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On the Performance Comparison of Fuzzy-Based Obstacle Avoidance Algorithms for Mobile Robots †

José Zúñiga, William Chamorro , Jorge Medina * , Pablo Proaño , Renato Díaz and César Chillán

Departamento de Automatización y Control Industrial, Facultad de Ingeniería Eléctrica y Electrónica, Escuela Politécnica Nacional, Quito 170143, Ecuador; jose.zuniga01@epn.edu.ec (J.Z.); william.chamorro@epn.edu.ec (W.C.); pablo.proano@epn.edu.ec (P.P.); victor.diaz@epn.edu.ec (R.D.); cesar.chillan@epn.edu.ec (C.C.)

* Correspondence: jorge.medinaj@epn.edu.ec

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Abstract: One of the critical challenges in mobile robotics is obstacle avoidance, ensuring safe navigation in dynamic environments. In this sense, this work presents a comparative study of two intelligent control approaches for mobile robot obstacle avoidance based on a fuzzy architecture. The first approach is a neuro-fuzzy interface that combines neural networks' learning capabilities with fuzzy logic's rule-based reasoning, offering a flexible and adaptable control strategy. The second is a classic Mamdani fuzzy system that relies on human-defined fuzzy rules, providing an intuitive approach to control. A key contribution of this work is the development of a fast comprehensive, model-based dataset for neural network training generated without the need for real sensor data. The results show the evaluation of these two systems' performance, robustness, and computational efficiency using low-cost ultrasonic sensors on a Pioneer 3DX robot within the Coppelia Sim environment.

Keywords: ANFIS; Mamdani; obstacle avoidance; fuzzy; mobile robots; intelligent control systems; IoT; ultrasonic sensors; synthetic dataset; CoppeliaSim

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1. Introduction

Mobile robots have become increasingly prevalent in various applications, from industrial automation to personal assistance. One of the critical challenges in mobile robotics is obstacle avoidance, which ensures the safe navigation of the robot in its environment [1]. Conventional control techniques have limitations in dealing with the inherent uncertainties and complexities of real-world environments [2].

Conventional, model-based control techniques often struggle to handle the inherent uncertainties and complexities of real-world navigation. These methods often rely on precise environmental models and struggle to adapt to unexpected obstacles or changing conditions [3]. To address these challenges, intelligent control systems, such as fuzzy logic and adaptive neuro-fuzzy inference systems, have emerged as promising solutions [4–6]. Fuzzy logic, inspired by human reasoning, excels in dealing with vagueness and linguistic information [7], while neural networks offer powerful learning capabilities for adapting to dynamic environments [8].

In this work, we present a comparative study of two intelligent control approaches for mobile robot obstacle avoidance: the adaptive neuro-fuzzy inference system (ANFIS) and the Mamdani fuzzy system. The ANFIS combines the learning capabilities of neural networks with the rule-based reasoning of fuzzy logic, offering a more flexible and adaptable control strategy [4]. Adaptive neuro-fuzzy inference system leverages the advantages of fuzzy logic to handle uncertainty in sensor data, ensuring smooth and intuitive control actions, while simultaneously employing the adaptive learning capabilities of neural networks to optimize performance over time [9]. The Mamdani fuzzy system, on the other hand, relies on a set of human-defined fuzzy rules to make decisions, providing a more intuitive approach to control [5]. Both intelligent control methods have been extensively studied and applied in the field of mobile robotics, and each approach has its own strengths and limitations [10]. This comparative study aims to evaluate the performance, robustness, and computational efficiency of these two control systems in the context of mobile robot obstacle avoidance, providing valuable insights for researchers and engineers working in this field.

