduce the methods and materials, Section three outlines the experimental outcomes, and Section four provides the conclusion.

2. Materials and Methods

The core focus of this paper lies in the application of fuzzy and neural controllers on mobile robots. Therefore, this section is dedicated to provide a comprehensive understanding of these components, as outlined below.

2.1 Mobile Robot System Description

The omni-robot depicted in figure 1, is a mobile robot equipped with a drive system, interfaces, a learning system for training, development and research capabilities.

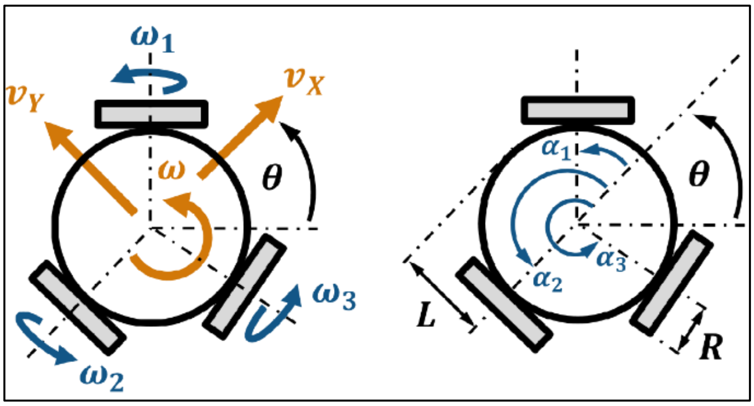

Figure 1: The main shape of the Omni-mobile robot platform

This system includes a powerful controller (PID) that provides intelligent functionality and is equipped with numerous sensors. Additionally, it features a user-friendly electrical interface, enabling seamless integration of additional sensors or actuators. Notably, infrared (IR) sensors are key components, serving as primary tools for detecting nearby objects and navigating around obstacles. Especially beneficial indoors, IR sensors are adept at identifying walls, furniture, and other obstacles, offering essential information for autonomous functionality. As depicted in figure 2, these sensors significantly improve the robot's awareness and manoeuvrability in diverse situations.

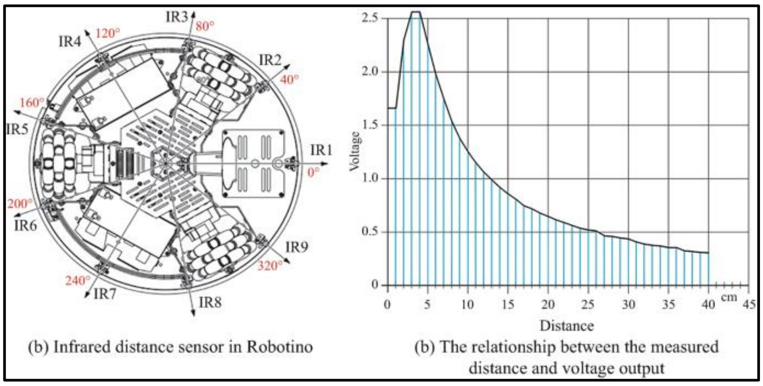

Figure 2: IR sensor in position

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2.2 Type-2 FLC design

This section focuses on the primary design considerations rather than delving into the intricacies of the type-2 FLC system. The focus is on addressing the fundamental design challenges. A type-2 FLC was developed after acquiring a deep understanding of the robot's dynamic system and its capability to accommodate a sophisticated algorithm aimed at guiding the mobile robot safely along its predetermined path.

2.2.1 Type-2 FLCs for Tracking a Path.

Figure 3 illustrates the system block diagram. Initially, the robot receives the coordinates of a designated destination point. The current position of the mobile robot is then acquired from odometry compared to the desired values. These sensor readings are utilized to fine-tune the parameters of the type-2 |FLC system to ensure that the robot maintains the necessary distance and to achieve the predefined objective.

