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APPLIED RESEARCH

Z-Number-Based Fuzzy Logic Approach for Mobile Robot Navigation

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ABSTRACT The primary objective of this study is to investigate the effects of mobile robot navigation using a fuzzy logic framework based on Z-numbers implemented within the Robot Operating System (ROS) Noetic. The methodology addresses uncertainty and imprecise information in robot navigation using extensive simulations performed using the TurtleBot3 robot in the ROS framework. Our unique approach enables the autonomous navigation of mobile robots in unknown environments, utilizing fuzzy rules with multiple inputs and outputs. The navigation strategy relies on the laser scan sensor, the Adaptive Monte Carlo Localization (AMCL) algorithm, and particle filter mapping, enabling real-time localization and mapping capabilities. Path planning incorporates local and global planners, while obstacle avoidance generates collision-free paths by dynamically detecting and circumventing obstacles in the robot's proximity. We employ Simultaneous Localization and Mapping (SLAM) techniques to estimate the robot's position and create a map of the environment. Our integration of these methods presents a promising solution for autonomous mobile robot navigation in real-world applications, thereby advancing the capabilities of robot systems in complex environments. Our results demonstrate the suitability and effectiveness of using a Z-number-based system in the navigation scenarios of mobile robots.

INDEX TERMS Z-number, fuzzy logic, mobile robot navigation, path planning, obstacles avoidance, simultaneous localization and mapping (SLAM).

I. INTRODUCTION

Mobile robot navigation is critical in robotics, especially in unknown or dynamic environments. Mobile robots must have reliable and robust navigation algorithms to handle environmental uncertainties and variations. Fuzzy logic-based approaches were extensively used in mobile robot navigation due to their ability to handle uncertainties and vagueness in the data. Fuzzy logic is a mathematical framework that facilitates reasoning and decision-making in uncertain situations. It has found widespread application across various domains, including mobile robot navigation.

Over the years, significant progress has been made in mobile robot navigation, with various approaches aimed at improving the autonomy and adaptability of robots in diverse environments. For instance, Zhou et al. [1] presented a self-organizing fuzzy neural network with hierarchical pruning for nonlinear system modeling. Zhang et al. [2] focused on visual navigation in complex environments using distributed deep reinforcement learning, while Kim and Nam [3] explored mobile navigation in confined spaces through deep reinforcement learning. Upadhyay et al. [4] dedicated their research to establishing trustworthy autonomous navigation in unpredictable settings. Likewise, Martini et al. [5] introduced a ROS2 modular framework for autonomous navigation with deep reinforcement learning. Ma et al. [6] introduced a mapless end-to-end navigation system based on deep reinforcement learning, and Ataka and Sandiwan [7] delved into growing robot navigation using deep reinforcement learning.

However, these methods also face real-world challenges, such as navigating through cluttered environments

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with movable obstacles [8], avoiding static obstacles [9], and addressing sensing performance issues when using depth cameras and Lidar for navigation [10]. Additionally, Dubey et al. [11] proposed a path optimization and obstacle avoidance approach based on the gradient method with potential fields. They developed a segmented structure for independent navigation using deep reinforcement learning via ROS2. In the meantime, Glukhov et al. [12] explored the integration of UWB and stereo cameras for indoor mobile robot navigation, while Khnissi et al. [13] implemented an optimized SLAM system based on ROS for mobile robots. Wang et al. [14] employed a fuzzy neural network for navigation control, and Liu et al. [15] introduced graph relational reinforcement learning for large-scale crowded environments. Kim et al. [16] presented an open-source, low-cost mobile robot system with efficient real-time navigation algorithms. Deshmukh and Hasamnis [17] tackled the challenge of autonomous navigation in GPS-denied indoor spaces. These studies underscore the importance of advanced machine learning techniques, particularly deep reinforcement learning, in enhancing robot navigation capabilities.

Reyes et al. [18] present a study on mobile robot navigation assisted by GPS, investigating the integration of GPS technology into the navigation system to improve accuracy and reliability. In their work, Ashokaraj et al. [19] present a novel approach to feature-based robot navigation by combining fuzzy logic, interval analysis, and the Unscented Kalman Filter (UKF). The authors investigate the utilization of fuzzy logic and interval analysis within this domain, offering valuable insights into their application. Wang et al. [20] propose an autonomous navigation method based on the Robot Operating System (ROS), while Wahab [21] introduces a dual artificial neural network for robot navigation. Warku et al. [22] focus on autonomous navigation using a graphical user interface in ROS. Moslemi and Sadedel [23] discuss behavior control and navigation using ROS-Gazebo. Villaseñ or-Carrillo et al. [24] present a navigation system based on fuzzy logic and different behavior patterns. In another study, Parasuraman et al. [25] discuss the theoretical and experimental investigations of mobile robot navigation utilizing an alpha(α)-level fuzzy system. They examine how fuzzy logic can enhance the navigation abilities of mobile robots. Chikurtev [26] focuses on simulating and navigating mobile robots in ROS and Gazebo. The author explores using these platforms to simulate and implement mobile robot navigation algorithms.

Akai et al. [27] propose a navigation system for mobile robots that combines magnetic sensors and lidar for localization in real-world environments. The authors employ Monte Carlo localization techniques to enhance the precision of robot navigation. Li and Mei [28] present a navigation and control system for a ROS-based mobile robot. They discuss the architecture and implementation of the system, highlighting the benefits of using ROS for developing robot navigation algorithms. The study conducted by Ren Yee et al. [29] proposes using a 2D LiDAR and an inclined laser rangefinder to enable the robot to avoid lower obstacles during navigation. Their method highlights the importance of sensor integration for effective obstacle detection. In a study by Allagui et al. [30], the authors investigate using a combination of fractional order PI and fuzzy logic controllers to enable autonomous navigation. Their research highlights the advantages of employing hybrid control strategies for mobile robots.

Strauss and Sahin [31] focus on autonomous navigation using a Q-learning algorithm in a natural environment. Their work demonstrates the efficiency of reinforcement learning techniques for robot navigation tasks. Josiah et al. [32] focus on enhancing mobile robot navigation through neuro-fuzzy methods, combining neural networks with fuzzy logic. Their approach aims to improve navigation capabilities effectively. Dupre and Yang [33] propose a two-stage fuzzy controller for mobile robot navigation, integrating with fuzzy rules to achieve efficient path planning and obstacle avoidance. Ayedi et al. [34] introduce a fuzzy controller for mobile robot navigation, emphasizing its effectiveness in handling uncertain environments and sensor noise. Aydın et al. [35] developed a fuzzy controller for leader-follower navigating of a mobile robot, specifically in a ROS-enabled environment. They demonstrate the applicability of fuzzy logic for coordinating the movement of multiple robots. Wildani et al. [36] propose a fuzzy logic-based control system for navigating robots semi-autonomously, integrating with remote control capabilities. Their approach showcases the versatility of fuzzy logic in enabling remote control and autonomous navigation simultaneously. Phueakthong and Varagul [37] present a mobile robot based on ROS2 for navigation applications. Brahimi et al. [38] describe navigating car-like mobile robots in unfamiliar urban areas. Kiran et al. [39] elaborate on designing and creating an independent mobile robot for mapping and navigation purposes. Xu et al. [40] describe the design and implementation of an autonomous navigation system utilizing ROS. Jin and Zhou [41] discuss the development and execution of a mobile robot navigation system built upon the ROS platform. These studies emphasize the significance of ROS in facilitating the advancement of autonomous navigation systems, covering key aspects such as mapping, localization, and exploration of unknown environments.

Gatesichapakorn et al. [42] propose a navigation system for autonomous mobile robots that uses a 2D LiDAR with an RGB-D camera based on ROS. Takaya et al. [43] present a simulation environment using ROS and Gazebo for testing mobile robots. Wang et al. [44] implement a subsumption model on ROS for mobile robots. Lee et al. [45] designed and implemented a ROS autonomous driving pallet robot system. Mendes et al. [46] integrate the ROS-based navigation stack with dynamic environmental information in the Gazebo simulation. Li and Shi [47] focus on localization and navigation for indoor environments based on ROS. Manav et al. work [48] focuses on adaptive path-following control for semi-trailer docking, addressing a crucial aspect of autonomous vehicle operations. Wu and Zaman [49] contribute to the literature with a LiDAR-based trajectory-tracking system for differential drive mobile robots, employing a fuzzy sliding mode controller. Nossier et al. present path-planning algorithms [50] and multi-obstacle avoidance strategies [51] grounded in support vector machines, catering to dynamic environments and autonomous vehicle safety. Meanwhile, Suarez-Rivera et al. [52] delve into adaptive trajectory tracking for wheeled mobile robots, addressing the challenges of real-time control. Parque's et al. work [53] explores advanced fairness functionals for smooth path planning, highlighting the ongoing efforts to enhance the efficiency and fairness of autonomous navigation algorithms. These papers collectively contribute to the evolving landscape of autonomous navigation, control, and path planning, showcasing advancements in diverse areas of research and development. The study by Huang et al. [54] investigates an energy-saving control approach for enhancing the trajectory-tracking performance of autonomous mobile robots. The authors address a critical concern in robotics by proposing a novel methodology to optimize energy consumption during robot navigation. This research contributes to the broader body of knowledge on autonomous robotics and control systems, offering a promising avenue for reducing energy consumption in real-world applications.

The primary objective of mobile robot navigation is to develop algorithms and techniques that enable robots to navigate complex and dynamic environments autonomously. The traditional fuzzy logic approach employs crisp numbers, representing membership degrees in fuzzy sets, to make decisions. However, crisp numbers may not adequately capture the full spectrum of uncertainties associated with real-world problems. To overcome this limitation, Zadeh [55] has introduced the concept of Z-numbers, an extension of fuzzy numbers. Z-numbers offer a more comprehensive modeling of uncertainties by considering the membership degree, non-membership, and hesitancy degrees.

Researchers have extensively explored various approaches based on fuzzy logic for mobile robot navigation in recent years, among which the Z-number-based fuzzy logic approach stands out. Z-numbers, an innovative extension of fuzzy sets, are utilized in this approach to provide a more precise representation of uncertainty in the navigation of mobile robots. It has demonstrated promising results in improving mobile robot navigation across diverse environments. Efficient navigation is a fundamental requirement for mobile robots, encompassing tasks like path planning, obstacle detection and avoidance, and trajectory tracking. Numerous techniques were proposed to achieve reliable and precise navigation, including the Z-number-based fuzzy logic (ZNFL) approach. ZNFL expands upon classical fuzzy logic by integrating Z-numbers, a concept that facilitates the representation of randomness and ignorance in uncertain systems. This enhancement exhibits substantial potential in mobile robot navigation, effectively managing uncertainty and imprecision in sensor measurements and environmental data.