Interestingly, while the adaptive neuro-fuzzy inference system offers greater adaptability and learning capabilities, the Mamdani fuzzy system may be more suitable for scenarios where the underlying system dynamics are well understood, and the control objectives can be easily translated into a set of fuzzy rules [11]. The choice between the adaptive neuro-fuzzy inference system and the Mamdani fuzzy system for mobile robot obstacle avoidance depends on the specific requirements of the application, the available data, and the level of uncertainty in the environment [12]. Autonomous robots are quite commonly used but the scale is limited to repeated tasks or indoor applications in most cases. For autonomous vehicles, the sensor technology must be made more accommodating since a diversity of possibilities occurs which populates into a huge dimensional problem [4]. In this context, the adaptive neuro-fuzzy inference system and the Mamdani fuzzy system can play a crucial role in enhancing the obstacle avoidance capabilities of mobile robots, paving the way for more reliable and versatile autonomous systems.

In this work, we assess the performance of ANFIS and classic Mandami fuzzy controllers for obstacle avoidance in unknown scenarios using the measurements given by low-cost ultrasonic sensors as sensing data. Both controllers use as a base trajectory controller a fuzzy cluster arrangement that handles the heading angle towards the desired goal and moves the robot with a constant velocity. It is worth mentioning that this work deals with static obstacle avoidance within a controlled environment. The development of a fuzzy neural network for the avoidance of moving (dynamic) obstacles, as well as a performance comparison with other types of controllers, is part of future research and will be presented in future works. A key contribution of this work lies in the development of a comprehensive, model-based dataset for training the ANFIS controller. This dataset is generated with random data within a range that emulates the low-cost sensor measurements, a combination of avoidance rules, and the model of the robot. The resultant is a synthetic dataset that does not require real sensor data, enhances the ANFIS training, and can be adapted to the robot's geometry and sensor models.

The performance assessment of both fuzzy topologies was carried out in simulation using the Pioneer DX3 robot within Coppelia Sim. The fuzzy systems were assembled and trained in Matlab which communicates with Coppelia Sim in real time. For the benefit of the community, the dataset generation along with the simulation files are available at https://github.com/WChamorro/Neuro-Fuzzy-Obstacle-Avoidance.git (accessed on 7 November 2024).

The rest of the paper is organized as follows: Methodology presents a detailed overview of the adaptive neuro-fuzzy inference system and the Mamdani fuzzy system, including their key components and decision-making processes applied to a robot to avoid obstacles considering data from ultrasonic sensors. Then, the results are presented with a discussion about them, and finally, relevant conclusions are presented.

2. Methodology

Adaptive neuro-fuzzy inference system (ANFIS) and classic Mamdani fuzzy systems represent two distinct approaches to modeling and control. ANFIS integrates the learning capabilities of neural networks with the interpretability of fuzzy logic, providing a powerful tool for handling complex, non-linear problems through adaptive learning [13]. In contrast, Mamdani fuzzy systems rely on a rule-based approach, where human expertise is encoded into a set of linguistic rules, offering intuitive and easily understandable solutions. The following sections bring details about the fuzzy architecture and the dataset generation for training the ANFIS.

2.1. Neuro-Fuzzy Inference System

The base robot's behavior is managed by a Sugeno fuzzy clustering approach, as shown in Figure 1a,c. This controller returns three sets of velocity: low, zero, and high based on the heading angle (HA). It is worth mentioning that the robot knows where the goal position is, and its 2D relative pose (to the starting point). The fuzzy clustering will be active when the sensors do not detect a closer obstacle [14].