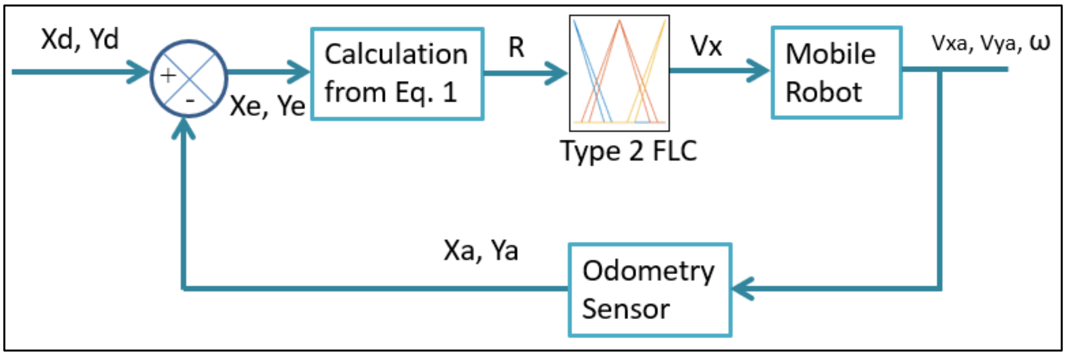

Figure 3: A block diagram for path tracking control employing type-2 fuzzy logic

The system block diagram outlines the process of guiding a mobile robot using type-2 FLC. Xd and Yd represent the desired values for the positions of the X and Y coordinates, while Xa and Ya represent the values of the position of the mobile robot. The errors represented by Xe and Ye are computed by subtracting the actual coordinates from the desired coordinates using a comparator. The parameter R represents the calculated resultant distance needed for the path, as determined by Equation (1). The instantaneous resultant distance (R) acts as an input variable for the type-2 FLC.

$$R = \sqrt{(Xd - Xa)^2 + (Yd - Ya)^2} \qquad (1)$$

2.2.2 The Type-2 FLC Block Consists of Three Primary Processing Stages as Follows.

- The Fuzzification Process: as it is challenging to ascertain the exhaustiveness of fuzzy rules tailored to specific applications, a set of three FLC rules was employed according to the requirements. Through numerous iterations aimed at determining optimal fuzzy sets and intervals for variables (R), the R fuzzifier was established with three sets distributed across a range of (0–1000) cm. This range encapsulates the spectrum of uncertainty for (R), depicted in figure 4.

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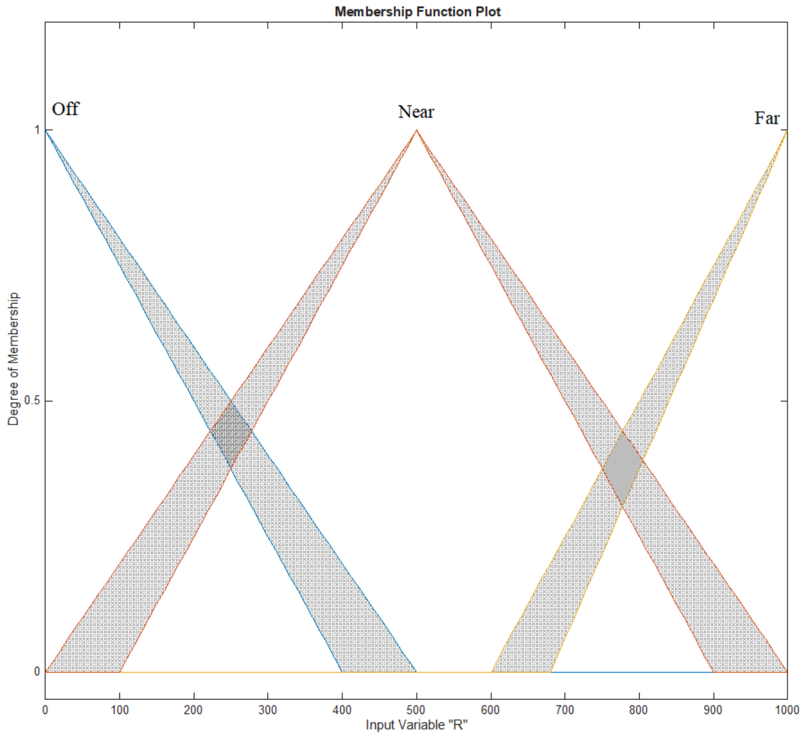

Figure 4: illustrates the resultant Type-2 Fuzzy Sets

- The Defuzzification Process: the crisp output value is determined by applying Mamdani's method. For linear velocity Vx, three actions—"Off," "Medium," and "Fast"—are employed, corresponding to speeds ranging from 0 to 400 mm/s. These selections were made to ensure ample time for the robot to respond to detected obstacles while maintaining smooth movement, as seen in figure 5.