The utilization of the ZNFL-based approach offers numerous advantages over alternative navigation techniques. Firstly, it enables robust navigation in uncertain and dynamic environments by effectively handling uncertainty and vagueness in sensor measurements and decision-making processes. Secondly, it eliminates the need for a complete map of the environment, rendering it suitable for real-world applications where the environment may change over time. Lastly, it demonstrates computational efficiency, a crucial characteristic for real-time navigation. Extensive research has been conducted on the ZNFL-based approach in the context of mobile robot navigation. For instance, Abdelwahab et al. [56] proposed a ZNFL-based trajectory tracking for P3dx wheeled mobile robots, which showed improved tracking performance compared to traditional methods. Mobile robots have attracted significant attention in various fields, including industrial automation, service robots, and military operations [57], [58].

L. A. Gardashova's [59] study explores using Z-Numbers in decision-making representations and methods, a mathematical tool representing uncertainty and vagueness. Z-numbers were used in finance, engineering, healthcare, and environmental management for portfolio optimization, risk assessment, investment decision-making, reliability analysis, project evaluation, and medical diagnosis. The review highlights the advantages of Z-numbers, such as handling uncertainties effectively, representing optimistic and pessimistic views, and capturing subjective preferences. However, limitations include complexity and expert knowledge in assigning Z-numbers. A crucial aspect of mobile robot functionality is navigation, which involves planning an optimal path from the robot's current location to its desired destination while avoiding obstacles. Kang et al. [60] discuss using Z-numbers in decision-making, incorporating linguistic and numeric information to represent uncertain data. The review highlights the advantages of Z-numbers over traditional approaches and showcases successful case studies and applications.

Abiyev et al. [61] propose a control framework incorporating Z-numbers and fuzzy logic to handle uncertainties and imprecise inputs in omnidirectional robot control. The paper discusses challenges in sensor measurements, complex dynamics, and environmental variations, emphasizing the need for a robust control system. Z-numbers provide a comprehensive representation of uncertainty, while the architecture involves acquiring Z-number inputs from sensors and processing them through fuzzy rules and reasoning. The experimental setup and methodology are detailed insights into selecting appropriate fuzzy rules and tuning membership functions to achieve desired control performance. The framework contributes to explicitly focusing on omnidirectional robot control. Yager et al. [62] studied the Z-Numbers theory, which incorporates imprecision and uncertainty. The study overviews Z-Numbers' foundations, representation, arithmetic operations, and comparison methods. It investigates applications in decision-making, risk analysis, and optimization problems. In the study conducted by Won et al. [63], the authors propose enhancing mobile robot navigation by utilizing vision-based Simultaneous Localization and Mapping (SLAM) and distributed filters. They discuss the implementation of these techniques and their impact on navigation performance.

The proposed system's development can be due to advancements in fuzzy logic and the increasing need for robust and reliable navigation systems. To leverage the power of Z-numbers to enhance the performance of mobile robots in challenging environments. This approach typically involves designing fuzzy logic controllers that utilize Z-numbers to handle uncertainties in sensor data, environment modeling, path planning, obstacle avoidance, and decision-making processes. Research on the Z-number-based fuzzy logic approach for mobile robot navigation is an ongoing area of study, with researchers continuously exploring new techniques, algorithms, and applications. The ultimate objective is to develop navigation systems that effectively manage uncertainties, providing reliable and efficient autonomous navigation for mobile robots in real-world scenarios. Thus, in this paper, our contributions are as follows:

- We present a Z-number-based Fuzzy Logic approach for mobile robot navigation with rules modeling the multiple inputs and outputs—our approach is inspired by the study [56]. Our scheme encodes the control rules based on instantaneous distance from the obstacles, target direction towards the goal, and current speed of the robot with the reliability term Z-number to evaluate the linear and angular velocities of the robot to perform specific tasks such as path planning, obstacle avoidance, and navigation. The consequent universe is computed by the Z-number interpolative reasoning based on α-cuts, and defuzzification is performed by the centroid method.
- To validate the Localization, mapping, and Simultaneous Localization and Mapping (SLAM), we performed rigorous computational and real-world experiments using a ROS-based environment and a TurtleBot3 Waffle Pi mobile robot based on ZNFL.
- Our results demonstrated that our approach is successfully implemented in various scenarios, providing unique insights to realize control algorithms toward robust and generalizable navigation performance.

The rest of the paper is organized: Section II presents the preliminary concepts; Section III describes the mobile robot navigation using Z-number base fuzzy logic. In Section IV, simulation studies, and Section V, experimental studies present insights on real-world tests. Section VI results are discussed, and Section VII concludes this paper.

II. PRELIMINARIES

In this section, we describe the fundamental ideas related to our approach.

A. TURTLEBOT3 WAFFLE PI MOBILE ROBOT

The TurtleBot3 Waffle Pi mobile robot is a popular differential wheeled robot used in robotics research and education. It consists of a structure with two driving wheels mounted on the front axle and two caster wheels on the rear axle.

1) KINEMATIC EQUATIONS

The kinematic equations describe the relationship between the robot's wheel velocities and its linear and angular velocities.

Let us define the following variables:

- V : Linear velocity of the robot.
- R : is the wheel radius.
- L : is the distance between the wheels.
- ω : Angular velocity of the robot.
- ωl and ωr are the angular velocities of the left and right wheels.

The kinematic equations for the TurtleBot3 mobile robot are as follows:

$$V = \frac{R}{2}(\omega_l + \omega_r) \tag{1}$$

$$\omega = \frac{R}{L}(\omega_r - \omega_l) \tag{2}$$

We can utilize Z-numbers to model uncertain wheel velocities. Zωl represents the Z-number for the left wheel's angular velocity ωl, while Zωr represents the Z-number for the right wheel's angular velocity ωr. Similarly, we have ZV for linear velocity V and Zω for angular velocity ω. To account for uncertainty, we represent each angular velocity as a Z-number with lower and upper bounds:

$$Z_{\omega l} = \left[Lw_l, U_{w_l}\right] \tag{3}$$

$$Z_{\omega r} = \left[Lw_r, U_{w_r}\right] \tag{4}$$

To obtain ZV, mathematical operations are performed on Z-numbers.

$$ZV = \frac{R}{2}(z_l + z_r)$$

which can be expressed as

$$ZV = \frac{R}{2}([a, b] + [c, d])$$

This computation can be simplified to

$$ZV = \frac{R}{2}[a + c, b + d] \tag{5}$$

yielding the value of ZV as a Z-number with an interval of [a + c, b + d]. This interval indicates the level of uncertainty in the linear velocity. By calculating the worst-case scenario for linear velocity, which is the sum of the lower and upper bounds of the Z-numbers for ωl and ωr, we can derive the Z-number-based fuzzy logic equations for linear velocity ZV.

$$ZV = \frac{R}{2}\left(z_{\omega l} - z_{\omega r}\right) \tag{6}$$

Similarly, for angular velocity (Zω), we subtract the lower bound of Zωl from the upper bound of Zωr while considering the robot's geometry:

$$z_{\omega} = RL\left(z_{\omega r} - z_{\omega l}\right) \tag{7}$$

The formula for calculating Zω is

$$z_{\omega} = \frac{R}{L}\left(z_{r} - z_{l}\right) \tag{8}$$

which can be simplified to

$$Z_{\omega} = \frac{R}{L}\left([c, d] - [a, b]\right)$$
$$Z_{\omega} = \frac{R}{L}[c - b, d - a] \tag{9}$$

when plugging in values for Zr and Zl. Zω is a Z-number representing the uncertainty in angular velocity and has an interval of [c - b, d - a].

2) DYNAMICS EQUATIONS

The dynamics equations describe the forces and torques acting on the robot, which are essential for motion control and stability analysis. In this simplified model, we assume the robot is on a flat surface with negligible friction and neglects the effects of external forces such as wind resistance or wheel slippage.

Let us define the following variables:

- m: Mass of the robot
- I: Moment of inertia of the robot
- R: Radius of the driving wheels
- Fl: Force applied to the left wheel
- Fr: Force applied to the right wheel
- Tl: Torque applied to the left wheel
- Tr: Torque applied to the right wheel

It is imperative to have a comprehensive comprehension of the wheel dynamics of the robot. This can be accomplished by utilizing equations that establish a connection between motor torque (τ) and wheel angular acceleration (α). Adopting this approach enables us to acquire valuable insights into the underlying mechanisms that govern the behavior of the robot's wheels. It is paramount to uphold accuracy and precision when modeling these dynamics, as it can significantly impact the robot's overall performance and functionality.

$$\tau = I * \alpha \tag{10}$$

The dynamics equations for the TurtleBot3 mobile robot can be derived as follows:

a: LINEAR DYNAMICS

Using Newton's second law of motion, the sum of forces in the x-direction equals the robot's mass times its linear acceleration.

$$Fl + Fr = m.a \tag{11}$$

Since the robot is in a pure rolling motion, the linear acceleration a can be expressed in terms of the radius R and angular acceleration α as $a = R.\alpha$

$$Fl + Fr = m.R.\alpha \tag{12}$$

b: ANGULAR DYNAMICS

The angular acceleration α is related to the torque and moment of inertia:

$$\frac{Tr - Tl}{\mathrm{I}} - \frac{Td}{\mathrm{I}} = \alpha \tag{13}$$
$$\dot{\omega} = \alpha \tag{14}$$

Wheel velocities: the wheel velocities (vl and vr) can be related to the linear and angular velocities:

$$v_{l} = v - \frac{L}{2}\omega \tag{15}$$
$$v_{r} = v + \frac{L}{2}\omega \tag{16}$$

Relationship between Forces and Torques: The forces Fl and Fr can be related to the torques Tl and Tr using the radius R and wheel radius r as follows:

$$Fl = \frac{Tl}{\mathrm{R}} \tag{17}$$
$$Fr = \frac{Tr}{\mathrm{R}} \tag{18}$$

The dynamics of each wheel can be modeled using a simplified friction model, which relates the wheel torque (T) to the wheel angular velocity ($\dot{\theta}$):

$$T = I \cdot \ddot{\theta} + B \cdot \dot{\theta} + Km \cdot V \tag{19}$$

where:

I : Moment of inertia of the wheel.
B : Damping coefficient.
Km : Motor constant.
V : Voltage applied to the motor.