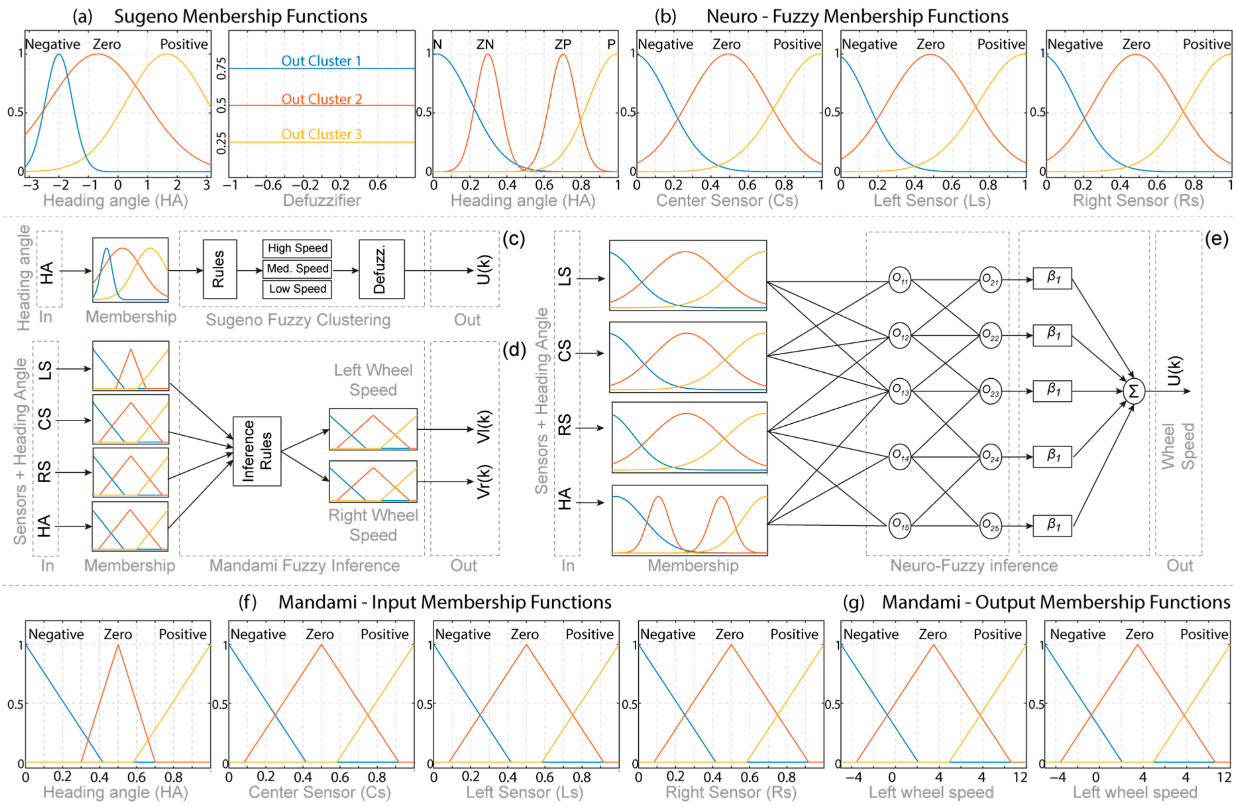

Figure 1. Fuzzy systems architecture: (**a**) Sugeno membership functions. (**b**) Neuro-fuzzy membership functions. (**c**) Sugeno clustering architecture. (**d**) Mandami architecture. (**e**) Neuro-Fuzzy architecture. (**f**) Mandami input membership functions. (**g**) Mandami output membership functions.

The ANFIS architecture shown in Figure 1b,e drives the robot's wheel speeds based on the inputs from each ultrasonic sensor: Right Sensor (RS), Central Sensor (CS), Left Sensor (LS), and the heading angle. This scheme was replicated for both wheels, and it was built with three sigmoidal membership functions for the sensors, and four for the heading angle for a more precise control. The Mamdani architecture in Figure 1d will be detailed in the following sections.

Model-Based Dataset Generation

The training dataset was created with uniformly generated random values representing the sensor readings. Low-cost ultrasonic sensors were used in this study to measure distance to the obstacles in meters. The shorter this distance, the more significant the control action required from the robot, whether it involves continuing to move forward, turning right, or turning left. In this work, we use the model of the sensor HC-SR04, which has a range from 2 to 400 cm and a 15-degree detection angle. The detection range was limited between d_{min} and d_{max} as shown in Figure 2a. This configuration ensures the robot can anticipate and avoid obstacles in advance, it also helps to prevent the sensors from receiving noisy data or errors due to distant objects. The desired heading angle is computed as $\theta = atan2(target_y, target_x)$, since we know the goal position noted with coordinates $(target_x,\ target_y)$.