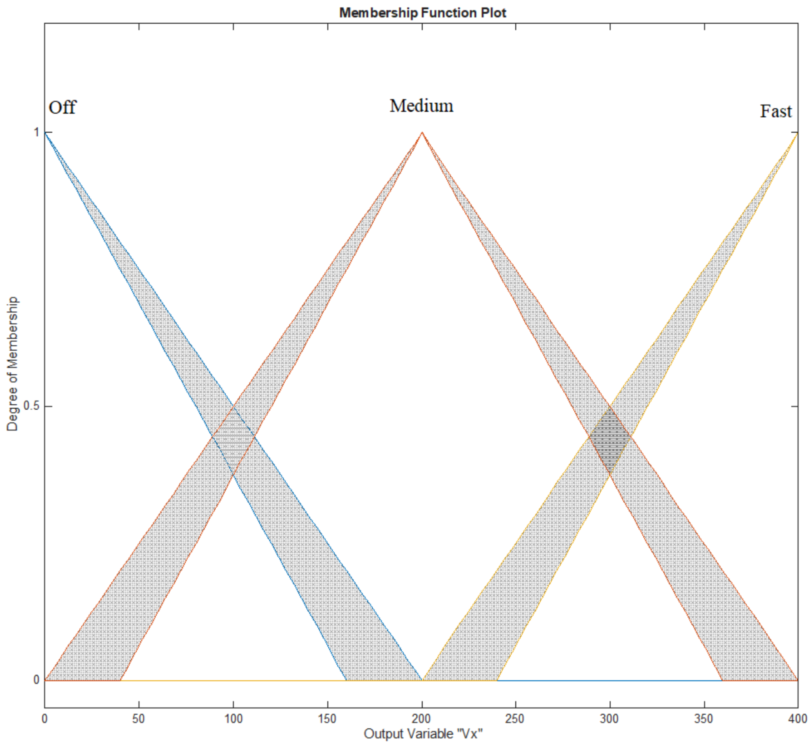

Figure 5: Vx velocity

- Fuzzy Production Rules: From the fuzzification process, three fuzzy production rules were derived and are presented in Table 1.

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Table 1: Type-2 fuzzy production rules

Rule	Vx
If R is Off	Off
If R is Near	Medium
If R is Far	Fast

2.3 The Multi-Layer Perceptron (MLP) Neural Network

MLP-NN possesses the ability to delineate intricate decision boundaries attributed to the nonlinear characteristics within its nodes [32].

2.3.1 Avoiding Obstacles Through NNs

As it is clear in figure 6, designing MLP-NN utilizing the backpropagation algorithm to attain linear velocity (Vy) and angular velocity (ω) entails the following topology:

- Input Layer: Consists of two nodes serving as inputs to the controller.

- Hidden Layer: Comprises five nodes.

- Output Layer: Consists of a pair of nodes that offer output values for linear velocity along the x-axis and angular velocity (ω).

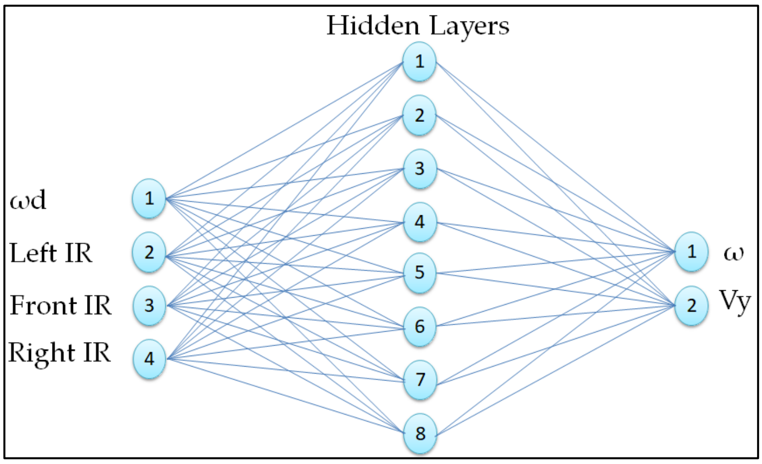

Figure 6: Designing the MLP-NN for obstacle avoidance

The NN receives two inputs. The first input from IR sensors (voltage) moves the robot away to the left or right according to the position of the obstacle. The second input aims to attain the necessary rotation for the robot to reach the goal. Once this angle is achieved, the robot can proceed directly towards the desired goal. The calculation of the required orientation (ω) is determined using Equation (2). The output information is transmitted directly to the half layers for further processing.

$$\theta e = atan2(Xd - Xa), (Yd - Ya) \qquad (2)$$

In this scenario:

- Δx = (Xd - Xa) indicates the intended real location of the robot in the environment, whereas Δy = (Yd - Ya) represents the current position. The resulting R provided by equation (1) signifies the distance between these positions.

- Equation (2) provides the necessary rotation for the robot to align with its predetermined target.

Doi: https://doi.org/10.54216/FPA.150208
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- In the second section of the NN, a topology comprising seven nodes are trained over 600 iterations, ensuring accurate data transmission to the output nodes for executing the necessary actions based on the mobile robot's instantaneous position.

- The end part of the NNs comprises the output layers, with a topology where each output node controls the angular velocity. Figure 7 illustrates the overall system block diagram.