These equations represent the kinematic and dynamics equations for the TurtleBot3 mobile robot. They can be used for motion planning, control, and trajectory generation of the robot.

To describe the relationship between forces, torques, accelerations, and the robot's mass and moment of inertia, we use ZF to represent the Z-number for the total force applied to the robot, Zτ for the entire torque applied, z_a for linear acceleration, and Zα for angular acceleration. To relate ZF to linear acceleration, we multiply the Z-number for force by the robot's mass (m):

$$ZF = m \cdot z_{a} \tag{20}$$

To relate $Z\tau$ to angular acceleration, we multiply the Z-number for torque by the robot's moment of inertia (I):

$$Z_\tau = I \cdot Z_\alpha \tag{21}$$

These Z-number-based fuzzy logic equations provide robust control in uncertain environments by incorporating uncertainty and imprecision in the mobile robot's kinematics and dynamics.

B. FUZZY LOGIC CONTROL (FLC)

The fuzzy controller uses fuzzy rules to determine the robot's desired speed, direction, and turning angle to navigate the environment safely. The proposed Z-number-based fuzzy controller is illustrated in Figure 1.

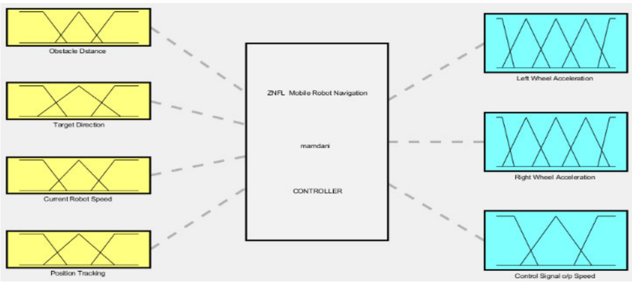


FIGURE 1. Proposed Z-number-based fuzzy controller.

In an FLC system with n inputs, a fuzzy system $Fi\ (i \epsilon\ [n])$ is defined as:

$$Fi = \{(xi, \mu_A(xi)) | \mu_A(xi) \epsilon [0, 1] \forall x_i \in R\} \tag{22}$$

The robot's control system utilizes a fuzzy inference system (FIS) to interpret the sensor data and determine the robot's actions. The FIS uses the Z-Numbers to represent the degree of membership or non-membership of the robot's location to the different obstacle zones in its path.

A rule base is developed based on expert knowledge and experience of the robot's environment. The rule base provides a series of fuzzy if-then rules that map sensor inputs to appropriate outputs that allow the robot to avoid obstacles.

The defuzzification can be computed by the centroid method. Let A_i and x_i denote the area and center of gravity of the i-th sub-region.

$$x^* = \frac{\sum_{i=1}^{n} A_i \cdot x_i}{\sum_{i=1}^{n} A_i} \tag{23}$$

$A_i = \int \mu_c(x)\ dx$, and n is the number of geometrical components.

III. MOBILE ROBOT NAVIGATION USING Z-NUMBER BASE FUZZY LOGIC

This section describes the Z-Number-based Fuzzy Logic (ZNFL) approach for mobile robot navigation under the ROS Noetic framework.

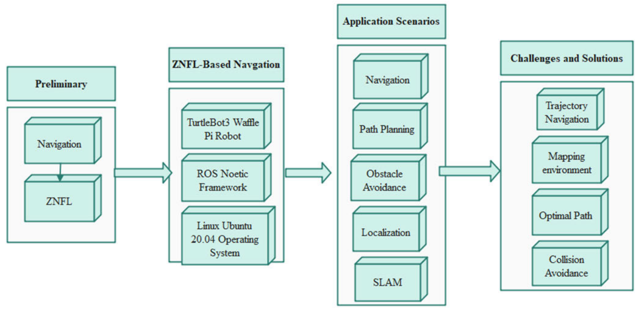


FIGURE 2. The architecture of the proposed system.

A. BASIC CONCEPT

The methodology for navigation of a mobile robot involves a series of steps and components that facilitate the smooth and accurate movement of the robot within its environment. The first step requires perception, where the robot gathers information about its surroundings using sensors such as cameras, LiDAR, or laser scan sensors. This perception module helps the robot to detect obstacles, recognize landmarks, and estimate its position and orientation in the environment. The next step is path planning, where the robot uses the information gathered from the perception module to determine the best trajectory to reach its destination. It involves generating a map of the environment and employing algorithms such as the Z-Number-based fuzzy logic algorithm to find the optimal path while avoiding obstacles. The robot must execute the navigation commands once the path is planned. The navigation control module utilizes a fuzzy logic controller to provide robust and adaptive control for the robot's movement. The fuzzy logic controller takes inputs from the perception module, such as the distance to obstacles. It utilizes a set of fuzzy rules to determine the appropriate actions for the robot. Figure 2 illustrates the architecture of the proposed system employed in this paper.

The architecture of the system effectively demonstrates the implementation of the proposed solution. The procedure uses fuzzy input and output with Z-number reliability to navigate. It leverages the Linux Ubuntu 20.04 operating system for the TurtleBot3 Waffle Pi Robot simulation in the ROS Noetic framework. The objective is to map the environment, determine the optimal and collision-free path, and navigate the trajectory.

1) Z-NUMBERS AND INTERPOLATIVE REASONING BASED ON Z-NUMBER

Z-numbers, also known as Zadeh numbers, are an extension of fuzzy numbers introduced by Lotfi A. Zadeh [55], the founder of fuzzy logic. Z-numbers are an extension of fuzzy sets and provide a way to represent uncertainty and imprecision quantitatively. They are beneficial for dealing with incomplete or uncertain information in decision-making and reasoning processes.

A Z-number is defined by a triplet (a, b, c)

$$\mu_z(x) = \exp\left[-(x-a)^2 \Big/ \left(a * b^2\right)\right] - \exp\left[-(x-a)^2 \Big/ \left(a * c^2\right)\right] \tag{24}$$

For instance, a common form of a triangular fuzzy number is defined by three parameters: a, b, and c, where a ≤ b ≤ c.

Where:

- "a" is the Z-Number's core or most representative value.
- "b" is the left spread, representing the degree of uncertainty or fuzziness on the left side of the core value.
- "c" is the proper spread, representing the degree of uncertainty or fuzziness on the right side of the core value.

The core value, a, typically represents the uncertainty's most probable or most representative value. At the same time, the left and right spreads, b and c, indicate the range of possible values around the core value.

Definition 1 [55]: A Z-number is an ordered pair of fuzzy numbers, denoted as Z = (A, B). The first component, A, establishes constraints on the values of the fuzzy variable X, while the second component, B, quantifies the reliability of A. The confidence degree of a Z-number is defined as the membership function with a degree of A at a specific point x. In contrast, the hesitation degree is the degree of membership function of the complement of A at the same point x. Z-number theory provides a flexible and robust framework for modeling uncertainty and vagueness in various applications. In Figure 3, triangular membership functions represent the constituents of Z-numbers [61].

$$\mu_A(x) = \begin{cases} 0, & - \leq x \leq a \\ \dfrac{x-a}{\mathrm{b}-\mathrm{a}}, & a \leq x \leq b \\ \dfrac{\mathrm{b}-x}{\mathrm{c}-\mathrm{b}} & b \leq x \leq c \\ 0, & \mathrm{c} \leq x \leq \infty. \end{cases} \tag{25}$$

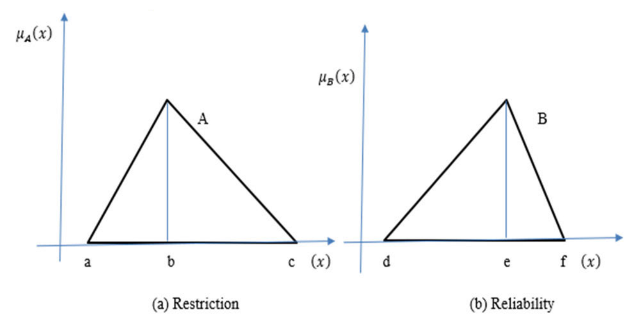


FIGURE 3. **Z-number Z = (A, B) (a) Restriction (b) Reliability.**

In this context, A denotes the fuzzy value of the variable, whereas B signifies the degree of truth, reliability measure, or probability associated with A. For instance, the expression "X is A" is referred to as a possibilistic restriction, and it is denoted as B(X):

$$\mathrm{B(X) : XisA \rightarrow Poss(X = u)} = \mu_{\mathrm{A}}(\mathrm{x}). \tag{26}$$

Here, $\mu_A(x)$ represents the membership function of A, which serves as a constraint linked to B(X). The symbol " u " denotes a generic value of X.

Definition 2 [64]: Fuzzy numbers are a fuzzy set category that utilizes continuous, piecewise-defined membership functions to quantify uncertainty and imprecision. These numbers serve as a means to represent approximate quantities quantitatively. A fuzzy number can be described by its membership function, which assigns a degree of membership to each value within a designated range. Mathematically, a fuzzy number A can be denoted as:

$$\mathrm{A} = \{(\mathrm{x}, \mu_{\mathrm{A}}(\mathrm{x})) | \mathrm{x} \in \mathrm{X}\} \tag{27}$$

Here, x represents a value within the range of the fuzzy number, while $\mu_A(x)$ represents the membership function that assigns a degree of membership to x. X denotes the universe of discourse or the range of possible values for the fuzzy number.

The membership function $\mu_A(x)$ often takes different mathematical forms to represent various fuzzy numbers, including triangular, trapezoidal, Gaussian, or more intricate shapes. These functions are defined using diverse mathematical equations based on the chosen shape and characteristics of the fuzzy number. E.g., Figure 4 illustrates the triangular membership for the Z-number Reliability.