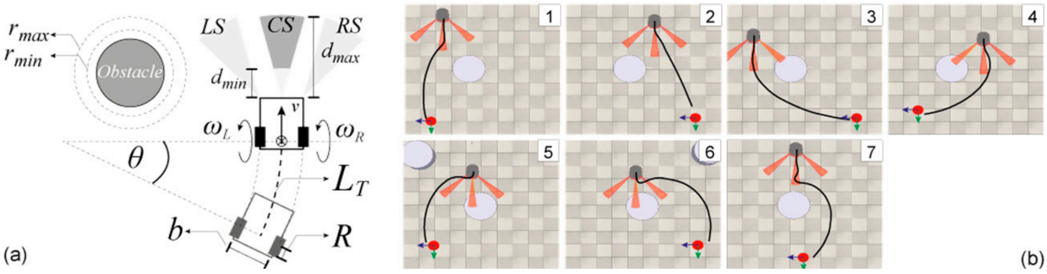

Figure 2. Tools for the dataset generation: (**a**) Robot geometry. (**b**) Avoidance rules visualization.

The dataset was generated in Python and requires only a specific set of parameters that depend on the geometry of the problem. The dataset is composed of the sensor data the heading angle, and the estimated right and left wheel velocities. The sensor data were randomly generated with a 25% bias focused on shorter distances and small alignment angles, as shown in Figure 3. The biased data are intended to enhance robot training for navigating tight spaces and handling multiple obstacles. It is worth mentioning that the data generated is normalized within their respective ranges to have an approach as general as possible.

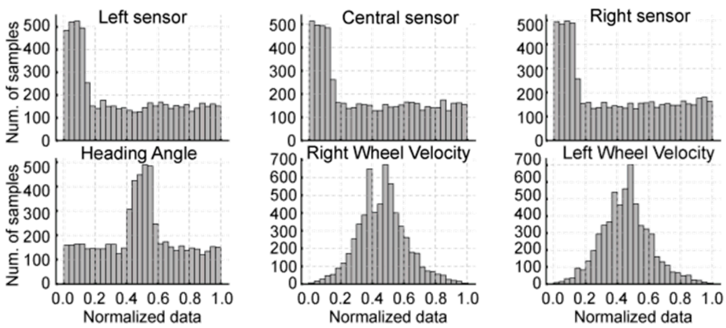

Figure 3. Training data distributions.

The wheel speeds in the dataset are estimated considering the robot's geometry and the sensor data following [15], as

$$\omega_{R/L} = \left(1 \pm \frac{b\theta}{2L_T}\right)\frac{v}{R}\ [\text{rad/s}] \tag{1}$$

where b is the distance between the robot's wheels, and R the radius of each wheel. L_T is the normalized robot's curvature length computed as follows:

$$L_T = d \cdot \left(L_{T_{max}} - L_{T_{min}}\right) + L_{T_{min}}\ \ [\text{m}] \tag{2}$$

recall that L_T is a normalized expression between L_{Tmin} and L_{Tmax}, which depends on the geometric characteristics of the robot as illustrated in Figure 2a. The remaining term v, is the estimated robot's linear velocity computed as follows:

$$v = v_{max} - \left(G_q \cdot \left(\frac{v_{mean}}{2}\right)\right)\ [\text{m/s}]\ \text{ with }\ G_q = 1 - 4d(1-d) \tag{3}$$

where G_q is a quadratic function that uses the sensor-measured distance d. G_q models a desired velocity boost if the sensors detect an obstacle closer to d_{min} or d_{max}, or a moderate speed in the mid-range. This behavior allows us to reach the goal as fast as possible if we have a clear path or produce faster reactions in the presence of an obstacle.

In the presence of an obstacle, the robot should decide which direction must be followed. These decisions are predefined by providing the knowledge with the statement of the possible avoidance rules pictured in Figure 2b. Cases 1 and 2 are the simplest to interpret because the robot must move away from the obstacle while approaching the target, without compromising trajectory. In cases 3 and 4, the target is in the same orientation as the obstacle, so a change to the desired angle is made to ensure the robot does not move too far from the obstacle, thereby avoiding trajectory compromise. For cases 5 and 6, the front sensor will detect the closest distance, so the position of the target will determine the robot's movement. Case 7 applies to the remaining cases, when the robot is aligned with the target, involving a real-time condition that consists of changing the orientation angle, forcing the wheels to make a sharper turn, and preventing the robot from colliding with the obstacle.