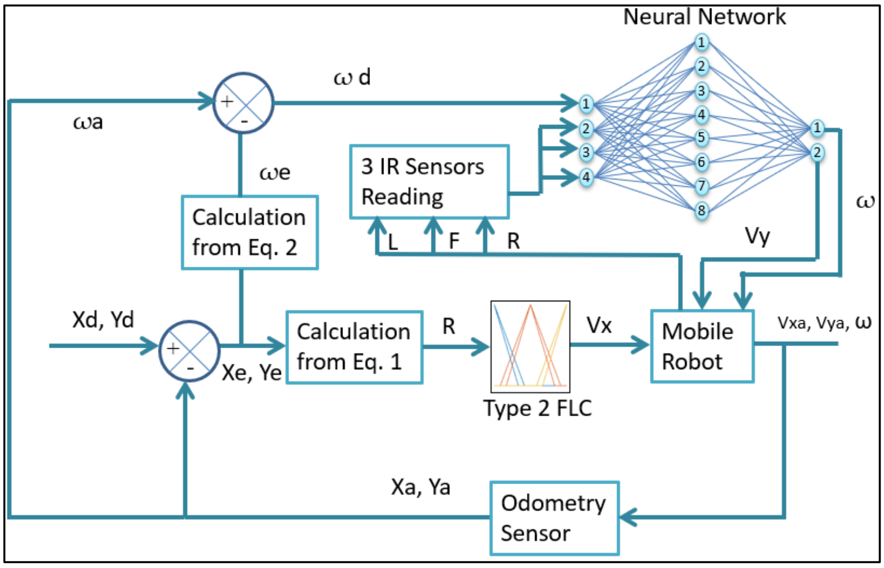

Figure 7: Overall system block diagram for the mobile robot's navigation

3. Results

This section presents three distinct real-time experiments. The first experiment assessed the algorithm's effectiveness in directing the mobile robot from its initial location to the designated goal location in an environment free of obstacles. Here, only the NN and type-2 FLC for orientation control and Vx movement were employed to navigate the robot in real time. In contrast, the second and third experiments evaluated the combined performance of both NN and type-2 FLC safe navigation, guiding the robot while manoeuvring around dynamic obstacles along its path. All the experiments demonstrated successful navigation, ensuring the robot's safe movement and achievement of the goal.

3.1. A Non-Obstacle Environment

In figure 8, a scenario with an obstacle-free environment was utilized to assess the controllers. The starting point was (0, 0), and the target location was (3000 mm, 2500 mm). Initially, the robot rotatesd until it reached θe; when θe reaches zero, it signifies that the robot is oriented towards its goal and can move straight towards it. In figure 9, the orange line along the x-axis represents the samples utilized during motion, whereas the magenta line along the y-axis illustrates their positions. Subsequently, it starts moving forward towards the goal. These data were gathered from the odometry of the mobile robot.

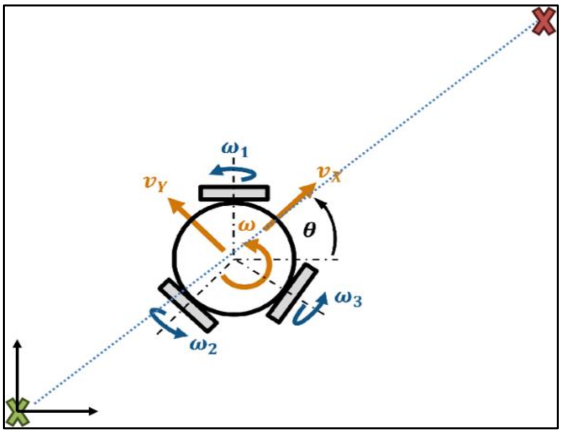

Figure 8: The free obstacles map

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The response times in both the X and Y directions are depicted in figure 10, utilizing 1400 samples. An initial delay was observed, attributed to the time the mobile robot required to adjust its orientation. During the transient response, a minor variation in position was noticeable due to slight disparities in motor synchronization. However, minimal steady-state error was observed by the conclusion of the experiment.

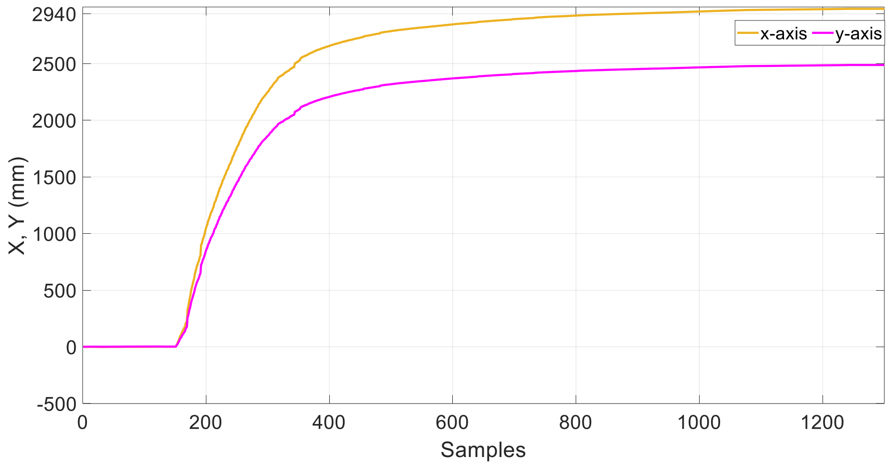

Figure 9: The movement of the mobile robot

No voltage readings above 1.5 volts were detected by the infrared sensors, indicating a clear path ahead devoid of obstacles. This observation aligned with the expected performance of the infrared sensors, as detailed in figure 10. To visually emphasize this threshold, a bold black line is drawn at the 1.5-volt mark, serving as a clear indicator of the sensor's response characteristics. This feature underscores the reliability of the sensors in accurately identifying the presence or absence of obstacles, contributing to the overall effectiveness of the robot's navigation system.