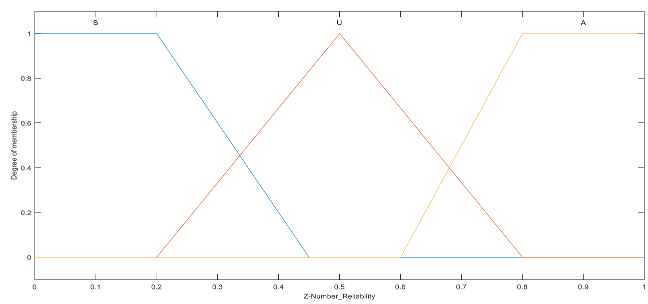


FIGURE 4. **Membership function for the Z-Number reliability.**

For instance, a common form of a triangular fuzzy number is defined by three parameters: a, b, and c, where a ≤ b ≤ c. The membership function for a triangular fuzzy number T can be expressed as:

$$\mu_T(x) = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{\mathrm{b}-\mathrm{a}}, & a \leq x \leq b \\ \dfrac{c-x}{\mathrm{c}-\mathrm{b}}, & b \leq x \leq c \\ 0, & x \geq c. \end{cases} \tag{28}$$

This equation illustrates the gradual increase and decrease of the membership degree as x traverses the range [a, c], reaching its maximum value of 1 at the core value b. It is essential to note that the specific mathematical equations used for fuzzy numbers may differ based on the chosen representation and the application domain. The basic idea behind interpolative reasoning is to approximate an unknown or uncertain Z-number based on the available Z-numbers and their associated degrees of similarity. The interpolation process involves finding the weighted average of the available Z-numbers, where the weights are determined by the degrees of similarity or proximity. It allows for estimating uncertain or imprecise values based on the available data. In a mobile robot navigation context, the triangular membership function of the antecedent and consequent universe is modeled in Figures 5 and 6, respectively.

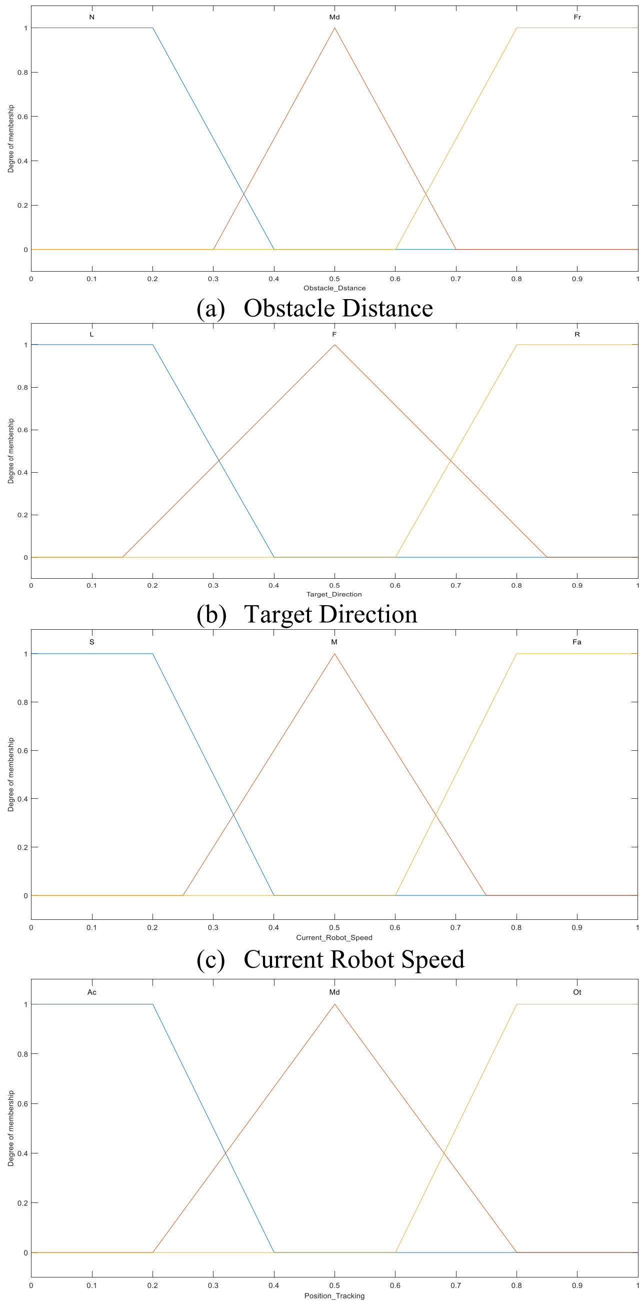
ZNFL rules for mobile robot navigation are demonstrated in Table 1. This table contains fuzzy logic control rules for your TurtleBot3 Waffle Pi mobile robot. These rules are utilized in fuzzy logic control to make decisions or control actions based on fuzzy sets and linguistic variables. Here are three rules for the robot's behavior based on different scenarios:

Rule 1: If the obstacle distance is near (N(S)), the target direction is to the left (L(S)), and the robot speed is slow (S(U)). The position tracking is accurate (Ac(S)), and both left and right wheel accelerations are large negative (LN(S)), resulting in a control signal of stop (St(S)).

Rule 2: If the obstacle distance is moderate (Md(S)), the target direction is forward (F(S)), the robot speed is medium (M(U)), and the position tracking is moderate (Md(U)). The left and right wheel accelerations are positive (P(S)), then the control signal is continued (C(S)).

Rule 3: If the obstacle distance is far (Fr(S)), the target direction is to the right (R(S)), and the robot speed is fast (Fa(S)). Still, if the obstacle is not in the target direction (Ot(U)), then the left and right wheel accelerations are large positive (LP(S)), resulting in a continuous control signal (C(S)).

The linguistic variables for obstacle distance are Near(N), Moderate(Md), and Far(Fr). The linguistic variables for the target direction are Left(L), Forward (F), and Right(R). The linguistic variables for current robot speed are Slow(S), Medium(M), and Fast(Fa), and the linguistic variables for position tracking are Accurate(Ac), Moderate(Md), Off-track(Ot), and the outputs linguistic variables for acceleration of left wheel are Large Negative(LN), Negative(N), Zero(ZR), Positive(P), Large Positive(LP)), the linguistic variables for acceleration of right wheel are Large Negative(LN), Negative(N), Zero(ZR), Positive(P), Large Positive(LP), and the linguistic variables for control signal are Stop(St), Continue(C), Change Direction(CD). The reliability terms for both the antecedent and consequent are defined over Small (S), Usually (U), and Always (A).



(a) Obstacle Distance
(b) Target Direction
(c) Current Robot Speed
(d) Position Tracking

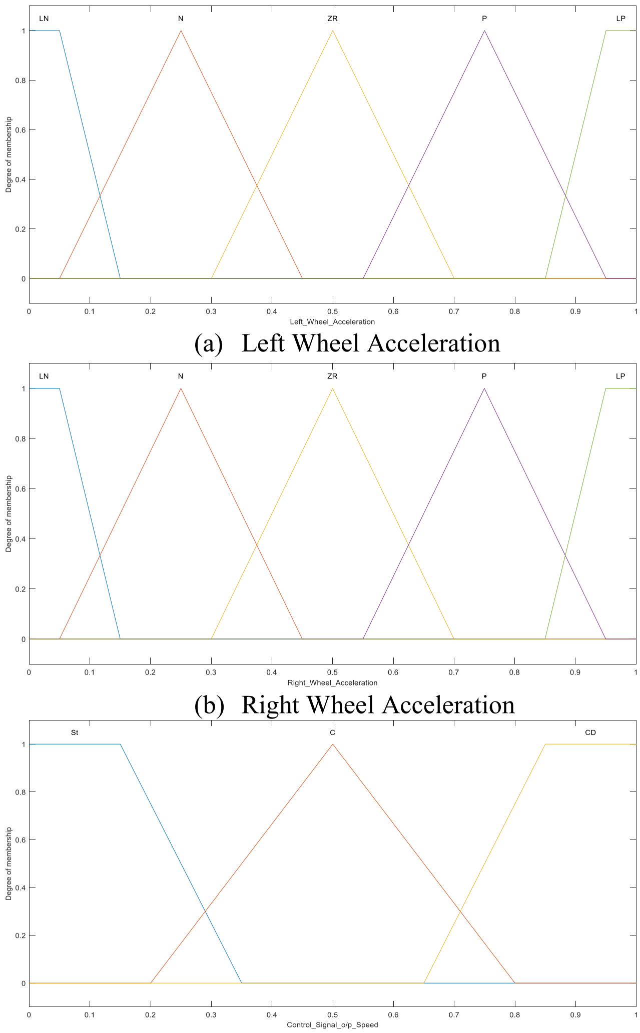
FIGURE 5. Membership functions for Antecedent Universe (a) Obstacle Distance (b) Target Direction (c) Current Robot Speed (d) Position Tracking.

IV. SIMULATION STUDIES

We perform rigorous computational experiments to evaluate the effectiveness and feasibility of the ZNFL-based navigation within the context of a TurtleBot3 Waffle Pi mobile robot. This section describes our configurations and presents our key findings.

A. SIMULATION SETTINGS

We implemented the model of the TurtleBot3 Waffle Pi mobile robot using ZNFL-based navigation using ROS Noetic and Gazebo. In ROS, we used the ROS Node for the Python environment to communicate with Gazebo by the subscriber and publisher of the node. Furthermore, RViz visualized the robot model and the robot environment.



(a) Left Wheel Acceleration

(b) Right Wheel Acceleration

(c) Control Signal output Speed

FIGURE 6. Membership functions for Consequent Universe (a) Left wheel Acceleration (b) Right wheel Acceleration (c) Control Signal output Speed.

Our computing environment was an Intel CORE i5, 2GB NVIDIA graphic card, 2.3GHz, 8GB RAM, and Ubuntu 20.04. To perform the approaches relevant to our scope, we implemented and contrasted navigation schemes based on ZNFL.

Furthermore, in line with the above motivations, the range of TurtleBot3 robot velocity is set to [-0.26 m/s, 0.26 m/s], and the range of the angular velocity is set to [-1.28 *rad/sec*, 1.28 *rad/s*] for the proposed approach. The value of the velocity boundaries is mentioned in the TurtleBot3 manual [65], so the higher values will be out of the scope of this robot model. For higher velocity, we suggest customizing the robot model to do your agenda, so this is out of the content of this paper, and we left it for future studies.

In a comprehensive simulation, we utilized the TurtleBot 3 robot in the ROS framework to create control signals for motion planning. We collected data from the robot's surroundings and various sensors, including its odometry.

TABLE 1. Lookup table of the fuzzy rules for mobile robot navigation.

