International Journal of Electrical and Computer Engineering (IJECE)
Vol. 15, No. 1, February 2025, pp. 1065~1078
ISSN: 2088-8708, DOI: 10.11591/ijece.v15i1.pp1065-1078

An efficient strategy for optimizing a neuro-fuzzy controller for mobile robot navigation

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Article Info

Article history:

Received Jun 11, 2024
Revised Sep 15, 2024
Accepted Oct 1, 2024

Keywords:

Accuracy
Complexity
Fuzzy clustering
Mobile robot
Reactive navigation
Rule base simplification

ABSTRACT

Autonomous navigation is one of the key challenges in robotics. In recent years, several research studies have tried to improve the quality of this task by adopting artificial intelligence approaches. Indeed, the neuro-fuzzy approach stands out as one of the most commonly employed methods for developing autonomous navigation systems. Nevertheless, it may encounter problems of accuracy, complexity, and interpretability due to redundancy in the fuzzy rule base, particularly in the fuzzy sets associated with the system's variables. In this work, a strategy is proposed to optimize an adaptive-network-based fuzzy inference system (ANFIS) controller for reactive navigation by addressing the problem of complexity and accuracy. It consists in combining a suite of methods, namely, data-driven fuzzy modeling, fuzzy sets merging, fuzzy rule base simplification, and parameter training. This process has produced a fuzzy inference system-based controller with high accuracy and low complexity, enabling smooth and near-optimal navigation. This system receives local information from sensors and predicts the appropriate kinematic behavior that enables the robot to avoid obstacles and reach the target in cluttered and previously unknown environments. The performance of the proposed controller and the efficiency of the followed strategy are demonstrated by simulation experiments and comparisons with state-of-the-art methods.

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1. INTRODUCTION

In robotics, autonomous navigation stands out as a widely studied area of research, crucial for various robotic applications like logistics and warehousing, search and rescue operations, exploration of hazardous environments, self-driving vehicles, and service robots. Its primary objective is to chart a safe path from an initial position to a target, enabling robots to fulfill tasks within a given environment without encountering obstacles. In the literature, there are two types of autonomous navigation: global path planning and local path-planning [1]. The first type is applied in previously known environments. It is based on static environment maps to determine from the outset an optimal path to reach a target. Whereas, the second type, that is reactive navigation, can be used in unknown and dynamic environments, as it can ensure instantaneous reactive behavior of the robot depending on the position in the workspace. In this type of navigation, the robot perceives its surrounding environment in each state using an onboard sensor system and decides its movement using an intelligent control system. This system uses local information as input and forecasts an output, which may be an adjustment of the steering angle or wheel velocities, to steer clear of obstacles nearby while moving toward the desired destination.

In the past few years, many research studies have approached the problem of autonomous navigation. Generally, there are two categories of methods: the classical methods which require intensive computation and do not operate efficiently in dynamic and uncertain environments, and heuristic methods which can deal with navigation problems in uncertain environments [2]. In addition, there are hybrid methods, which combine classical and heuristic methods to improve the safety, optimality, and smoothness of navigation in complex and dynamic environments. In Table 1, we summarized the state-of-the-art approaches that address the problem of path-planning for mobile robots.