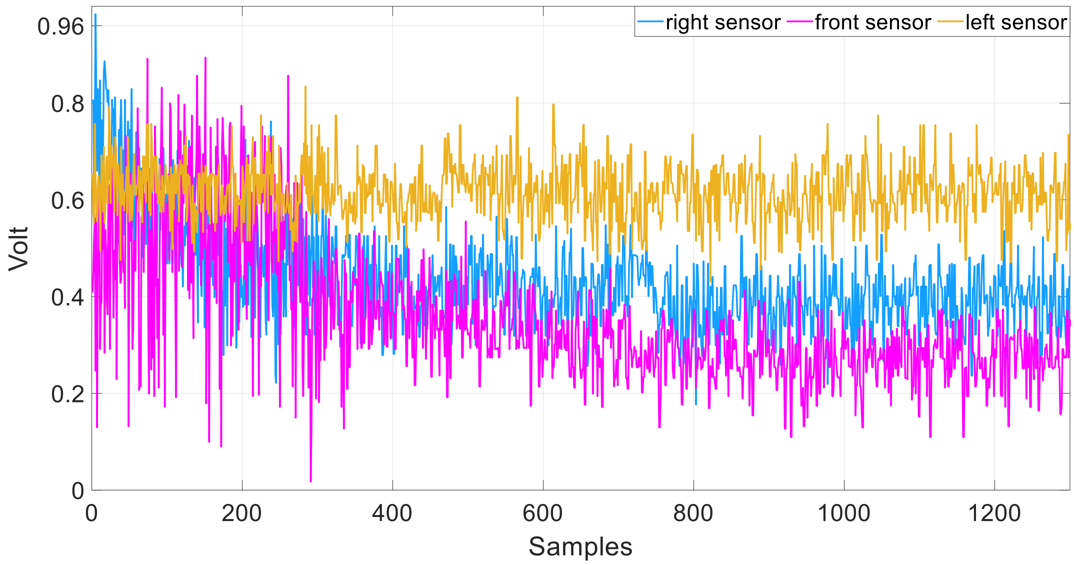

Figure 10: Three IR sensor readings

Figure 11 illustrates that as the robot initiated a turn toward the specified angle, all three motors operated in unison, propelling the robot in the same direction. Once the desired rotation angle was established, the mobile robot proceeded to advance toward the target destination. This forward movement was translated into counter-clockwise rotation for the left motor, clockwise rotation for the right motor, and cessation of movement for the rear motor, aligning the mobile robot with the pre-programmed planned dynamic movements programmed into it.