Obstacle Distance	Target Direction	Robot Speed	Position Tracking	Left Wheel Acceleration	Right Wheel Acceleration	Control Signal
N(S)	L(S)	S(U)	Ac(S)	LN(S)	LN(S)	St(S)
Md(S)	F(S)	M(U)	Md(U)	P(S)	P(S)	C (S)
Fr(S)	R(S)	Fa(S)	Ot(U)	LP(S)	LP(S)	C(S)
N(S)	F(U)	Fa(U)	Ac(S)	P(U)	N(U)	CD(U)
Md(S)	R(U)	S(U)	Ot(U)	ZR(U)	LN(U)	CD(U)
Fr(S)	L(U)	M(U)	Md(U)	N(U)	P(U)	CD(U)
N(S)	F(U)	S(U)	Ac(S)	ZR(S)	LN(U)	CD(U)
Md(S)	L(U)	M(S)	Ot(U)	LN(S)	ZR(S)	CD(S)
Fr(S)	R(U)	Fa(A)	Md(U)	P(U)	LN(U)	CD(U)
N(S)	R(U)	M(S)	Ot(S)	LN(A)	LN(A)	St(S)
Md(S)	F(U)	S(U)	Ot(U)	N(U)	P(U)	CD(U)
Fr(S)	L(U)	Fa(A)	Md(U)	ZR(U)	N(U)	CD(U)
N(U)	L(U)	M(U)	Ot(U)	ZR(U)	ZR(U)	St(A)
Md(U)	F(U)	S(U)	Ac(S)	ZR(A)	LN(S)	St(S)
Fr(U)	R(U)	M(U)	Md(A)	ZR(A)	P(S)	CD(U)
N(U)	R(U)	Fa(A)	Ac(A)	P(A)	LN(A)	CD(A)
Md(U)	L(U)	S(U)	Ot(U)	LN(U)	LN(U)	St(S)
Fr(U)	F(U)	M(U)	Md(U)	ZR(U)	ZR(U)	St(U)
N(U)	L(U)	Fa(A)	Ac(S)	P(U)	N(U)	CD(A)
Md(U)	F(U)	S(U)	Ot(U)	LN(U)	ZR(U)	CD(S)
Fr(U)	R(S)	M(U)	Md(U)	LN(A)	LN(A)	C(U)
N(U)	F(S)	S(U)	Ac(S)	ZR(U)	ZR(U)	St(A)
Md(A)	L(S)	M(U)	Ot(U)	LP(U)	ZR(U)	CD(S)
Fr(A)	R(S)	Fa(A)	Md(U)	P(U)	LN(U)	CD(U)
N(U)	R(S)	M(U)	Ac(S)	LN(A)	LN(A)	St(S)
Md(A)	F(S)	S(U)	Ot(U)	LN(U)	ZR(U)	CD(S)
Fr(A)	L(U)	M(S)	Md(U)	ZR(U)	LN(U)	CD(U)
N(A)	L(U)	S(S)	Ot(A)	ZR(A)	ZR(A)	St(A)
Md(A)	F(U)	S(S)	Ac(S)	ZR(U)	LN(U)	CD(S)
Fr(A)	R(U)	M(S)	Md(U)	ZR(U)	P(U)	CD(U)
N(A)	R(U)	Fa(S)	Ac(U)	P(A)	LN(A)	CD(A)
Md(A)	L(U)	S(S)	Ot(U)	LN(U)	LN(U)	St(S)
Fr(A)	F(U)	M(A)	Md(U)	ZR(U)	ZR(U)	St (U)
Md(A)	F(U)	S(A)	Ot(U)	LN(U)	ZR(U)	CD(S)
Fr(A)	R(U)	M(A)	Md(U)	LN(U)	LN(U)	C(U)
N(U)	F(U)	S(A)	Ac(S)	ZR(A)	ZR(A)	St(A)
Md(A)	L(U)	M(A)	Ot(U)	LN(U)	ZR(U)	CD(S)
Fr(A)	R(U)	Fa(A)	Md(U)	P(U)	N(U)	CD(A)
N(U)	R(U)	M(U)	Ac(A)	LN(U)	LN(U)	C(S)
Md(A)	F(U)	S(U)	Ot(A)	LN(U)	ZR(U)	CD(S)
Fr(A)	L(U)	M(U)	Md(A)	ZR(U)	LN(U)	CD(U)
N(U)	L(U)	S(U)	Ot(A)	ZR(A)	ZR(A)	St(A)
Md(A)	F(U)	S(U)	Ac(A)	ZR(U)	LN(U)	CD(S)
Fr(A)	R(U)	M(U)	Md(A)	ZR(U)	P(U)	CD(U)
N(U)	R(A)	Fa(A)	Ac(S)	P(U)	LN(U)	CD(A)
Md(A)	L(A)	S(U)	Ot(U)	LN(A)	LN(A)	St(S)
Fr(A)	F(A)	M(U)	Md(U)	ZR(U)	ZR(U)	St(U)
Md(A)	F(A)	S(U)	Ot(U)	LN(A)	ZR(A)	CD(U)
Fr(A)	R(A)	M(U)	Md(U)	LN(U)	LN(U)	C(U)
N(U)	F(A)	S(U)	Ac(S)	ZR(U)	ZR(U)	St(U)
Md(A)	L(U)	M(U)	Ot(U)	LN(U)	ZR(U)	CD(S)
Fr(A)	R(A)	Fa(A)	Md(U)	P(A)	LN(A)	CD(A)
N(U)	R(A)	M(U)	Ac(S)	LN(U)	LN(U)	St(S)
Md(A)	F(S)	S(U)	Ot(U)	LN(U)	ZR(U)	CD(S)
Fr(A)	L(U)	M(U)	Md(U)	ZR(U)	LN(U)	CD(U)
N(U)	L(A)	S(U)	Ot(A)	ZR(A)	ZR(A)	St(A)
Md(A)	F(S)	S(U)	Ac(S)	ZR(U)	LN(U)	CD(S)
Fr(A)	R(U)	M(U)	Md(U)	ZR(U)	P(U)	CD(U)
N(U)	R(U)	Fa(A)	Ac(S)	P(U)	LN(U)	CD(A)
Md(A)	L(U)	S(U)	Ot(U)	LN(S)	LN(S)	St(S)
Fr(A)	F(S)	M(U)	Md(U)	ZR(U)	ZR(U)	St(U)
Md(A)	F(U)	S(U)	Ot(U)	LN(U)	ZR(U)	CD(S)
N(U)	F(U)	S(U)	Ac(S)	ZR(U)	ZR(U)	St(U)
Md(A)	L(U)	M(U)	Ot(U)	LN(U)	ZR(U)	CD(S)
Fr(A)	R(U)	Fa(A)	Md(U)	P(U)	N(U)	CD(U)
N(U)	R(U)	M(U)	Ac(S)	LN(U)	LN(U)	St(S)

We employed the Z-number method to address potential uncertainty or imprecision in decision-making and sensor data. This navigation approach emphasizes path planning and obstacle avoidance while factoring in uncertainty, which we calculated through Z-numbers regarding probability and possibility. Throughout the simulation, we adjusted the sensor data values of the environment using Z+-numbers and Z^{-}-Numbers to update the antecedent and consequent universe.

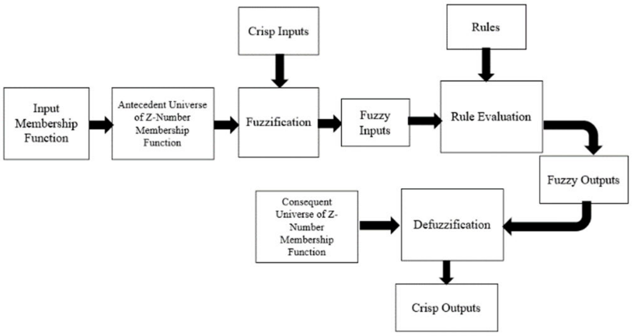


FIGURE 7. A framework for Fuzzy Logic Controllers based on Z-numbers.

Figure 7 showcases the incredible potential of ZNFL through its seamless integration of Z-numbers and a fuzzy logic controller. The presented framework is crucial for addressing uncertainties in control. By integrating Z-numbers and fuzzy logic, we have created an effective solution. This tool is essential for achieving optimal control outcomes.

The methodology combines Z-numbers with fuzzy logic to address uncertainty in robot navigation. It involves creating Z-number-based fuzzy rules, converting sensor data into Z-numbers, and using Z-number arithmetic to make decisions in uncertain environments. This approach has been successfully demonstrated through extensive simulations with the TurtleBot3 robot, showcasing its potential for autonomous navigation in unknown environments.

Z-Numbers: Z-numbers are a mathematical extension of traditional fuzzy logic. They represent uncertain information more robustly by incorporating two membership functions: one for the degree of certainty and one for the degree of uncertainty. For instance, a Z-number (0.7, 0.2, 0.6) signifies a high degree of confidence (0.7) and a low degree of uncertainty (0.2) and comes with an associated probability (0.6) regarding a particular element's membership in a fuzzy set.

B. METHODOLOGY IN DETAIL

1) INTEGRATION OF Z-NUMBERS INTO FUZZY LOGIC

Z-numbers are integrated into the fuzzy logic framework by mapping elements to degrees of certainty and uncertainty using paired membership functions. These functions capture the likelihood and unlikelihood of a part belonging to a fuzzy set.

2) NAVIGATION STRATEGY USING Z-NUMBERS

In practice, we create fuzzy rules for robot navigation that take Z-numbers as inputs and generate Z-numbers as outputs. We define linguistic variables and fuzzy membership functions for inputs (e.g., distance to obstacles, angle to the target) and outputs (e.g., steering angle). Fuzzy rules describe the navigation behavior, such as "IF Distance is (0.7, 0.2, 0.6) AND Angle is (0.5, 0.1, 0.8), THEN Steering is (0.6, 0.2, 0.7)." Z-number arithmetic combines these rules to calculate the final Z-number output for the steering angle.

3) EXECUTION IN PRACTICE

In real-world scenarios, sensor data from the robot's environment is collected. This sensor data is converted into Z-numbers to represent uncertainty and imprecision. The fuzzy rules, incorporating Z-number arithmetic, are applied to determine the appropriate steering angle for the robot. The robot executes the navigation strategy based on the calculated Z-number steering angle.

4) ADAPTATION AND LEARNING

Z-numbers also enable adaptive control and learning by updating membership functions and fuzzy rules based on the robot's experiences in different environments.

C. TRAJECTORY SCENARIOS

we used trajectory following scenarios to evaluate the performance and generalized ability of the ZNFL approach. In particular, we used the line and circle scenarios based on the ROS framework.

1) LINE TRAJECTORY

We used the two-point formulae for the line trajectory to calculate the line distance. Were the initial point (0,0) and the final position (7,7), the two-point distance formula computes our desired line with a distance as follows:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{29}$$

The ROS bag data can be plotted in MATLAB to visualize the line trajectory results. The ROS bag file format is commonly used in ROS for storing ROS message data. MATLAB provides functionality to read and plot the data stored within a ROS bag file. The data can be plotted as a graph, with the x-axis representing time and the y-axis representing the sensor readings or control signals. The rqt-graph shows the implementation process in the ROS Gazebo environment.