The dataset was generated using a Python script yielding synthetic adjustable data to train the ANFIS. Figure 4 shows the result of the training process that was carried out with the neuro-fuzzy designer in MATLAB 2024A [16].

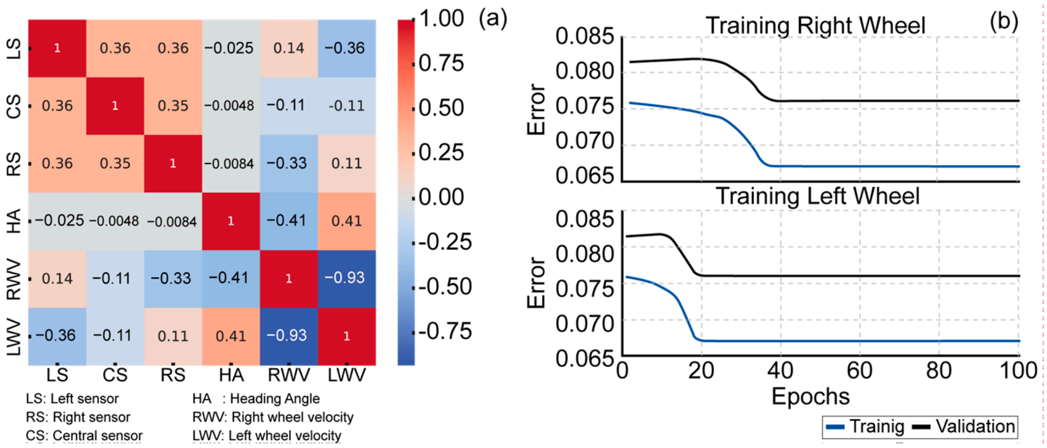

Figure 4. ANFIS training results: (**a**) Correlation Matrix. (**b**) Training error.

The generated dataset for the neuro-fuzzy scheme was split into 80% for training and 20% for validation. The training error stabilizes after 30 epochs approximately, as shown in Figure 4b. The validation error is slightly higher than the training error, indicating that the ANFIS is capable of generalizing with a lower error. As shown in Figure 4a, LS, CS, and RS sensors exhibit moderate positive correlations with each other (0.36), indicating that they typically detect similar features in the environment. The heading angle shows a very low correlation with the sensors, suggesting minimal direct influence from sensor readings. The right wheel velocity (RWV) and left wheel velocity (LWV) display a strong negative correlation (−0.93), reflecting the expected inverse relationship during differential steering maneuvers. The heading angle also moderately correlates with wheel velocities, showing a negative correlation with RWV (−0.41) and a positive correlation with LWV (0.41), indicating the significant role of wheel velocities in determining the robot's heading.

2.2. Mamdani Fuzzy Inference System

The Mamdani fuzzy inference system (FIS) pictured in Figure 1d,f,g, enables inference based on the evaluation of one or more membership sets according to a predetermined number of rules proposed by an expert system designer [17]. Unlike a Sugeno-type fuzzy inference system, Mamdani allows for multiple inputs and outputs [18]. Consequently, it is not necessary to separate the calculations for the speeds of the left and right wheels of the motor. The following sections describe the structure of this fuzzy approach.

2.2.1. Membership Functions for Inputs and Outputs

The membership function of each input variable (sensors and heading angle) was built with three triangular fuzzy sets, which are uniformly distributed, as shown in Figure 1f,g. For the variables related to the distance sensors, the following fuzzy sets are defined with triangular functions with these parameters: Close: [−0.42, 0, 0.42], Medium: [0.08, 0.5, 0.92], Far: [0.6, 1, 1.42]. The output membership functions are similarly constructed with triangular fuzzy sets: Slow: [−0.42, 0, 0.42], Normal: [0.08, 0.5, 0.92], Fast: [0.6, 1, 1.42]. These intervals were set based on the desired robot's speed limitations.