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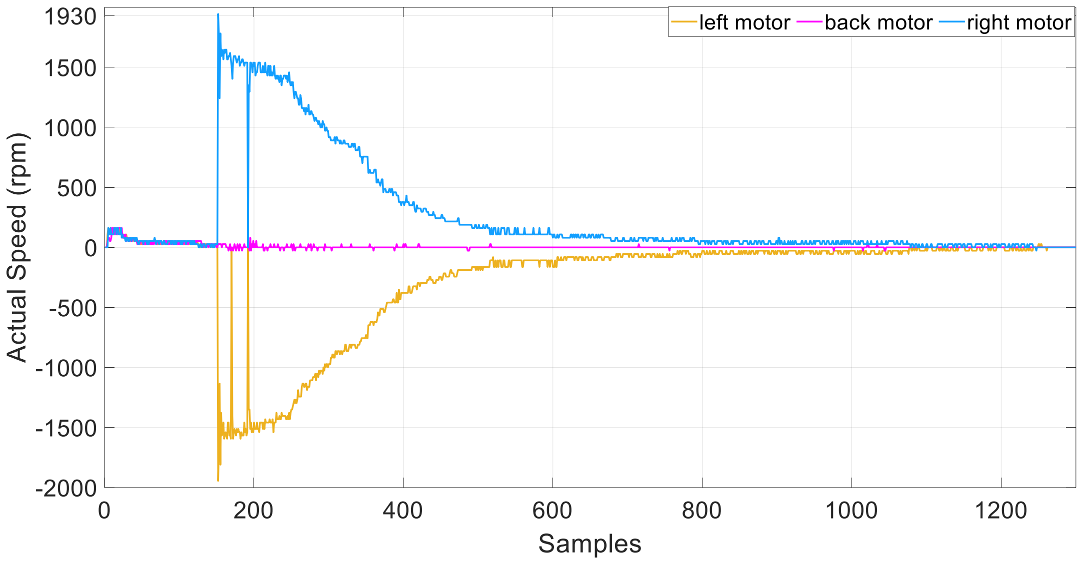
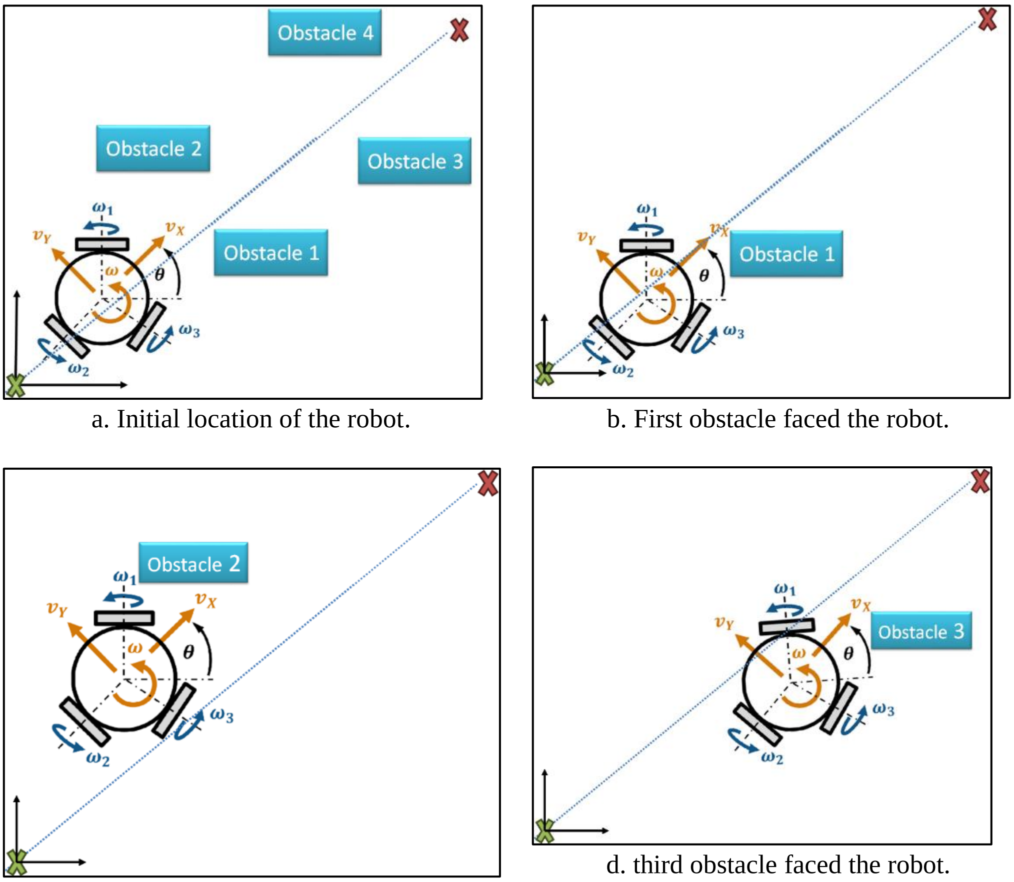


Figure 11: The motor speed of the mobile robot

3.2 An Obstacle Environment

In figure 12, the operational arena surrounding the robot was deliberately populated with four distinct obstacles, each situated strategically around the robot's periphery. This setup served as a real-world simulation, presenting the robot with dynamic challenges to navigate through in its workspace. The navigation process was meticulously orchestrated through a series of sequential movements guided by type-2 fuzzy control actions.



a. Initial location of the robot.

b. First obstacle faced the robot.

c. Second obstacle faced the robot.

d. third obstacle faced the robot.

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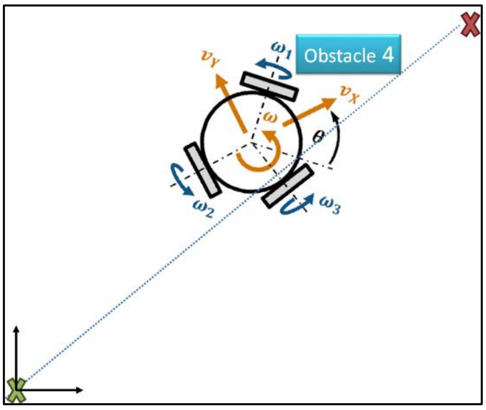
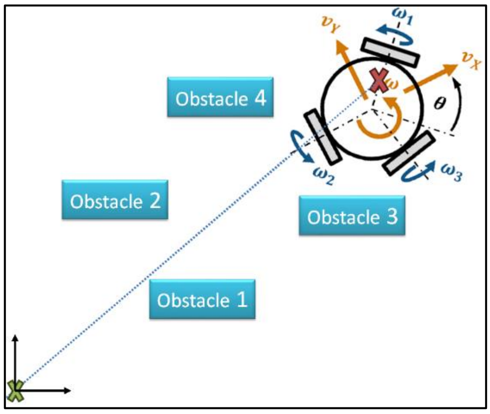


e. Fourth obstacle faced the robot.



f. The robot avoids all obstacles and reach the target.