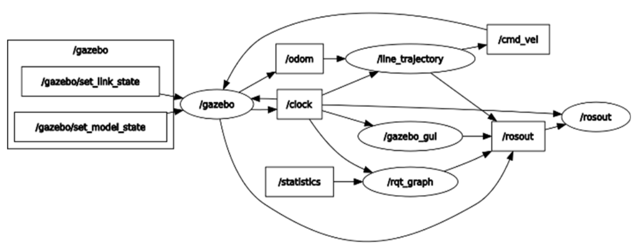


FIGURE 8. Line trajectory rqt_graph.

2) CIRCULAR TRAJECTORY

To conduct the circular motion of the robot, we used the circumference formulas to enter the radius value in a ROS launch file. Because we used r = 2 in our simulation, the circumference formula for the circular route is:

$$C = 2\pi r \tag{30}$$

The ROS bag data can be plotted in MATLAB to visualize the circular trajectory results. The data can be imported into MATLAB using the ROS Toolbox, which provides tools and functions for working with ROS data, as shown in Figure 9.

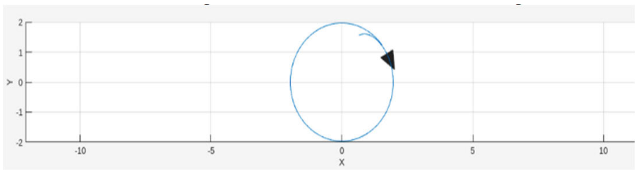


FIGURE 9. Circular trajectory of turtlebot3 waffle pi mobile robot using MATLAB ROS toolbox.

The ROS-based simulation is demonstrated in the rqt-graph.

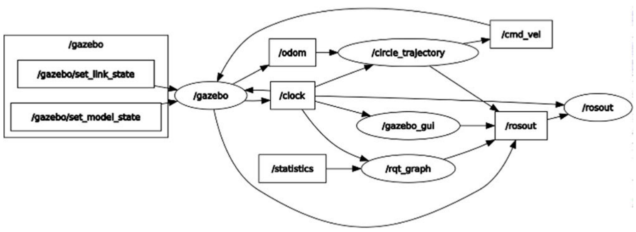


FIGURE 10. Circular trajectory rqt_graph.

D. NAVIGATION SCENARIOS

The Navigation Stack within ROS comprises software packages offering essential resources for achieving autonomous navigation in mobile robots. It encompasses various modules, including localization, mapping, and path planning, which collaborate harmoniously to enable the robot's independent navigation. Among the approaches employed for mobile robot navigation, there exists a Z-Number-based fuzzy logic approach, which draws upon the principles of fuzzy logic and Z-Numbers. This approach aims to enhance the precision and resilience of the Navigation Stack by integrating uncertainty into the navigation process. Algorithm 1 depicts the Z-number-based fuzzy algorithm for the proposed navigation.

The mapping module implemented in this system utilizes the Particle Filter Mapping (PFM) algorithm, a particle filter-based technique for generating a map of the surrounding environment. Like the Adaptive Monte Carlo Localization (AMCL) algorithm, the PFM algorithm employs a group of particles to estimate the positions of obstacles within the environment. As the robot moves through the environment, the PFM algorithm dynamically updates the map by incorporating sensor measurements.

Algorithm 1 Z-Number based Fuzzy Logic Approach for Mobile Robot Navigation

1. Initialize the ROS node for the robot.
2. Set up the robot's sensors.
3. Set up ROS topics and messages.
4. Define the membership functions for the input variables.
5. Define the membership functions for the output variables.
6. Define the membership functions for the Z-Number Reliability.
7. Define the rules for the fuzzy inference system, which maps the input variables to the output variables.
8. Implement the fuzzy logic algorithm using the Z-number-based approach.
9. Defuzzify by centroid method to obtain crisp output values for robot and angular velocity.
10. Publish velocity and angular velocity commands to the robot
11. Use the ROS navigation stack or auto navigation node to plan the robot's path.
12. Implement the motion controller to control the robot's movement based on the desired speed and steering angle.
13. Test the system in a simulation environment.
14. Iterate 3-13 on the system and adjust the membership function and rules if needed to improve performance.
15. Terminate the ROS node when the robot completes the task.

1) PATH PLANNING AND OBSTACLE AVOIDANCE

Path planning is a crucial undertaking in the navigation of mobile robots. It involves the determination of a safe and efficient route for the robot to reach its destination while simultaneously avoiding obstacles and adhering to the motion constraints of the robot. Path planning is categorized into two main types: global path planning and local path planning. Using local and global planners allows for a more efficient and effective path-planning process, as the local planner can quickly generate trajectories that avoid nearby obstacles. In contrast, the global planner can create a path that avoids obstacles and reaches the desired goal location.

Obstacle avoidance, or collision-free path planning, is also crucial in mobile robot navigation. Designing a control system that allows a robot to navigate its surroundings while avoiding obstacles is a significant task. By tackling this challenge, the approach uses fuzzy logic and Z-Number theory to generate control commands for the robot based on sensory input from its environment.

In implementing the approach, the robot is outfitted with sensors, such as laser scans, which provide environmental information. This sensory data is then fed into the control

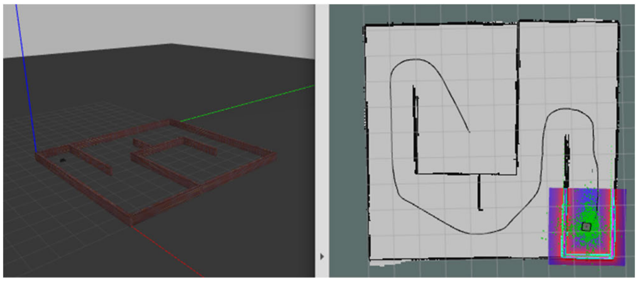


FIGURE 11. Mobile robot navigation and path planning scenario demonstrating the ability to avoid obstacles and follow a collision-free path.

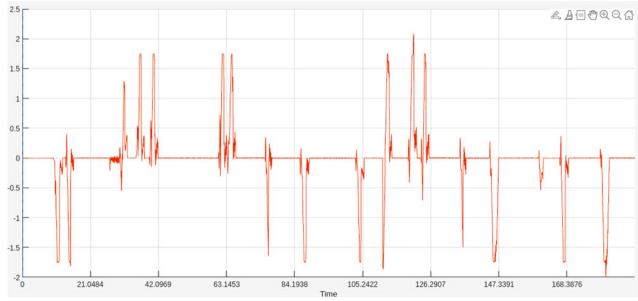


FIGURE 13. Time graph demonstrating the real-time obstacles avoiding scenario through MATLAB using ROS toolbox.

system, which processes it using fuzzy logic and Z-Number theory to generate commands for the robot's actuators. The initial phase involves utilizing fuzzy logic to assess the robot's distance from obstacles along its trajectory. It defines fuzzy sets for different distances from the robot to obstacles. For example, there might be a fuzzy set for "far," "medium," and "near" distances. The robot's sensory data is then mapped onto these fuzzy sets using membership functions. The next step is to use the Z-Number theory to handle uncertainty in the sensory data. It involves representing the sensory data as Z-numbers, fuzzy numbers with more uncertainty. Z-numbers can be used to describe uncertain measurements or combine multiple sensory data sources. Once the sensory data has been processed using fuzzy logic and Z-Number theory, the control system generates commands for the robot's actuators. These commands are designed to steer the robot from obstacles and towards its goal. As an illustration, when the robot nears an obstacle, the control system can instruct it to turn left or right to avoid it. The result has been obtained from the ROS bag data using a laser scan through MATLAB ROS Toolbox.

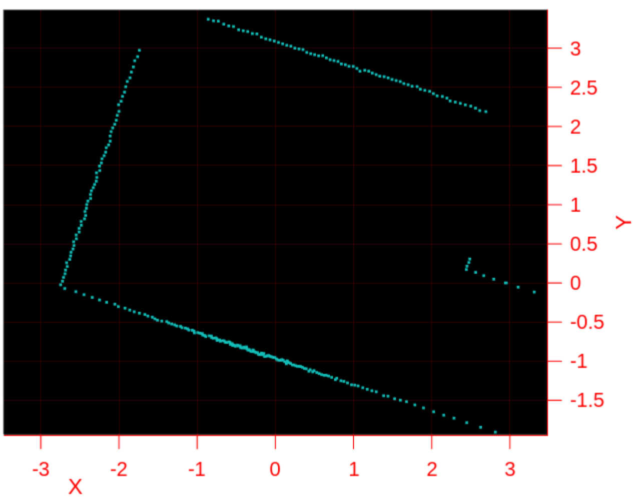


FIGURE 12. Obstacle avoidance through ROS bag data through MATLAB using ROS toolbox.

By implementing this approach, the robot's real-time obstacle avoidance time graph is obtained from the MATLAB ROS bag data, shown in Figure 13.

The implementation of this functionality in ROS Gazebo and RViz is presented in Algorithm 2, showcasing the robot's navigation capability. At the same time, avoid obstacles and successfully follow a path free of collisions.

2) LOCALIZATION

In the context of mobile robots, localization involves using sensors to gather data about the robot's surroundings and determine its position and orientation within the environment. The accuracy and efficiency of localization algorithms significantly impact the overall performance of mobile robots. The sensor measurements' uncertainty and the environment's inherent imprecision are handled using fuzzy logic and Z-number theory. By implementing the Z-number-based fuzzy logic approach into the ROS, utilizing the framework's existing capabilities becomes feasible while integrating the advantages of Z-numbers and fuzzy logic theory for localization purposes. Algorithm 3 illustrates the Z-number-based fuzzy algorithm for localization.

3) SIMULTANEOUS LOCALIZATION AND MAPPING (SLAM)

Simultaneous Localization and Mapping SLAM revolves around constructing a map for an unknown environment while determining the robot's precise location within the environment. This complex problem is of utmost importance for enabling the autonomous navigation of mobile robots in unknown and unfamiliar environments. The SLAM algorithm utilizes the obtained map to estimate the robot's position and orientation through odometry and sensor data. The Z-Number theory represents the uncertainty related to each sensor measurement. This uncertainty is then merged with the uncertainty in the map to estimate the robot's position and orientation more precisely. The flowchart, as depicted in Figure 14, summarizes the implementation process performed in the SLAM algorithm.