2.2.2. Inference and Defuzzification

To evaluate a Mamdani-type fuzzy set, it is necessary to develop rules, which are also defined by the designer. The base rules allow handling the avoidance cases displayed in Figure 2b. Other rules were added based on the possible combinations between input and output membership functions. For the defuzzification of the FIS output, the centroid method (COG) is applied, as it provides balanced, smooth, and natural results, which enhance the performance of the mobile robot control [9].

3. Results and Discussion

The fuzzy strategies for obstacle avoidance were evaluated through simulation using Coppelia Sim, where we assembled virtual scenarios of different complexity with obstacles of different shapes. Whitin Copelia the scenarios were configured with the Bullet engine as a physics computation motor due to its high performance in collision detection and rigid body dynamics, making it suitable for real-time applications for obstacle avoidance.

The Pioneer 3DX used in the experiments was set with geometry constants based on the real robot specifications to: $b = 0.381$ [m], $R = 0.195$ [m]. The robot's maximum velocity was set to $v_{max} = 1.2$ [m/s] which leads to considering an average velocity of $v_{mean} = 0.6$ [m/s]. The path's curvature is constrained to $L_{T_{min}} = 0.3$ [m] and $L_{T_{min}} = 1.2$ [m]. The low-cost sensor model mounted in the virtual robot is the HC-SR04 from which we use constrained distance measurements from $d_{min} = 0.3$ [m] to $d_{max} = 1$ [m]. Recall that the sensing data and wheel speed were normalized from 0 to 1 to generate the training dataset for the ANFIS.

Avoidance Experiments

The ANFIS and Mamdani fuzzy strategies were assessed in two complex scenarios. Scenario A was built with scattered obstacles with rounded and squared shapes. In the center of the scenario, we place an elongated object that will test the avoidance capabilities due to the curve that the robot should make to reach the goal. The results in scenario A are pictured in Figure 5, where the ANFIS scheme handles all the obstacles efficiently. As expected, the robot navigates closely to the large obstacle until it can turn towards the goal. On the other hand, the Mamdani approach produces an unnecessary loop while trying to avoid the large obstacle and detecting another obstacle on its path. Note that in Figures 5 and 6, the ultrasonic beams are shown in red when no obstacle is detected and in yellow when an obstacle is present.

Scenario B emulates a narrow corridor where the robot should navigate closely to the walls. This experiment includes a closed curve towards the goal as displayed in Figure 6. The ANFIS results in this scenario, shown in Figure 6a, show a clean trajectory while the robot navigates closely to the walls even during the closed curve, where the robot follows the shape of the wall. In Figure 6b the Mandami approach tries to face the goal all the time, yielding an oscillatory behavior in the presence of a persistent obstacle. This issue is related to the constant set of membership functions that were designed to address generic avoidance cases. The distribution of membership functions in the Mamdani-type system was not subjected to a tuning process; instead, a uniform distribution was directly applied across the entire evaluation range of the term set. This approach may require a fine tuning since the robot responses aggressively to an obstacle which may produce large deviations from the goal.

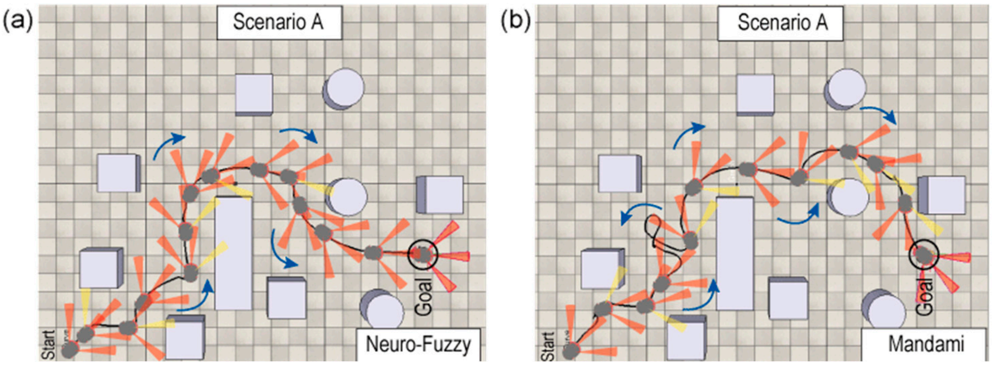

Figure 5. Experiments in scenario A: (**a**) ANFIS performance. (**b**) Mandami performance.