Figure 12: A setting where obstacles obstruct the robot’s path

In figure 13, the robot encountered four obstacles positioned on different sides within its real-time workspace. The fuzzy-2 control actions guided the robot through a series of steps: initially, it rotates until achieving the desired orientation (Step 1), followed by movement in both the X and Y directions (Step 2). Upon detecting an obstacle approximately 800 mm away, the robot shifted to the left (Step 3), then repeated steps 1 and 2. Subsequently, encountering another obstacle at a similar distance prompted the robot to adjust to the right (Step 5). The same scenario was repeated until the robot avoided all the obstacles. In obstacle-free conditions, the robot readjusted its angle to proceed efficiently towards its target, maintaining a trajectory illustrated in figure 14. This path was refined through 1100 samples, ensuring minimal steady-state error as it progressed toward the desired position.

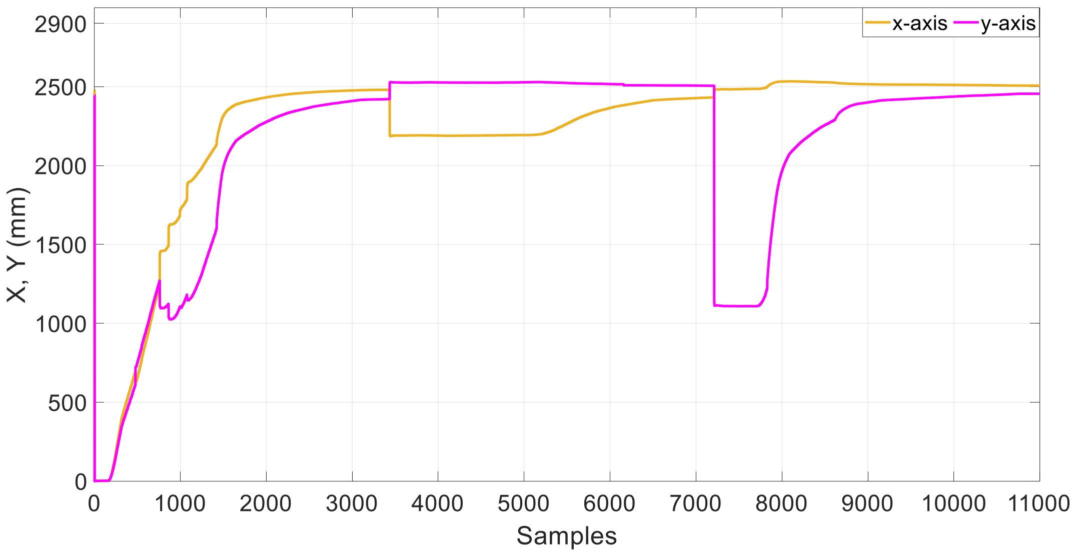


Figure 13: Movement of the robot on the x and y-axis

Figure 14 displays the infrared (IR) sensor readings utilized for obstacle avoidance. Initially, the front sensor registered a voltage reading exceeding 1.5 V at a time response of 800, indicating the presence of an obstacle. Subsequently, as the robot manoeuvred away from the obstacle, the sensor reading diminished to less than 1 V, signalling avoidance of the obstacle. A similar sequence unfolded when the left sensor detected a second obstacle, prompting the robot to adjust its position accordingly. This pattern was repeated with obstacles three and four, with the robot dynamically responding to each detected obstacle by modifying its trajectory to evade them. Ultimately, through a series of navigational adjustments guided by the IR sensor data, the robot successfully circumvented all the obstacles, reoriented itself towards the goal, and proceeded to reach its predetermined target destination.