The SLAM mapping package in ROS provides a good framework for building a map of the environment. It scans and poses data from the odometry frame to generate a 2D coverage area map. In our proposed method, we used ZNFL-based SLAM because mapping uses data from the odometry frame, which is the actual data pose, so any possible error is only caused by scan sensor data. It is launching the

Algorithm 2 Z-Number based Fuzzy Logic Approach for Mobile Robot Path Planning and Obstacles Avoidance

1. Initialize the ROS node for the robot navigation system
2. Set up the robot's sensors.
3. Set up ROS topics and messages
4. while True:
5. Read the current position of the robot from the sensors
6. Read the desired goal position from the user or task planner
7. Read any obstacles detected in the robot's path from the sensors
8. Define the Z-number sets and their membership functions for each input variable (current position, goal position, obstacles)
9. Define the output variables for the fuzzy logic controller, including the robot's linear and angular velocities
10. Define the Z-number sets and their membership functions for each output variable (linear velocity, angular velocity)
11. Define the fuzzy rules for the controller based on the input variables and their respective membership functions
12. Implement the fuzzy inference engine to determine the output variables based on the input variables and fuzzy rules
13. Implement the defuzzification process (centroid method) to convert the fuzzy output variables into crisp values for the robot's linear and angular velocities.
14. Send the velocity commands to the robot's motor control system to navigate to the desired goal position while avoiding any obstacles in the robot's path.
15. Check if the robot has reached its goal position or encountered a new obstacle.
16. If yes, stop the robot and exit the loop.
17. If not, repeat steps 3-15 until the robot reaches its goal position or encounters a new obstacle.
18. Terminate the ROS node when the robot completes the task.

mapping package, which provides SLAM capabilities. The mapping package takes in sensor data and builds a map of the environment while estimating the robot's pose using the IMU sensor or odometry information, such as the position and orientations of the robot, and laser scan sensor to evaluate the obstacles in the environment, which are depicted in Figure 15.

In SLAM, Z-numbers represent uncertainty and imprecision associated with different aspects of the problem, such as sensor measurements, map features, and robot poses. The methodology involves a particle filter-based approach to SLAM, where each particle represents a hypothesis about the robot's path and the map. Z-numbers can represent the certainty and uncertainty associated with each particle's

Algorithm 3 Z-Number based Fuzzy Logic Approach for Mobile Robot Localization

1. Initialize the ROS node for the robot Localization system
2. Set up the robot's sensors.
3. Set up ROS topics and messages.
4. Define fuzzy logic controller using Z-Numbers.
5. Define membership functions for input and output variables
6. Read sensor data from the robot's odometry or localization sensors
7. Calculate the robot's position and orientation using a localization algorithm (e.g., EKF or AMCL)
8. Convert calculated position and orientation into linguistic labels using membership functions
9. Apply fuzzy rules to determine linguistic output labels
10. Convert linguistic output labels back into numerical values
11. Implement the defuzzification process (by centroid method) to convert the fuzzy output variables
12. Publish numerical values representing the robot's estimated position and orientation
13. while True:
    a. Read updated sensor data
    b. Recalculate position and orientation
    c. Convert to linguistic labels
    d. Apply fuzzy rules
    e. Convert back to numerical values
    f. Publish updated position and orientation
14. Handle errors or exceptions.
15. Monitor the system for changes.
16. If yes, stop the robot and exit the loop
17. If not, repeat steps 3-16
18. Terminate the ROS node when the robot completes the task.

hypothesis. The key idea is that if the robot's path is known, the map features are conditionally independent, and each feature's estimation can be treated as a separate problem. For each map feature, Z-numbers can represent the estimated position and uncertainty. The mapping problem is separated into individual issues, one for each feature in the map. Z-numbers are particularly useful in managing several noise and data association errors. They provide a natural way to represent uncertainties and imprecisions in sensor measurements and feature locations.

In practice, the SLAM algorithm using Z-numbers within the particle filter framework is executed as follows: Initialize a set of particles, each representing a hypothesis of the robot's path and the map. As the robot moves and collects sensor measurements (e.g., laser scans or visual data), update the particles using the motion model and sensor model. For each map feature, maintain a Z-number representation that includes the degree of certainty, uncertainty, and associated probability based on the sensor measurements. Update the

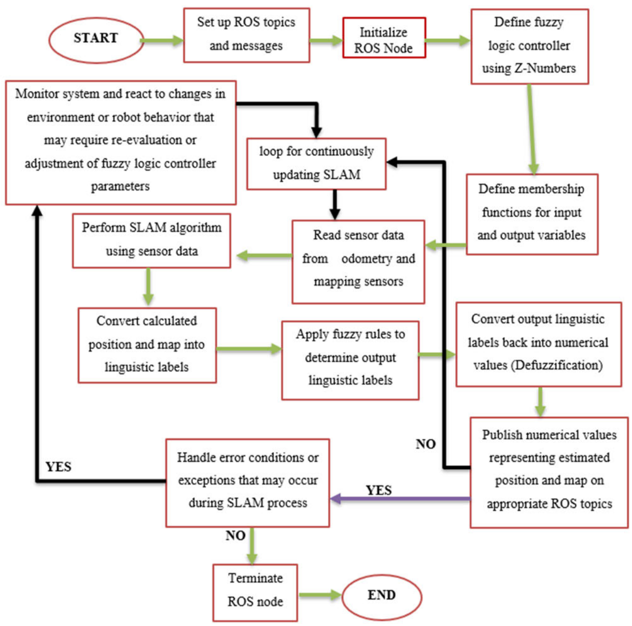


FIGURE 14. ZNFL-based SLAM algorithm flowchart.

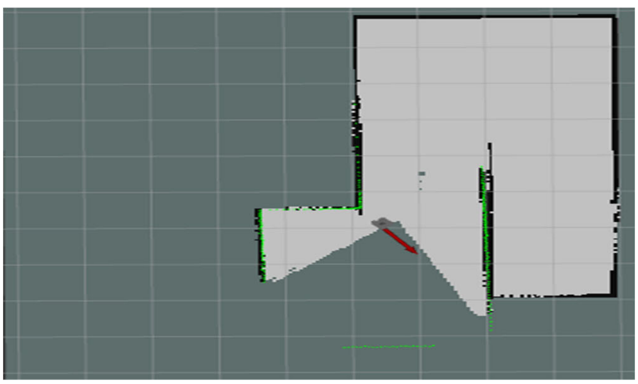


FIGURE 15. ZNFL-based SLAM demonstrating the robot environment simulation in RViz.

Z-number-based representations of map features as new information becomes available. Use Z-number arithmetic and the particle filter framework to estimate the robot's path and the map. Over time, the particles converge to represent the most likely robot path and map. Z-numbers offer several advantages, such as handling various noise distributions, ease of implementation, natural representation of multimodal beliefs, and resilience to data association errors.

Integrating Z-numbers into the SLAM framework can effectively address uncertainty and imprecision, improving the robot's ability to simultaneously estimate its path and create an accurate map of the environment, even in challenging and noisy conditions.

V. EXPERIMENTAL STUDIES

This section delves into the experimental studies conducted to assess the software-based simulation of the proposed system. These studies aimed to comprehensively evaluate this innovative navigation method's effectiveness, versatility, and dependability within a simulated environment. The experimental configuration involves a mobile robot with a two-wheeled differential drive system, modeled and simulated using the Robot Operating System (ROS) within a Linux (Ubuntu) environment. The robot also has a two-caster wheel for balancing purposes. The specific mobile robot employed for this study is the TurtleBot3 waffle pi, a small and affordable platform widely used in research and education, depicted in Figure 16.

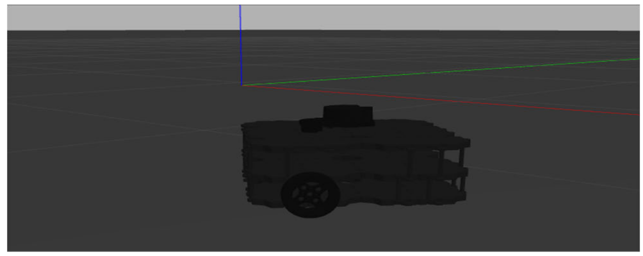


FIGURE 16. Turtlebot3 waffle pi mobile robot.

The Z-number-based fuzzy logic controller was seamlessly integrated into the ROS navigation stack to control the robot's movements effectively.

The sensors used in the experiment include a laser scan sensor for detecting obstacles, an IMU sensor for measuring the robot's orientation, and a wheel encoder for measuring the robot's speed. A LiDAR sensor has been mounted on the turtlebot3 waffle pi mobile robot chassis that can measure distance in all directions (360 degrees). The environment consists of boundary walls and objects. The following flowchart summarizes the setups that are performed in this paper.

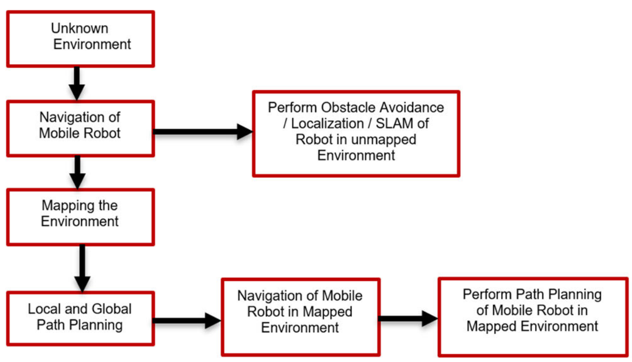


FIGURE 17. Environmental setup flowchart for the proposed system.

When the robot moves in the environment, the values from the laser scan sensor and the odometry frame in ROS are translated into a graphical representation containing information about the climate regarding occupied and accessible spaces. The robot navigates while running ROS's Gmapping package in the background. Once the whole environment is covered, the Gmapping package is closed, which generates the map as an image.

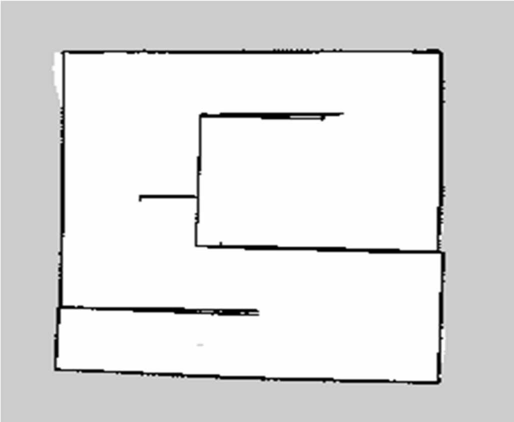


FIGURE 18. Mapping the environment.