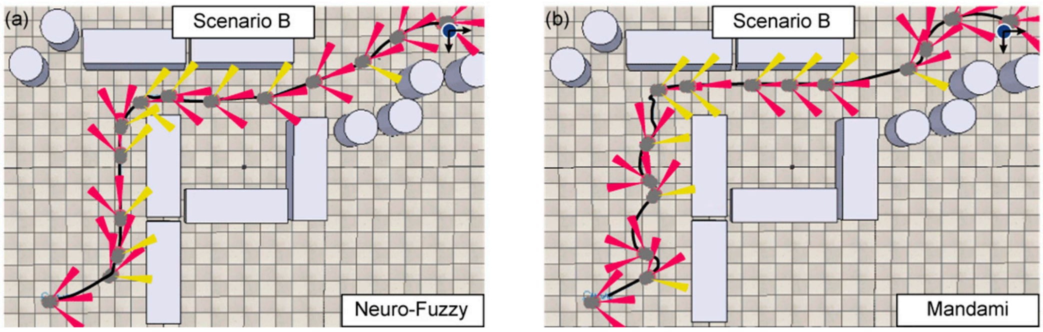

Figure 6. Experiments in scenario B: (**a**) ANFIS performance; (**b**) Mandami performance.

Evaluating obstacle avoidance schemes in robotics and autonomous systems can be approached through both qualitative and quantitative methods. Qualitatively, one can assess the effectiveness of the scheme by observing the robot's ability to navigate around obstacles without collisions, maintaining smooth and natural movement patterns. Quantitative evaluation involves measuring specific metrics such as velocity and acceleration. By analyzing these parameters, one can determine the efficiency and responsiveness of the avoidance scheme, ensuring that the robot moves at an optimal speed while minimizing abrupt changes in acceleration, which can indicate inefficient or unsafe maneuvers. In this sense, the ANFIS produced smooth displacements with controlled accelerations as shown in Figure 7b-bottom. This yields controlled movements and avoids unnecessary oscillations, especially while sensing large walls. In both scenarios, the ANFIS shows constant velocities with minimal acceleration especially when the robot navigates closely to the walls, see Figure 7b-top. On the other hand, the Mandami approach tends to oscillate while avoiding an obstacle. In this case, large accelerations are observed in Figure 7a-bottom, which may cause deviations or loops as the one observed in scenario A.

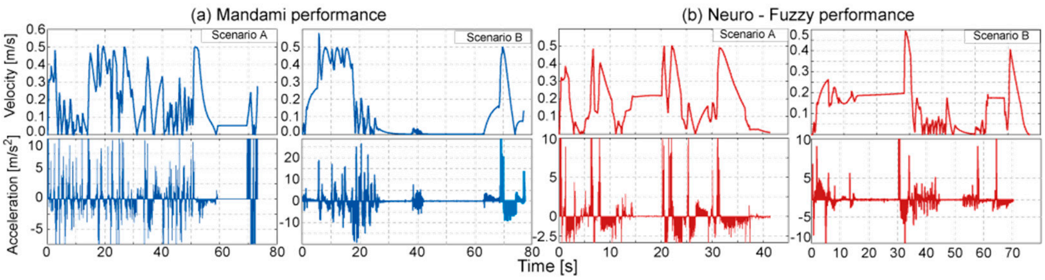

Figure 7. Velocity and Acceleration performance results: (**a**) Mandami; (**b**) ANFIS.

