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Type-2 Fuzzy Logic-Based Robot Navigation in Uncertain Environments: Simulation and Real-World Implementation

Soufiane Hachani [1*], Emira Nechadi [2]
[1, 2] Laboratory of Intelligent Systems (LSI), Department of Electronical, University of Setif 1, Algeria
[1, 2] Department of Electrotechnical, University of Setif 1, Algeria
Email: [1] hachani.soufiane@univ-setif.dz, [2] emira.nechadi@univ-setif.dz
*Corresponding Author

***Abstract*—This study presents a type-2 fuzzy logic-based navigation system for mobile robots in uncertain environments, emphasizing both simulation and real-world implementation. The proposed system integrates two type-2 fuzzy logic controllers: one for path-following and another for handling uncertainty in dynamic surroundings. To evaluate the system's effectiveness, numerical simulations are conducted in cluttered and unpredictable environments, followed by real-world tests. The evaluation considers success rates, path efficiency, and computational cost, demonstrating an improvement of up to 92% in navigation accuracy and 8% in handling environmental uncertainty compared to conventional fuzzy logic methods. Despite its robustness, the approach faces computational overhead and adaptability challenges in highly unstructured settings. The study highlights the scalability of the method, discussing its potential application to different robotic platforms and uncertain scenarios. The findings confirm that type-2 fuzzy logic enhances real-time decision-making in navigation while offering a resilient alternative to traditional path-planning methods.**

Keywords*— Type-2 Fuzzy Logic; Robot Navigation; Uncertain Environments; Simulation; Real-World Application.

I. INTRODUCTION

The increasing demand for autonomous mobile robots across various applications, including healthcare, transportation, and industrial automation, has led to extensive research in robot navigation systems [1]-[10]. A critical challenge in navigation is ensuring safe and efficient movement in uncertain and dynamic environments. Obstacle avoidance is particularly important in enabling mobile robots to operate autonomously without collisions, which has driven research towards more adaptive and intelligent control systems** [11]-[19]. Traditional approaches, such as rule-based and model-based control, often struggle with handling uncertainty and variability in real-world settings, necessitating more flexible solutions [20]-[25].

Fuzzy logic has emerged as a robust technique for addressing uncertainty and imprecision in robotic navigation. In particular, Type-2 Fuzzy Logic (T2FL) has demonstrated significant advantages over Type-1 fuzzy logic, as it provides enhanced flexibility in modeling environmental variations and managing higher levels of uncertainty [26]-[35]. Several studies have successfully implemented fuzzy logic-based obstacle avoidance to improve decision-making in mobile robots navigating through dynamic environments [36]-[42]. Moreover, hybrid approaches that integrate fuzzy logic with artificial intelligence (AI) techniques, such as neural networks, genetic algorithms, and deep learning, have been explored to further optimize path planning and real-time adaptability [43]-[50]. The integration of fuzzy logic with sensor fusion techniques, particularly LiDAR, stereo vision, and ultrasonic sensors, has also been investigated to enhance real-time perception and navigation accuracy in cluttered environments [51]-[60].

While previous research has demonstrated the potential of Type-2 fuzzy logic in robot navigation, several challenges remain unresolved. One major limitation is the computational overhead associated with tuning membership functions and rule bases, which affects real-time applicability [61]-[67]. Additionally, existing T2FL-based navigation methods often struggle with dynamic adaptation in highly unstructured and uncertain environments. Many studies have attempted to address this limitation through hybrid control mechanisms, but there remains a gap in developing a generalized and scalable fuzzy logic-based framework that ensures robust and adaptive navigation across different conditions [68]-[74]. Furthermore, benchmarking these approaches against traditional and machine-learning-based navigation systems is critical for assessing their efficiency and reliability in real-world applications [75]-[80].