Table 1. State-of-the-art approaches for mobile robot path planning

Paper	Year	Approach	Navigation type	Objectives/advantages
[3]	2024	Improved elephant herding optimization	Global path planning	This swarm intelligence algorithm is used to plan the optimal path.
[4]	2023	Improved simulated annealing	Local path planning	The proposed approach is used to avoid moving obstacles in dynamic environments.
[5]	2023	Dhouib-matrix-SPP	Global path planning	This technique challenges the shortest path problem.
[6]	2023	Improved water flow potential field method and the beetle antennae search algorithm	Global path planning	This hybridization is used to solve obstacle avoidance and local optimum problems.
[7]	2022	Improved A* algorithm	Global path planning	This algorithm incorporates a bidirectional alternating search approach to overcome issues of computation time, large turning angles, and the unsmoothed path.
[8]	2022	Forward search optimization and subgoal-based hybrid path planning	Global path planning	This approach is used to reduce and smooth the path.
[9]	2022	Domain knowledge-based genetic algorithms	Global path planning	This algorithm aims to enhance the capability of conventional genetic algorithms in terms of time.
[10]	2022	Enhanced ant colony algorithm	Global path planning	This algorithm integrates historical paths and improves global search ability and stability
[11]	2022	Hybrid-adaptive-network-based fuzzy inference system (Hybrid-ANFIS)	Local path planning	In this approach, ANFIS is used for the local path-planning task, whereas global positioning system (GPS) and heading sensors are used for the global path-planning task.
[12]	2021	Morphological dilation Voronoi diagram roadmap algorithm	Global path planning	This algorithm is used to solve problems of computation complexity in complex environments.
[13]	2020	Strategy for a multi-robot system inspired by the Bug-1 algorithm	Global path planning	This strategy is used to avoid obstacles while reaching a target by the shortest path.
[14]	2020	GPS-ANFIS	Local path planning	In this method, ANFIS is designed to avoid obstacles and sensor data fusion is used to reach the target
[15]	2019	Cuckoo optimization algorithm	Local path planning	The proposed algorithm aims to find a short, safe, smooth, and collision-free path in different environments.
[16]	2018	Grey wolf colony optimization (GWCO)	Global path planning	The GWCO algorithm with the safe boundary concept is used to overcome the edged obstacle problem.
[17]	2018	Teaching-learning-based optimization-ANFIS (TLBO-ANFIS)	Local path planning	TLBO algorithm and least squares estimation (LSE) method is used to adjust the premise and consequent parameters respectively in ANFIS controller.
[18]	2017	Dijkstra's algorithm, objective particle swarm optimization	Global path planning	This approach focuses on minimizing the path length and maximizing the path smoothness.
[19]	2017	Fuzzy-wind driven optimization algorithm	Local path planning	The WDO algorithm is used to adjust the input/output membership function parameters of the fuzzy controller
[20]	2016	Invasive weed optimization-ANFIS (IWO-ANFIS)	Local path planning	The invasive weed optimization algorithm and least squares estimation method are employed to adjust the premise and consequent parameters respectively in the ANFIS controller.
[21]	2015	Improved artificial potential filed	Global path planning	This method is used to escape from deadlock problems.
[22]	2015	cuckoo search-ANFIS (CS-ANFIS)	Local path planning	The cuckoo search (CS) algorithm and the LSE method are utilized to adjust the parameters of both the premise and consequent parts in the ANFIS controller.
[23]	2015	ANFIS	Local path planning	Conventional ANFIS is used to design a controller for online path planning in unknown environments.
[24]	2015	Efficient artificial bee colony (EABC) algorithm	Local path planning	The EABC algorithm improves the performance by using elite individuals to preserve good evolution.