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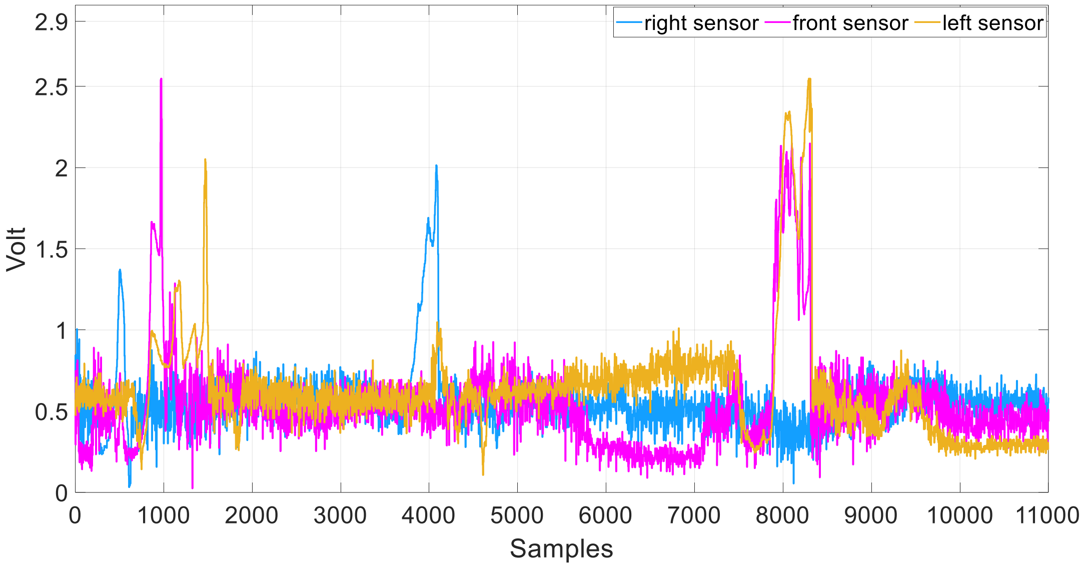

Figure 14: IR sensor readings

As described in the first experiment, the diagram depicts the robot as it began to rotate towards the specified angle. During this rotation, all three motors collaborated, driving the robot in a unified direction. Once the desired rotation angle was achieved, the robot transitioned into forward motion towards its target destination. This forward movement was achieved through counter-clockwise rotation of the left motor, clockwise rotation of the right motor, and the halting of movement for the rear motor. These coordinated motor actions corresponded to the programmed dynamic movements of the robot, ensuring its smooth progression along the designated path as it's clear in figure 15.

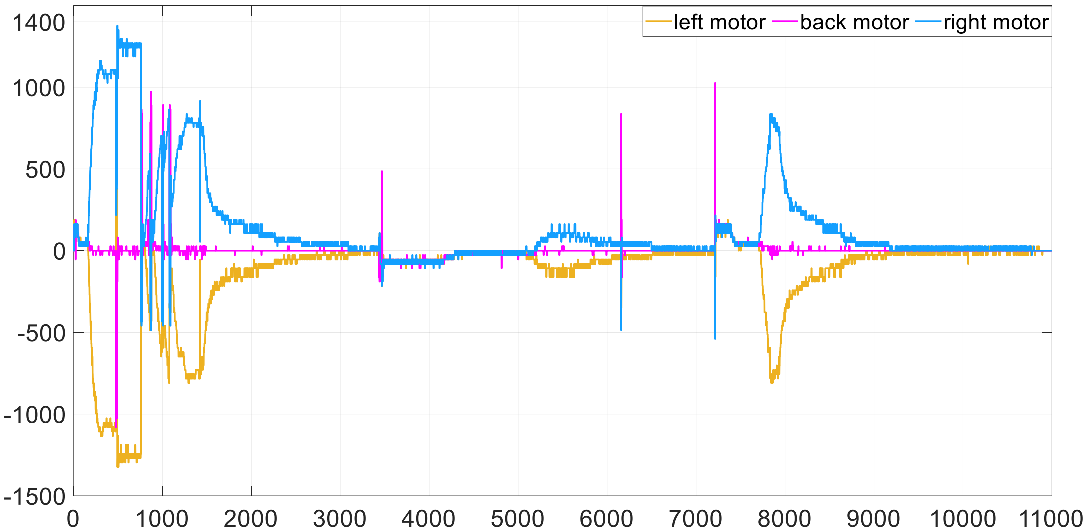

Figure 15: The motor speeds of the mobile robot

6. Conclusion

An NN coupled with a type-2 FLC was introduced to identify and circumvent both stationary and moving obstacles, employing three infrared sensors. These sensors provided analogue voltage data representing obstacle distances in the NN network controller received voltage inputs from these sensors. A type-2 FLC, comprising nine fuzzy rules, was specifically crafted to govern the mobile robot navigation. It received two inputs: the resultant obstacle distance. By judiciously regulating these inputs, the robot achieved controlled movement along its predefined path. The fuzzy algorithm regulated the linear velocity along the x-direction, while the NN governed the angular velocity. With this composite controller design, everything was well planned for static and dynamic obstacle avoidance. The controller's efficacy was tested in real-time on different conditions to determine if it could work well. Data that was extracted provided useful information regarding an evaluation of the responses from proposed type-2 fuzzy and NN controllers. They were employed as high-level controllers in this study, and the

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designed controllers depicted exceptional performance in speed as well as a minimum steady state error while avoiding static and dynamic obstacles. The experiments confirmed that the control system performs effectively in real-life situations. Besides, its resulting hardware system was flexible with remarkable dynamic response enhancing accuracy towards overall efficiency for obstacle avoidance.

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