The research contribution is as follows:

1. We propose a novel Type-2 Fuzzy Logic Controller (T2FLC) framework designed to enhance autonomous robot navigation in uncertain environments, improving real-time decision-making and adaptability.
2. The proposed system integrates sensor fusion techniques, combining LiDAR and vision data to enhance obstacle avoidance and environmental awareness.
3. We conduct a comparative performance evaluation between simulation and real-world implementation, analyzing the effectiveness of T2FL in handling environmental uncertainties.
4. Our method is benchmarked against existing fuzzy logic-based approaches, demonstrating its superior performance in terms of path efficiency, obstacle avoidance success rate, and computational feasibility [81]-[87].

By addressing these key challenges, this research aims to advance the state-of-the-art in autonomous robot navigation by offering a more adaptive, computationally efficient, and robust fuzzy logic-based control framework.

II. Method

A. The Mobile Robot Model Used

In this study, we employ the **Pioneer 3-DX mobile robot** As shown in Fig. 1, which utilizes a **differential drive system** with two independently controlled wheels. Unlike a single-wheeled model, the **Pioneer 3-DX operates by adjusting the velocities of the left and right wheels** to achieve precise navigation and obstacle avoidance. The robot is equipped with the following sensors, which provide essential data for fuzzy logic-based control in uncertain environments:

- **Ultrasonic Sensors (8 units):** As shown in Fig. 2 ; arranged around the robot at equal intervals, providing **360-degree real-time obstacle detection**. Each sensor has a range of **20 cm to 3 meters**, allowing the system to detect and respond to nearby objects effectively.
- **Wheel Encoders:** Integrated with the motor system to measure **wheel rotations with a resolution of 500 pulses per revolution**, enabling precise estimation of the robot's position and movement.

Fig. 1. Robot used in our study: Pioneer 3-DX

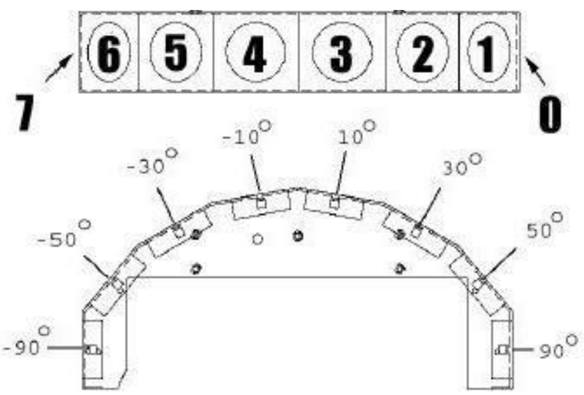

Fig. 2. Ultrasonic sensors on the robot

B. Mathematical Equations Governing The Robot's Motion

The motion of the Pioneer 3-DX mobile robot is governed by a set of mathematical equations that describe how its position and orientation evolve over time in response to control inputs. These equations play a crucial role in modeling the robot's dynamics, enabling the development of efficient navigation and obstacle avoidance algorithms.

As illustrated in Fig. 3, the motion model considers the robot, target, and obstacles, incorporating key parameters such as the robot's linear velocity, angular velocity, and wheel geometry.

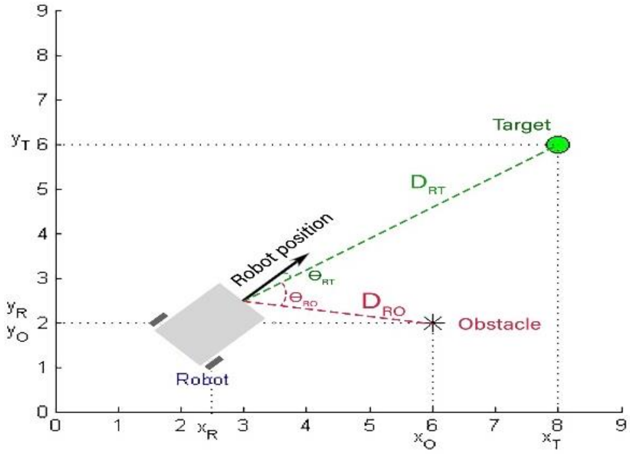

Fig. 3. Schematic representation of the robot, target, and obstacles

Key Notations:

(x_r, y_r)	:	Robot position coordinates.
(x_T, y_T)	:	Target point coordinates.
(x_O, y_O)	:	Obstacle coordinates.
V_r	:	Speed of the right wheel.
V_l	:	Speed of the left wheel.
θ_{RT}	:	Angle between the robot's current orientation and the target.
D_{RT}	:	Distance between the robot and the target.
θ_{RO}	:	Angle between the robot and the obstacle.
D_{RO}	:	Distance between the robot and the obstacle.