According to our recently published literature survey [25], Over the last decade, researchers have shown significant interest in the neuro-fuzzy approach. The systems based on this approach combine the advantages of fuzzy logic with neural networks. On the one hand, fuzzy systems handle uncertainty and imprecision through linguistic variables and rules, thus contributing to the design of controllers capable of operating in real-time. Neural networks, on the other hand, enable data-driven self-learning to adjust the parameters of the fuzzy system's membership functions. For instance, Pothal and Parhi [23] designed an adaptive-network-based fuzzy inference system (ANFIS)-based navigation controller capable of avoiding obstacles and reaching the target in previously unknown environments. This architecture uses hybrid learning, involving the adjustment of the nonlinear parameters in the premise part through the gradient descent method while fine-tuning the linear parameters in the consequent part via the least squares estimation (LSE) method. Whereas, Mohanty and Parhi [22] implemented a CS-ANFIS-based controller of 81 fuzzy rules such that the premise parameters are adjusted using the cuckoo-search (CS) algorithm. The use of this nature-inspired metaheuristic minimized the computation and overcame the local minima problem. Following the same strategy, Parhi and Mohanty [20] proposed a mobile robot navigation controller of 721 fuzzy rules based on invasive weed optimization-ANFIS (IWO-ANFIS). In this model, the non-linear parameters are optimized using the IWO metaheuristics. To implement a navigational model based on teaching-learning-based optimization-ANFIS (TLBO-ANFIS), Aouf *et al*. [17] used the TLBO metaheuristic to adjust the premise parameters. Furthermore Gharajeh and Jond [14] designed a global positioning system-ANFIS (GPS-ANFIS) based navigation controller. This technique divided navigation into two tasks, global control based on GPS data when the robot is far from obstacles and local control based on ANFIS to avoid the nearest obstacles. This strategy improved the target-seeking and slightly minimized the number of fuzzy rules for the ANFIS controller since the target position is not taken into account as an input variable for the ANFIS model.

Nevertheless, all these ANFIS-based studies have used the grid partitioning method to generate the fuzzy sets and rule base. In grid partitioning, the input space of the system is divided into a predefined number of intervals along each dimension. These intervals form a grid, and each grid cell represents a fuzzy set. The number of intervals along each dimension determines the granularity of the partitioning and hence the complexity of the resulting fuzzy inference system. Thus, this technique often produces complex systems, as it does not take into account the physical meaning and distribution of the data points [26].

In this paper, we propose a strategy to model an ANFIS-based controller for reactive navigation of mobile robots in cluttered and previously unknown environments. It is adopted to optimize the complexity of the ANFIS architecture, minimize the computational cost, and improve the interpretability of the resulting fuzzy system while maintaining high accuracy. This strategy consists in combining a set of methods, namely, data-driven rule base modeling using a clustering algorithm, fuzzy set merging using a similarity technique, redundant rule merging, and parameter training using the ANFIS model.

The remaining sections of this article are structured in the following manner. In section 2, we will explain the methods incorporated into the proposed strategy to model the navigation controller. These include the ANFIS architecture used to train the premise and consequent parameters of a Takagi-Sugeno fuzzy inference system (TS-FIS), data-driven fuzzy rule modeling focusing on the subtractive clustering algorithm, fuzzy set merging using a similarity technique, and redundant fuzzy rule merging. In section 3, we will present an experimental study of the proposed strategy, simulation results to demonstrate its efficiency compared with state-of-the-art methods, and a discussion to summarize the advantages of the proposed strategy in the mobile robotics field.

2. PROPOSED METHOD

Reactive navigation enables a mobile robot to move in previously unknown environments, avoiding obstacles and moving toward a target. This navigation must be safe, smooth, and effective. In this context, we aimed to model a mobile robot controller based on a TS-FIS which must address the accuracy/complexity trade-off. This system receives four sensor data which are: the front obstacle distance (FOD), the left obstacle distance (LOD), the right obstacle distance (ROD), and the target angle (TA) for predicting the robot's steering angle (SA), which must be a suitable kinematic behavior in the workspace. In Figure 1, we illustrate the components of the fuzzy inference system (FIS) representing the autonomous navigation controller of a robot with these input and output variables. To model this controller, considering the constraints of accuracy and complexity, the proposed strategy involves a set of steps from the dataset generation to the production of an efficient TS-FIS containing a simplified rule base. In Figure 2, we explain the sequence of steps in this strategy, namely: dataset generation, data-driven rule base modeling, fuzzy set merging, fuzzy rule merging, parameter training, and fuzzy system evaluation.