As shown in Figure 7, the acceleration frequency is lower in the neuro-fuzzy control compared to the Mamdani control. This smoothness allows the robot to move more fluidly, avoiding getting stuck when evading an obstacle. Additionally, a lower acceleration frequency has the advantage of preventing mechanical wear and fatigue, particularly in experiments with a real robot.

One of the efficiency parameters used to determine the efficacy between the two controllers is the performance ratio. This metric is defined as the ratio between the shortest distance the robot can travel, which is the straight line the robot would take in an obstacle-free environment, and the distance actually traveled by the robot in each experiment. In this way, efficiency in identical scenarios can be compared using a dimensionless parameter, where the perfect distance (completely straight trajectory) would result in a performance ratio of 1. The lower this value, the poorer the performance of the controller analyzed in a given scenario.

Table 1 gives a clear overview of the metrics from each experiment. It includes the Root Mean Square (RMS) values for both speed and acceleration. When using the Mamdani-type fuzzy controller, there are significant changes in acceleration during orientation shifts. However, with the neuro-fuzzy controller, these peaks are greatly reduced, suggesting that this controller aims to keep the speed constant. In Scenario B, the values are quite similar and stay below one, mainly because the presence of multiple obstacles forces the robot to move more slowly. However, the time it takes for the robot to reach its target is significantly reduced when using the neuro-fuzzy control.

Table 1. Performance statistics in the test scenarios.

Statistics	Scenario A		Scenario B	
	ANFIS	Mandami	ANFIS	Mandami
Trajectory time [s]	41.45	29.65	70.45	77.17
Traveled path [m]	14.47	13.21	18.02	20.46
RMS velocity [m/s]	0.24	0.24	0.19	0.20
RMS acceleration [m/s^2]	1.09	2.07	0.74	0.68
Performance ratio	0.87	0.85	0.82	0.74
Computational time per cycle [ms]	1.3	0.56	1.3	0.56

4. Conclusions

The results show the effectiveness of using intelligent control systems, specifically the adaptive neuro-fuzzy inference system (ANFIS) for obstacle avoidance in mobile robots. Findings highlight several key insights: ANFIS controller exhibited superior performance in complex obstacle avoidance scenarios compared to the Mamdani fuzzy system. This is primarily due to ANFIS's ability to adapt and learn from the environment, resulting in smoother and more efficient navigation. In scenarios with scattered and complex obstacles, ANFIS managed to navigate without unnecessary loops or deviations, unlike the Mamdani system which sometimes struggled with large obstacles. The ability of ANFIS to adjust its parameters dynamically allowed it to handle unexpected changes and obstacles more effectively. Overall, the neuro-fuzzy controller demonstrates significant advantages in maintaining smoother and more efficient control, particularly in more complex scenarios with obstacles. In Scenario B, where multiple obstacles are present, the neuro-fuzzy controller not only reduces the trajectory time from 77.17 s (Mamdani) to 70.45 s but also maintains a favorable balance between speed and acceleration. This improvement in trajectory time suggests that the neuro-fuzzy controller can navigate obstacles more effectively, achieving faster goal attainment. Despite the slightly higher RMS acceleration in Scenario B, the neuro-fuzzy controller still manages to maintain efficient control, as indicated by a higher performance ratio of 0.82 compared to 0.74 for the Mamdani controller. This ratio highlights the neuro-fuzzy controller's ability to find a more optimal path, staying closer to the ideal straight-line trajectory even in complex environments.

In narrow corridor scenarios, ANFIS maintained a clean trajectory closely following the walls, even during sharp turns. In contrast, the Mamdani system exhibited a sinusoidal trajectory due to aggressive responses to obstacles, indicating the need for fine-tuning to improve performance in such environments. Quantitative analysis of velocity and acceleration showed that ANFIS provided controlled movements with minimal unnecessary oscillations, especially when navigating close to walls. The Mamdani approach, however, led to larger accelerations and deviations, which can be inefficient and potentially unsafe. A significant contribution of this work is the development of a comprehensive, model-based dataset for training the ANFIS controller. This synthetic dataset, generated without real sensor data, enhances the training process and can be adapted to various robot geometries and sensor models, providing a versatile tool for future research.

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