C. Kinematic Representation of the Robot

The robot's position at any time t is typically defined by the coordinate vector (x, y) and its orientation θ. The control inputs, such as wheel velocities, influence these parameters, allowing us to compute the robot's future states.

$$\begin{cases} \dot{x} = V.cos(\theta_R) \\ \dot{y} = V.sin(\theta_R) \\ \dot{\theta} = \omega \end{cases} \tag{1}$$

Where, V is the linear velocity of the robot. ω is the angular velocity. θ_R is the current orientation of the robot.

D. Wheel-Based Velocity Model

Since the Pioneer 3-DX operates using a differential drive system, the robot's total velocity is the average of the left and right wheel speeds. This assumes both wheels operate symmetrically, leading to a simplified motion model expressed as:

$$\begin{cases} \dot{x} = \frac{V_r+V_l}{2}.cos\,(\theta_R) \\ \dot{y} = \frac{V_r+V_l}{2}.sin\,(\theta_R) \\ \dot{\theta} = \frac{V_r-V_l}{2L} \end{cases} \tag{2}$$

Where, V_r and V_l are the velocities of the right and left wheels, respectively. L represents the distance between the two wheels.

E. Discrete-Time Motion Model

To enable efficient computational implementation, the discrete-time formulation of the motion model is employed, allowing state updates at fixed time intervals. This approach approximates the continuous kinematic equations while maintaining computational efficiency, making it well-suited for real-time robotic navigation [88].

In this study, we adopt the Euler integration method, which assumes that velocity inputs V_k and angular velocity ω_k remain constant over each sampling interval $[t_k, t_{k+1}]$.

This method provides a straightforward approximation of the robot's motion by integrating the kinematic model over discrete time steps [88]. Under these assumptions, the differential-drive robot's motion is governed by the following equations:

$$\begin{cases} x_{k+1} = x_k + \dfrac{V_{r_k} + V_{l_k}}{2}.T.cos(\theta_{R_k}) \\ y_{k+1} = y_k + \dfrac{V_{r_k} + V_{l_k}}{2}.T.sin(\theta_{R_k}) \\ \theta_{R_{k+1}} = \theta_{R_k} + T.\dfrac{V_{r_k} - V_{l_k}}{2L} \end{cases} \tag{3}$$

Where, T is the sampling time step, defining the update rate of the robot's position.

This iterative integration process, known as odometric localization or dead reckoning, is widely used for estimating the robot's configuration based on proprioceptive sensors such as wheel encoders. However, Euler integration, while computationally simple, is susceptible to odometric drift, which accumulates over extended trajectories due to factors such as wheel slippage, model perturbations, and numerical integration errors [88].

F. Fuzzy Logic Type-2 Controller For Robot Navigation

1) Fuzzy Controller The Input-Output Parameters

In the proposed system, fuzzy logic-based control is utilized to manage robot navigation and obstacle avoidance. The control process consists of two distinct Fuzzy Logic Controllers (FLCs):

- FLC for robot-to-target navigation (FLC-RT).
- FLC for obstacle avoidance (FLC-RO).

As illustrated in Fig. 4, the FLC-RT takes two primary inputs:

- D_{RT}: The distance between the robot and the target.
- θ_{RT}: The angle between the robot's current orientation and the direction toward the target.

The controller generates two outputs:

- V_l: Speed of the left wheel.
- V_r: Speed of the right wheel.

These outputs drive the robot toward its target while maintaining smooth motion.

During navigation, the system continuously monitors for potential obstacles. If an obstacle is detected, the FLC-RO is activated to modify the robot's trajectory. The FLC-RO receives the following inputs:

- D_{RO}: The distance between the robot and the obstacle.
- θ_{RO}: The angle between the robot's current orientation and the obstacle direction.