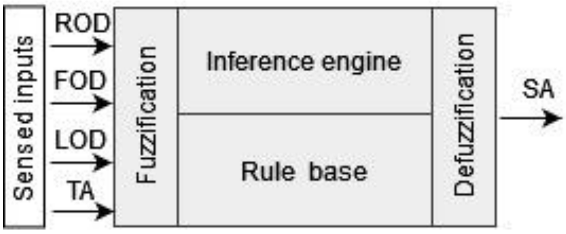

Figure 1. The components of a fuzzy inference system for the navigation controller

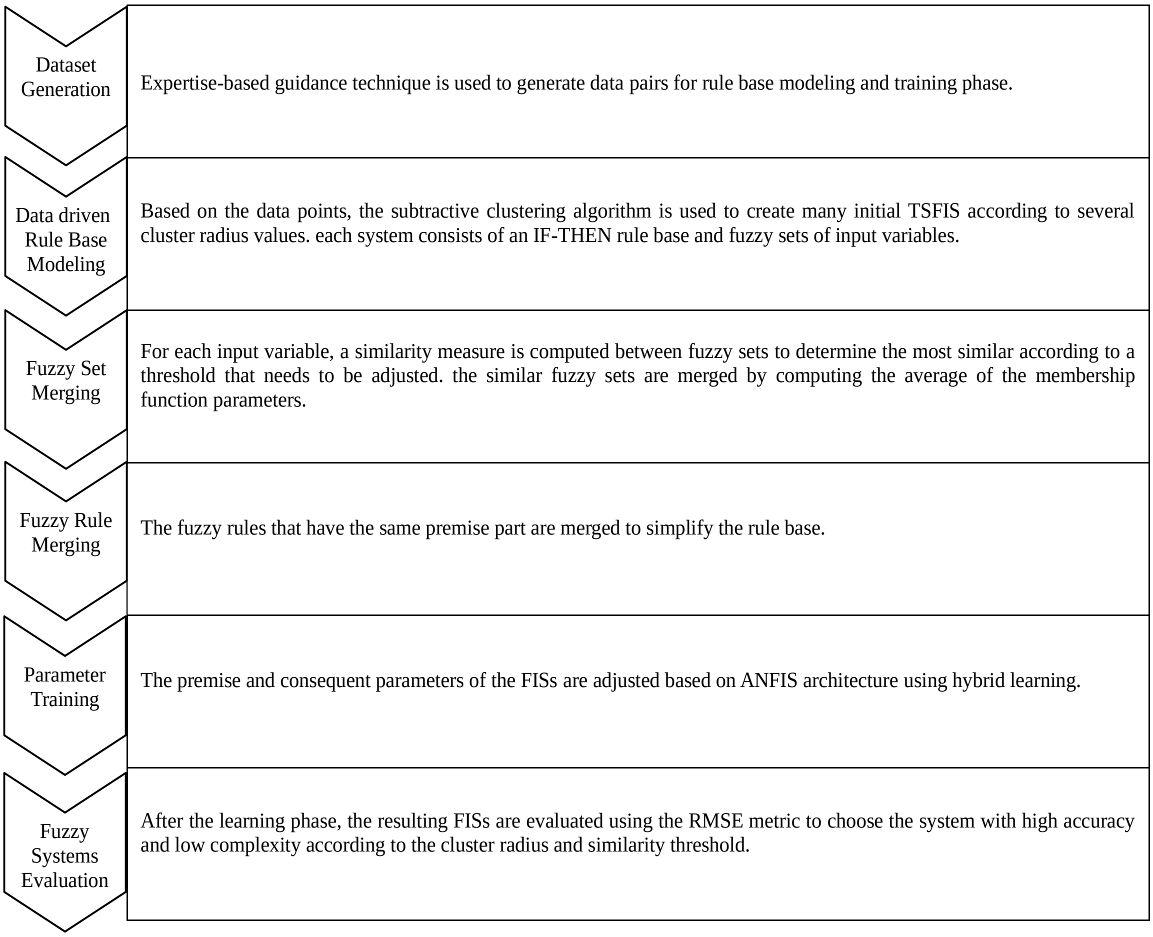

Figure 2. Steps of the proposed strategy for modeling and optimizing an ANFIS-based controller for mobile robot navigation