The ZNFL architecture is employed in experimental research for path planning and obstacle avoidance scenarios. It uses fuzzy logic to evaluate sensory data and make action decisions, such as recognizing obstacles, calculating the best pathways, and modifying trajectories depending on real-time data. ZNFL responds to changing environmental variables and makes real-time decisions intending to develop and evaluate an intelligent system capable of navigating complicated settings, avoiding obstacles, and dynamically shifting trajectories to optimize desired outcomes.

In this work, all the experiments were carried out on an Intel core i5 CPU (2.3GHz) with 2GB NVIDIA graphic card, 8GB of RAM running the Ubuntu Focal Fossa (20.04.02) distribution of Linux with Python 3.10, and ROS Noetic Ninjemys.

The proposed method is launching the Gmapping package, which provides odometry data for ZNFL-based SLAM capabilities. The Gmapping package takes in sensor data and builds a map of the environment while estimating the robot's pose using the odometry information, such as the position and orientations of the robot. We carefully designed a variety of experimental scenarios to test the effectiveness and adaptability of the Z-number-based fuzzy logic approach. These scenarios covered obstacle avoidance in changing environments, reaching goals in cluttered areas, planning paths in unfamiliar terrain, and exploration tasks. We tested various obstacle configurations, starting points, and goals to simulate real-world situations.

A. DATA COLLECTION AND METRICS

Throughout each experiment, extensive data was gathered, which covered a wide range of parameters. These parameters included sensor data, encompassing environmental factors such as obstacle positions, distances, and readings from various sensors. Robot pose data was also closely monitored, recording the precise location and orientation of the robot within the simulation. Navigation performance metrics were measured to evaluate critical indicators such as the time to reach the goal, path length, and energy consumption. Lastly, detailed data on the control signals generated by the z-number-based fuzzy logic controller outputs were collected with precision.

B. PERFORMANCE EVALUATION

We have thoroughly evaluated our performance using a variety of essential metrics, including our Navigation Success Rate (%), Path Accuracy (cm), Obstacle Avoidance, and Computational Efficiency in real-time (ms). Our Navigation Success Rate measures the percentage of successful scenario completions, which we achieve through fuzzy logic with a Z-Number-based approach. We also assess our robot's path proximity to the ideal path with our Path Accuracy metric, and our Obstacle Avoidance metric examines the system's ability to navigate obstacles while minimizing collisions. Lastly, we assess our computational efficiency in real time to ensure optimal responsiveness.

TABLE 2. Comparative evaluation analysis between the Z-number-based navigation across various parameters.

parameter Scenario	Z-Number-based Navigation vs. Time	Z-Number-based Path Accuracy (cm) vs. Robot Velocity	Z-Number-based Obstacle Avoidance vs. Robot Changing Direction	Real-time Computational Efficiency (ms) vs. Z-Number Reliability
1	12s vs 85%	7cm vs 0.5 m/s	90% vs 30^0 change	12ms vs 95%
2	14s vs 88%	8cm vs 0.6 m/s	88% vs 45^0 change	14ms vs 93%
3	11s vs 94%	6cm vs 0.4 m/s	92% vs 60^0 change	11ms vs 97%
4	15s vs 85%	9cm vs 0.7 m/s	86% vs 75^0 change	15ms vs 91%

This table provides a comprehensive overview of the experimental results, highlighting the robustness and adaptability of the Z-number-based fuzzy logic approach across different navigation parameters.

VI. RESULTS AND DISCUSSIONS

The experimental and simulation study demonstrated that the proposed Z-number-based fuzzy logic approach achieved effective navigation performance in various simulated environments. The mobile robot successfully avoided obstacles, reached target destinations, and maintained a smooth trajectory during navigation. The approach showed robustness in handling uncertain and imprecise information by utilizing Z-numbers, allowing for more flexible decision-making in incomplete or ambiguous data. One important implication of the study's findings is the potential for enhancing mobile robot navigation capabilities in real-world scenarios. The navigation system can handle uncertainties commonly encountered in dynamic environments by incorporating the Z-number-based fuzzy logic approach into the ROS framework. This adaptability to uncertain conditions is particularly crucial for autonomous robots operating in unpredictable and complex surroundings, such as search and rescue missions or industrial automation.

Moreover, the study demonstrated the advantage of using Z-numbers over traditional crisp or fuzzy logic methods. Z-numbers enable a more accurate representation of uncertainty by considering the fuzzy membership function's lower and upper bounds. This feature allows for a more comprehensive evaluation of the robot's environment and the generation of more precise control actions. The results suggest that Z-numbers can effectively mitigate the adverse effects of uncertain information, contributing to safer and more reliable navigation.

Another implication of the study is the potential for further improvements and optimizations. While the Z-number-based fuzzy logic approach showed promising results, there is room for efficiency and computational complexity enhancements. Future research could explore techniques to streamline the decision-making process and reduce the computational load, making the approach more suitable for real-time applications and resource-constrained platforms.

The interpretation of the results obtained from the study highlights the effectiveness of the Z-number-based fuzzy logic approach for mobile robot navigation under ROS. The approach's ability to handle uncertainty and imprecise information through Z-numbers opens up new possibilities for robust and adaptive navigation systems. The findings have significant implications for developing autonomous robots operating in dynamic environments, with potential applications in robotics-assisted healthcare, logistics, and exploration.

The results obtained from our simulations validate the effectiveness of the proposed method. By incorporating Z-numbers into fuzzy logic, we overcame the limitations of traditional crisp logic approaches and fuzzy logic using real numbers. The ability to represent uncertainty and ambiguity through Z-Numbers allowed the robot to handle complex navigation scenarios more effectively. The performance of our approach can be attributed to the flexibility and adaptability provided by Z-Numbers. The robot could give various sensory inputs of varying degrees of importance, which improved its capacity to make decisions and led to more intelligent and effective navigation. It is important to note that while our approach demonstrated significant improvements, there are still areas for further research and enhancement. The optimization of fuzzy logic rules and membership functions, as well as the integration of additional sensors and algorithms, could enhance the performance of our approach even further. Our proposed method shows promising results and represents a valuable contribution to mobile robotics. Combining Z-numbers and fuzzy logic provides a robust framework for addressing navigation challenges in dynamic and uncertain environments, opening up new possibilities for developing intelligent robotic systems.

A. COMPARATIVE ANALYSIS

We compared our Z-Number-Based Fuzzy Logic Approach with existing methods: the traditional crisp logic approach and a fuzzy logic approach using real numbers. The traditional crisp logic approach used a binary representation for obstacle detection and avoidance, while the fuzzy logic approach employed real numbers to represent the degree of obstacle avoidance. The Z-number-based fuzzy logic approach effectively handles uncertainty in robot navigation tasks using Z-numbers to denote membership and non-membership degrees. This approach provides flexibility in representing and reasoning about the robot's navigation behavior, allowing linguistic rules and fuzzy membership functions to be easily adapted. ZNFL also allows for human-like reasoning, enabling robots to navigate more naturally and intuitively. However, comparing the Z-Number-Based Fuzzy Logic Approach with other methods like SLAM, Probabilistic Robotics, and path planning and obstacle avoidance algorithms is better handling for uncertainties, accuracy, and robustness in mobile robot navigation. The comparative analysis of the Z-number-based fuzzy logic approach and traditional navigation methods are presented in Table 3.

TABLE 3. Comparative analysis of traditional vs. Z-number-based fuzzy logic navigation.

Experiment	Z-number-based Navigation Success Rate (%)	Z-number based path Accuracy (cm)	Z-number based Obstacle Avoidance (%)	Real-time Computational Efficiency (ms)
Scenario 1 (Z-number)	92%	7	90%	12
Scenario 1 (Traditional)	85%	8	82%	16
Scenario 2 (Z-number)	88%	8	88%	14
Scenario 2 (Traditional)	80%	9	78%	18
Scenario 3 (Z-number)	94%	6	92%	11
Scenario 3 (Traditional)	87%	7	85%	17
Scenario 4 (Z-number)	85%	9	86%	15
Scenario 4 (Traditional)	78%	10	76%	19

Advantages of the ZNFL-based navigation over other traditional methods:

- Z-number-based fuzzy logic navigation incorporates an additional level of uncertainty modeling. It recognizes that in real-world scenarios, there often needs to be more precise or ambiguous information that needs to be considered.
- Traditional fuzzy logic, which uses membership functions to express degrees of truth, Z-Numbers provide a more comprehensive approach to handling uncertainty.
- By utilizing Z-Numbers, ZNFL navigation can effectively handle situations where precise information is lacking or conflicting data is present. It captures the uncertainty associated with linguistic variables and accounts for the range of possibilities.

- The inclusion of Z-numbers enables more robust and accurate decision-making in navigation systems. It allows for better handling of complex and dynamic environments where uncertainty is prevalent, leading to improved performance.
- ZNFL navigation provides enhanced reliability by considering and managing uncertainty effectively.

VII. CONCLUSION

This study introduces a Z-number-based fuzzy logic approach for mobile robot navigation in uncertain and imprecise environments. The proposed method is implemented on the TurtleBot3 Waffle Pi mobile robot using the Robot Operating System (ROS) Noetic. It integrates various methods, including mapping, navigation, path planning, obstacle avoidance for collision-free paths, and Simultaneous Localization and Mapping (SLAM).

Efficient navigation from one point to another in a straight line is possible using the line trajectory scenario. In contrast, the circular trajectory scenario enables the robot to move in a circular path, which helps explore an area or circumvent obstacles. The proposed approach incorporates mapping, navigation, path planning, and obstacle avoidance to ensure accurate robot localization and safe navigation without colliding with obstacles.

Collision-free path planning techniques allow the robot to dynamically select alternative paths when necessary. Lastly, the SLAM techniques enable the robot to localize in the environment while constructing a map simultaneously. This is crucial for robust and reliable navigation in unknown or partially known environments.

Future work suggestions to enhance the proposed approach's robustness, adaptability, and efficiency in navigating various environments include integrating machine learning techniques, dynamic path planning, multi-robot collaboration, cognitive mapping, knowledge representation, and real-time performance optimization.

A hybrid approach that combines reinforcement learning or deep learning with a Z-number-based fuzzy logic technique can be beneficial to enhance mobile robot navigation. This integration can improve adaptability and decision-making capabilities in dynamic and unstructured environments by leveraging the advantages of fuzzy logic and machine learning. Additionally, it may be worth exploring methods to train or optimize fuzzy logic rules using machine learning algorithms. By incorporating machine learning into this research, we can unlock fresh opportunities to enhance mobile robot navigation in complex and ever-changing situations.

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