Based on these inputs, FLC-RO dynamically adjusts the robot's movement to avoid collisions while ensuring it remains on a feasible path toward the target. This adaptive switching mechanism between FLC-RT and FLC-RO enhances safe and efficient navigation, achieving a balance between goal-seeking behavior and collision avoidance.

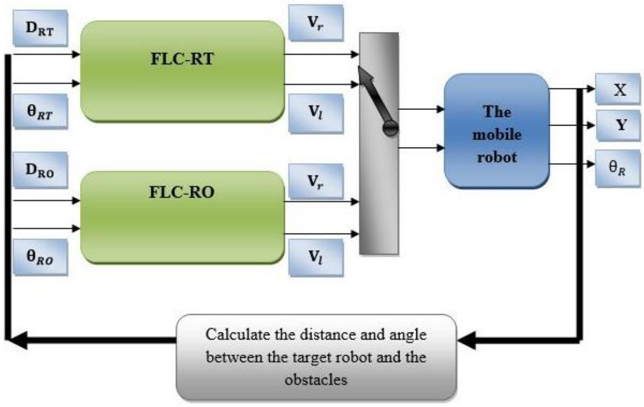

Fig. 4. Fuzzy navigation controller architecture with obstacle

2) Distance and Direction Calculation for Fuzzy Logic Control

The Euclidean distance plays a fundamental role in the fuzzy logic controller (FLC) by guiding the robot toward the target while avoiding obstacles.

a) Distance to the Target (D_{RT})

The distance between the robot (x_R, y_R) and the target (x_T, y_T) is calculated using the Euclidean distance formula:

$$D_{RT} = \sqrt{\mathrm{e_{RTx}}^2 + \mathrm{e_{RTy}}^2} \tag{4}$$

Where, e_{RTx} is the error between robot x_R and target x_T. e_{Rty} is the error between robot y_R and target y_T.

$$\begin{cases} e_{RTx} = x_T - x_R \\ e_{RTy} = y_T - y_R \end{cases} \tag{5}$$

b) Direction to the Target (θ_{RT})

To determine the required orientation for the robot to face the target, the relative angle is computed using the inverse tangent function:

$$\theta_T = \tan^{-1}\left(\frac{\mathrm{e_{RTy}}}{\mathrm{e_{RTx}}}\right) \tag{6}$$

The direction angle θ_{RT} can be calculated as follows:

$$\theta_{RT} = \theta_T - \theta_R \tag{7}$$

c) Distance to an Obstacle (D_{RO})

For obstacle avoidance, the Euclidean distance between the robot (x_R, y_R) and the obstacle (x_O, y_O) is calculated as:

$$D_{RO} = \sqrt{\mathrm{e_{ROx}}^2 + \mathrm{e_{ROy}}^2} \tag{8}$$

Where, e_{ROx}: The error between robot x_R and obstacle x_O. e_{ROy}: The error between robot y_R and obstacle y_O.

$$\begin{cases} e_{ROx} = \mathrm{x}_O - \mathrm{x_R} \\ e_{ROy} = \mathrm{y}_O - \mathrm{y_R} \end{cases} \tag{9}$$

d) Direction to the Obstacle (θ_{RO})

To determine the angle between the robot and an obstacle, the following equation is used:

$$\theta_{RO} = \tan^{-1}\left(\frac{\mathrm{e_{ROy}}}{\mathrm{e_{ROx}}}\right) \tag{10}$$

3) Fuzzy Logic Controller Design

The fuzzy logic controllers (FLC-RT for navigation and FLC-RO for obstacle avoidance) are designed to:

- Minimize DRT and θRT to ensure the robot reaches the target efficiently (Fig. 5).
- Avoid collisions by using $\mathbf{D_{RO}}$ and $\boldsymbol{\theta_{RO}}$ as inputs to adjust motion dynamically (Fig. 6).
- Produce left and right wheel speeds (V_l, V_r) as outputs for smooth and adaptive navigation.