2.1. ANFIS architecture

The ANFIS architecture, introduced by Jang [27], is a neuro-fuzzy model designed to address various challenges such as nonlinear function modeling, control system modeling, and chaotic time series prediction. This adaptive network integrates the elements of a TS-FIS and performs learning thanks to the least mean squares (LMS) algorithm, which efficiently maps system inputs and outputs. Its learning mechanism employs a hybrid approach: adjusting the nonlinear parameters of the premise part via gradient descent in the backward pass, and tuning the linear parameters of the consequent part using the LSE method in the forward pass. To explain the ANFIS architecture, we consider a TS-FIS with two input variables x and y, and an output z. Assuming that this system contains two IF-THEN rules expressed as:

$R1$: $If\ x\ is\ X_1\ and\ y\ is\ Y_1\ Then\ f_1 = p_1 x + q_1 y + r_1$
$R2$: $If\ x\ is\ X_2\ and\ y\ is\ Y_2\ Then\ f_2 = p_2 x + q_2 y + r_2$

where X_i and Y_i are the fuzzy sets associated respectively with the input variables x and y, p_i, q_i, and r_i are the linear parameters of the consequent part. In Figure 3, we illustrate the ANFIS architecture that corresponds to the TS-FIS considered above, and in Table 2, we detail the layers and parameters of this architecture.

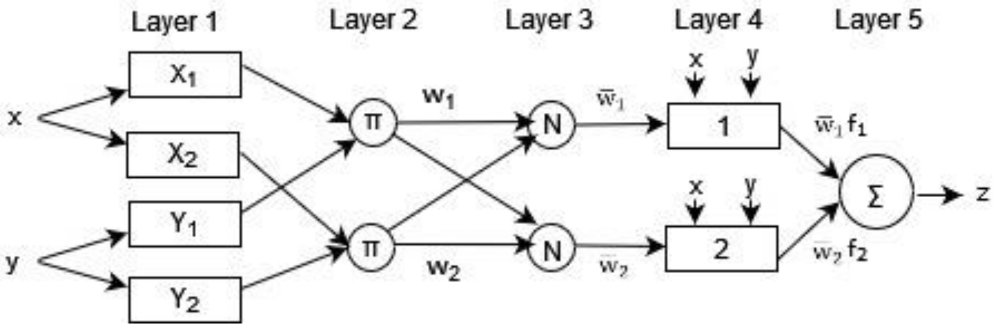

Figure 3. ANFIS architecture for the considered TS-FIS

Table 2. Description of ANFIS architecture

Layer	Description	Node function	
1	It represents the fuzzification phase. Within this layer, the nodes calculate the membership degree for the fuzzy sets X_i. Various types of membership functions can be employed during the fuzzification process. In this study, Gaussian functions are selected due to their suitability for the data distribution and their minimal parameter representation. To adjust the function's parameters a_i and c_i, the gradient descent method is applied.	$O_i^1 = u_{X_i}(x) = e^{\frac{-(x-c_i)^2}{2a_i^2}}$	(1)
2	Within this layer, the premise elements of a fuzzy rule are joined using the T-norm product operator to express the intersection, which determines the firing strength W_i of this rule.	$O_i^2 = w_i = u_{X_i} \times u_{Y_i}$	(2)
3	It is employed to normalize the firing strength w_i.	$O_i^3 = \bar{w}_i = \frac{w_i}{\sum_{n=1}^{2} w_n}$	(3)
4	It represents the linear functions of the rule's consequent parts. In the learning phase, the parameters p_i, q_i and r_i are tuned via the LSE method.	$O_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i)$	(4)
5	It uses the defuzzification formula to compute the overall system's output.	$O_i^5 = \sum_i \overline{w_i}\, f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$	(5)