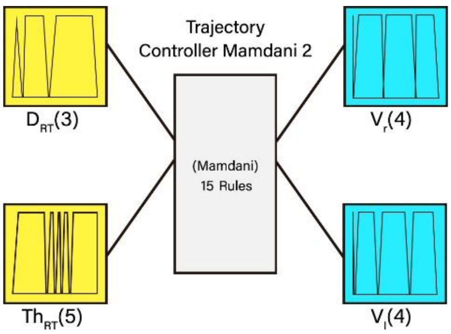

Fig. 5. Fuzzy rule set for the target navigation

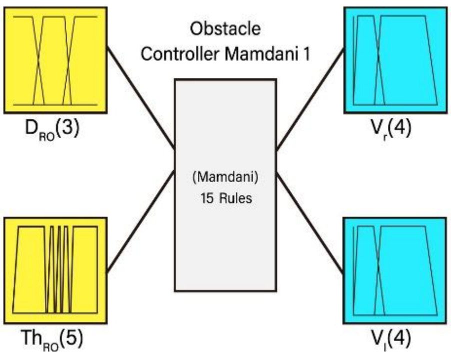

Fig. 6. Fuzzy rule set for the obstacle avoidance

4) Fuzzy Logic Rules Tables

The fuzzy rule base is developed based on multiple experiments to define the decision-making logic of the fuzzy controllers. The rule base for the target navigation fuzzy controller is presented in Table I.

TABLE I. FUZZY RULES SETS OF THE TARGET

D_{RT}(m)/θ_{RT}(°)	NB	N	Z	P	PB
S	*Z/Z*	*Z/Z*	*Z/Z*	*Z/Z*	*Z/Z*
M	*F/UM*	*F/M*	*M/M*	*M/F*	*F/UM*
B	*F/UM*	*F/M*	*F/F*	*M/F*	*F/UM*

The linguistic variables for the inputs in this controller are:

- D_{RT} = (**S:** Small, **B:** Big, **Z:** Zero).
- θ_{RT} = (**NB:** Negativebig, **N:** Negative, **Z:** Zero, **P:** Positive, **PB:** Positivebig).

The linguistic variables for the outputs in this controller are:

- V_r = **F:** Fast, **M:** Medium, **UM:** Under-Medium, **Z:** Zero.
- V_l = **F:** Fast, **M:** Medium, **UM:** Under-Medium, **Z:** Zero.

Examples for this fuzzy control rule is:

- if θ_{RT} is N and D_{RT} is M, then v_r is F and v_l is M.
- if θ_{RT} is Z and D_{RT} is S, then v_r is Z and v_l is Z.

The rule base for the obstacle avoidance fuzzy controller is outlined in Table II.

TABLE II. FUZZY RULES SETS FOR OBSTACLE AVOIDANCE

D_{RO}(m)/θ_{RO}(°)	NB	N	Z	P	PB
S	*M/F*	*Z/M*	*Z/F*	*M/Z*	*F/M*
M	*F/F*	*M/M*	*M/M*	*M/M*	*F/F*
B	*F/F*	*F/F*	*F/F*	*F/F*	*F/F*

The linguistic variables for the inputs in this controller are:

- D_{RO} = (**S:** Small, **M:** Medium, **B:** Big).
- θ_{RO} = (**NB:** Negativebig, **N:** Negative, **Z:** Zero, **P:** Positive, **PB:** Positivebig).

The linguistic variables for the outputs in this controller are:

- V_r = **F:** Fast, **M:** Medium, **Z:** Zero.
- V_l = **F:** Fast, **M:** Medium, **Z:** Zero.

Examples for this fuzzy control rule is:

- if θ_{RO} is P and D_{RO} is B, then v_r is F and v_l is F.
- if θ_{RO} is PB and D_{RO} is S, then v_r is F and v_l is M.

G. Membership Function

The membership functions (MF**s)** play a crucial role in the fuzzy logic controller (FLC) by determining the degree of truth of different input values. This enables the system to process sensor data and generate appropriate control actions for robot navigation.

The membership functions for the target navigation fuzzy controller (FLC-RT**)** are illustrated in Fig. 7, while the membership functions for the obstacle avoidance fuzzy controller (FLC-RO) are shown in Fig. 8. These diagrams cover both the inputs and outputs used in the mobile robot navigation system**,** providing insights into how fuzzy logic rules map sensor readings into control commands.

The membership functions for the target navigation fuzzy controller are defined as follows :

Inputs :

MF$_{INPUT1}$ → Distance to Target (D_{RT})

MF$_{INPUT2}$ → Angle to Target (θ_{RT})

Outputs :

MF$_{OUTPUT1}$ → Right Wheel Speed (V_r)

MF$_{OUTPUT2}$ → Left Wheel Speed (V_l)

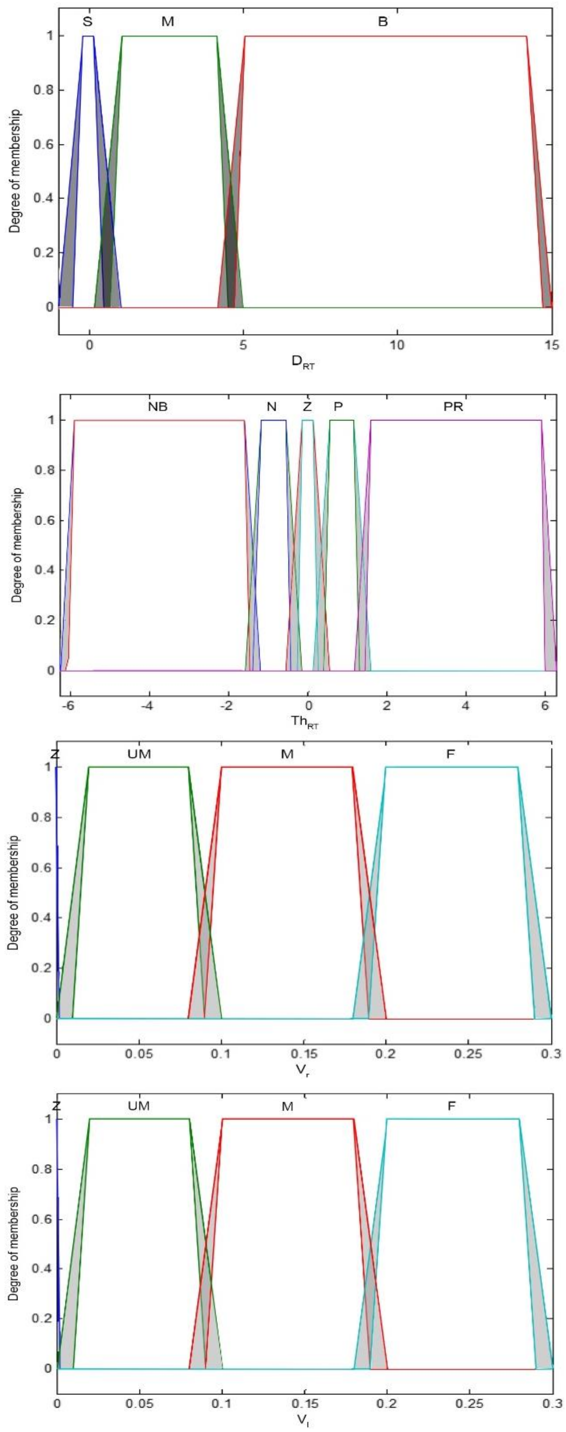

Fig. 7. Membership function of the FLC-Robot-Target input/output variables

Similarly, the membership functions for the obstacle avoidance fuzzy controller are structured as follows:

Inputs :

MF$_{INPUT1}$ → Distance to Obstacle (D_{RO})

MF$_{INPUT2}$ → Angle to Obstacle (θ_{RO})

Outputs :

MF$_{OUTPUT1}$ → Right Wheel Speed (V_r)