2.2. Data-driven rule base modeling

In reactive navigation, the robot faces input/output situations, which consist in acquiring local information from the environment and predicting a kinematic behavior that will enable it to navigate efficiently. The uncertain character of the information leads to fuzzy modeling. In our case, we use a TS-FIS based on an IF-THEN rule base whose premise parts use fuzzy sets for the fuzzification of the input variables. To model a system that reflects reality, the data-driven fuzzy modeling technique is adopted. It is based on clustering algorithms that can partition a dataset into clusters according to the distribution of data points in space to assign membership functions and generate fuzzy IF-THEN rules. In our case, the subtractive clustering algorithm is used. This technique, introduced by Chiu [28], is a fast one-pass algorithm for determining the number of clusters and the center of each one. It depends on the potential of each data point, taking into consideration the density of adjacent data points and a parameter called the cluster radius. Thus, the likelihood value for a data point x_i to define a cluster center is calculated as (6):

$$P_i = \sum_{j=1}^{k} e^{-\frac{4}{r_a^2}\|x_i - x_j\|^2} \tag{6}$$

where k is the number of data points in an M dimensional space, $\|x_i - x_j\|^2$ is the Euclidean distance, and r_a is the cluster radius, which defines the area of the cluster influence and determines the number of clusters. Each cluster center defines a fuzzy rule. Indeed, for a fuzzy system with n obtained clusters, n fuzzy rules are generated and each input variable is associated with n fuzzy sets.

2.3. Fuzzy set merging

Data-driven fuzzy modeling is an effective method for generating a FIS that corresponds to data points. However, it may produce fuzzy models with redundant information when there is a high degree of similarity between fuzzy sets that cover nearly identical areas within the input variable's domain. This increases the complexity of the model and complicates the linguistic interpretability of the system. To overcome this problem before moving on to the training stage, the strategy proposes to merge the most similar fuzzy sets by applying a similarity threshold on the membership functions. To compute the degree of overlap between the fuzzy sets X_i and X_j of an input variable, we use the Jaccard similarity measure based on the intersection and union operators (∩ and ∪ respectively) of the fuzzy sets as (7):

$$S(X_i, X_j) = \frac{|X_i \cap X_j|}{|X_i \cup X_j|} \tag{7}$$

where | | is the set cardinality. In the case of a discrete universe $U = \{x_t | \ t = 1, 2, \ \dots n\}$, formula (7) can be expressed using the membership functions as (8):

$$S(X_i, X_j) = \frac{\sum_{t=1}^{n}\left[\mu_{X_i}(x_t) \wedge \mu_{X_j}(x_t)\right]}{\sum_{t=1}^{n}\left[\mu_{X_i}(x_t) \vee \mu_{X_j}(x_t)\right]} \tag{8}$$

where ∧ and ∨ are the minimum and maximum operators respectively.

The fuzzy sets that present a similarity above a certain threshold are substituted with a new fuzzy set whose membership function parameters are the average of the membership function parameters of the initial fuzzy sets. Figure 4 depicts an example of overlapping between two Membership functions MF_1 and MF_2 associated respectively with two fuzzy sets X_1 and X_2. This overlapping results in a high degree of similarity between the fuzzy sets according to (8).