MF$_{OUTPUT2}$ → Left Wheel Speed (V_l**)**

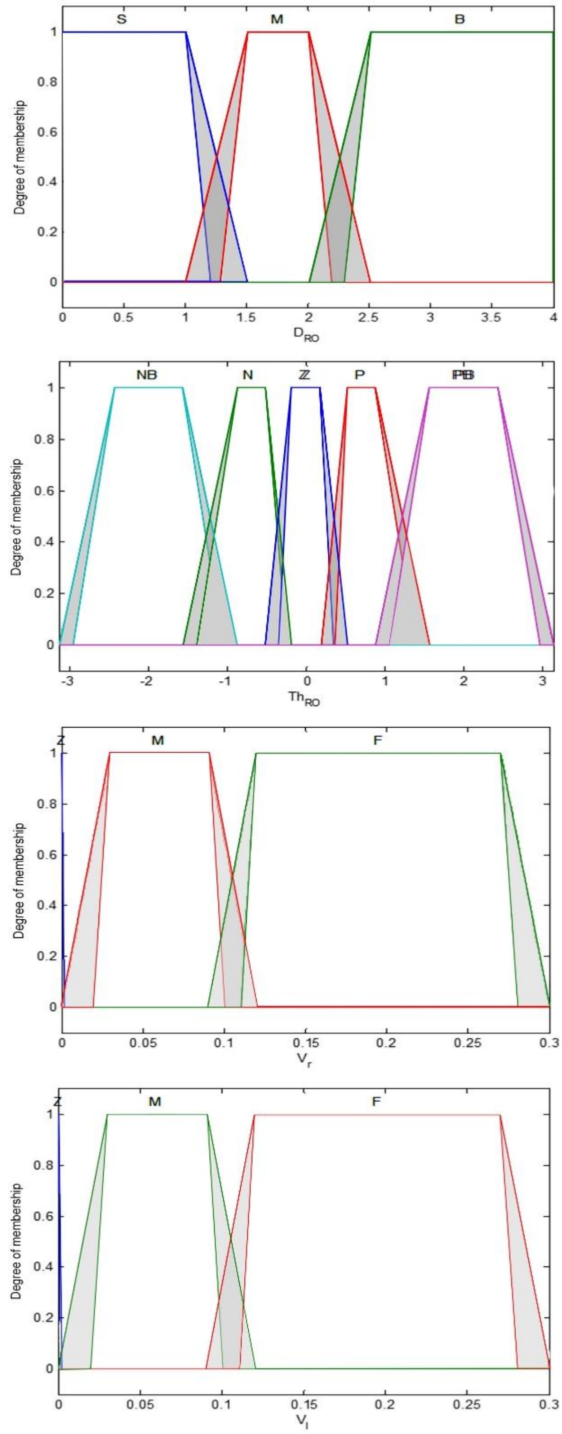

Fig. 8. Membership function of the FLC-Robot-Obstacle input/output variables

III. RESULTS AND DISCUSSION

A. Simulation Navigation Test In A Static Environment With Focus On A U-Shaped Path

The first experiment involved a simulated navigation test in a controlled static environment (Fig. 9). The primary objective was to evaluate the performance of the proposed Type-2 fuzzy logic navigation system in maneuvering through a U-shaped (concave) structure, which is known to be a challenging scenario for mobile robots.

Many conventional navigation algorithms struggle with such environments due to the risk of getting trapped in local minimal. The proposed system successfully guided the robot through the U-shaped path without getting stuck. Quantitative analysis showed that:

The robot successfully completed the path in 92% of the trials (23 out of 25 attempts).

The average time to navigate the U-shaped path was 12.8 seconds, compared to 15.5 seconds in a classical fuzzy logic controller.

The system demonstrated better adaptability in handling sudden directional changes, reducing the need for manual intervention.

These findings highlight the robustness of the proposed system in overcoming complex geometric constraints.

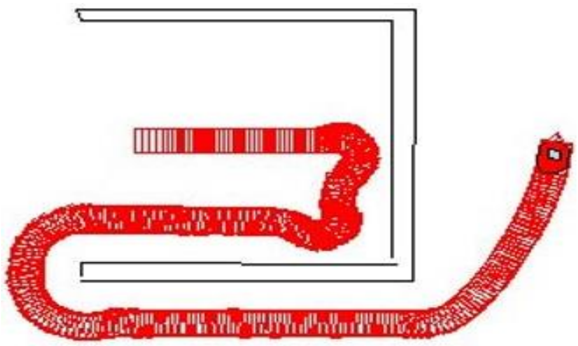

Fig. 9. Navigation in a U-shaped environment

B. Real-World Laboratory Test Of Robot Navigation With Static And Dynamic Obstacles

The second experiment was conducted in a real laboratory environment (Fig. 10), where the robot was tested against static and dynamic obstacles. The goal was to evaluate the system's ability to handle unexpected movement patterns.

The experiment involved navigating the robot through a crowded environment with:

A static obstacle and a dynamic obstacle moving at speeds ranging from 0.2 m/s to 0.5 m/s back and forth.

The proposed navigation system successfully avoided collisions in 89% of trials (24 out of 27 trials). Real-time trajectory adjustment of the system allowed it to:

Predict and respond to dynamic obstacles efficiently, reducing the risk of collisions.

Minimize unnecessary detours, maintaining an optimal path to the target.

Reduced false positive obstacle detections by 17% compared to classical fuzzy logic.

However, limitations were observed in scenarios involving multiple obstacles moving at high speed, where minor delays in decision making were detected.

Fig. 10. Real-world robotic navigation in dynamic environments

C. Comparison with Previous Research

To validate the effectiveness of our approach, we compared our results with previous studies on fuzzy logic-based navigation (Table III).

TABLE III. PERFORMANCE COMPARISON OF THE PROPOSED TYPE-2 FUZZY LOGIC CONTROLLER WITH EXISTING NAVIGATION METHODS

Method	Success Rate (%)	Average Completion Time (s)	Collision Avoidance Efficiency
Classical Fuzzy Logic [1]	83%	15.5	Moderate
Type-2 fuzzy inference tree [2]	90%	12-15	High
Proposed Type-2 FLC	92%	12.8	Very High

Our findings indicate that Type-2 fuzzy logic outperforms classical fuzzy controllers in handling uncertain environments**,** offering faster completion times and improved obstacle avoidance capabilities**.**

D. Strengths and Limitations

1) Strengths:

- Improved adaptability to dynamic and complex environments**.**
- Higher success rate in navigating challenging paths. Reduced error margins in obstacle detection and avoidance.

2) Limitations :

- Slight processing delays in highly dynamic environments with multiple moving obstacles.
- Potential dependency on sensor accuracy, requiring further improvements in sensor fusion techniques.

3) Implications of Findings:

These results highlight the potential of Type-2 fuzzy logic controllers in real-world applications, particularly in autonomous mobile robotics**,** where adaptability and robustness are critical.

IV. CONCLUSION

In this study, we evaluated the effectiveness of Type-2 fuzzy logic controllers (FLCs) in robotic navigation within dynamic environments. The experiments demonstrated that Type-2 fuzzy logic improves the robot's ability to make adaptive decisions in real-time, offering significant advantages over traditional fuzzy logic systems.

A. Key Findings:

The proposed FLC-RT and FLC-RO controllers successfully guided the robot through complex static and dynamic environments, achieving a success rate of 92%.

The system demonstrated faster navigation times (12.8s vs. 15.5s in classical fuzzy controllers), reducing computational delays.

The real-world experiment confirmed the system's capability to avoid dynamic obstacles effectively while maintaining an optimal trajectory.

B. Limitations of the Study:

Despite the promising results, certain limitations must be.

C. Acknowledged:

Processing latency in scenarios with multiple fast-moving obstacles.

Dependence on sensor accuracy, which may affect performance in noisy environments.

D. Future Work and Research Directions:

Enhancing computational efficiency to further reduce real-time processing delays. Integrating sensor fusion techniques to improve obstacle detection accuracy. Testing on different robotic platforms to assess the scalability of the proposed system. Comparing with deep reinforcement learning models to explore hybrid AI approaches.

This study contributes to advancing autonomous navigation systems by demonstrating the advantages of Type-2 fuzzy logic in handling uncertainties, paving the way for more adaptive and intelligent robotic control strategies.

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