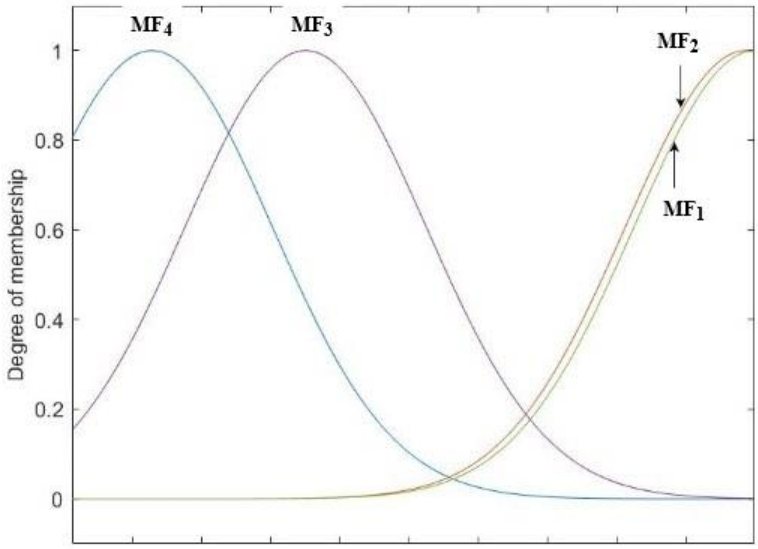

Figure 4. High overlapping between two membership functions MF_1 and MF_2

2.4. Fuzzy rule simplification

After applying the fuzzy set merging phase on an initial FIS, the peers of similar fuzzy sets are replaced in all the premise parts of the rules. In this way, we can obtain a rule base with redundancy in which there are rules with the same premise part. To simplify the base, redundant rules are replaced by a single rule that retains the same premise part. While the linear parameters of the consequent part are computed by averaging the linear parameters of the merged rules as indicated in (9):

$$V_r = \frac{1}{n}\sum_{i=1}^{n} V_i \tag{9}$$

where n is the number of redundant rules, V_i is a vector of the linear parameters of the i^{th} rule, and V_r is a vector of the linear parameters of the resulting rule. Figure 5 shows the flowchart of the proposed algorithm for the rule-base simplification. It comprises two phases: fuzzy set merging and redundant rule merging.

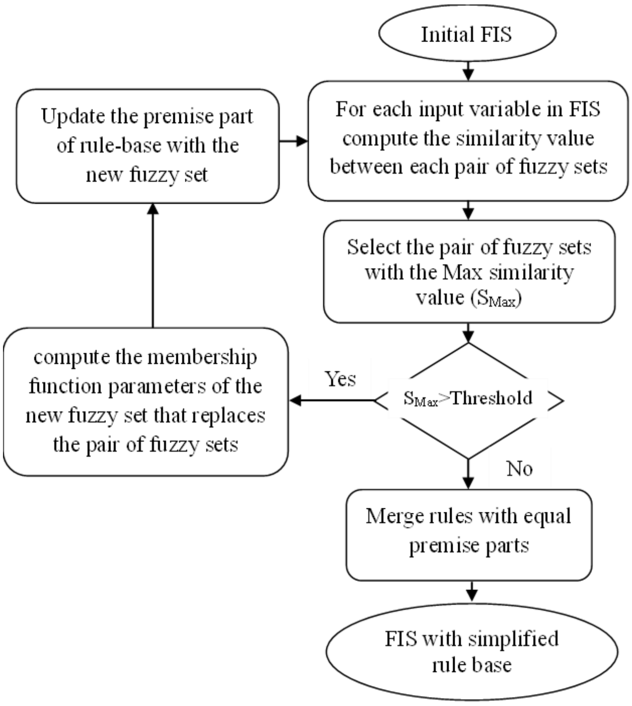

Figure 5. Flowchart of the proposed algorithm for the rule-base simplification

3. EXPERIMENTAL RESULTS AND DISCUSSION

This section presents an experimental study that illustrates the efficiency of the proposed strategy in optimizing an ANFIS-based controller for autonomous navigation. This controller is designed to ensure safe, smooth, and effective navigation in cluttered and previously unknown environments. For this, the section is divided into four subsections: experimental context, experimental study for the proposed strategy, simulation results, and discussion.

3.1. Experimental context

To implement an ANFIS-based controller for mobile robot navigation according to the strategy outlined in the previous section, we present the experimental context below. First, we describe the robot's specific characteristics. Next, we specify the implementation and simulation platform used to carry out all phases of this work. Lastly, we discuss the dataset generation technique, which enables the ANFIS controller to learn and adapt to complex navigation challenges.

3.1.1. Robot characteristics

A three-wheel differential-drive mobile robot is considered. It is equipped with a minimum of sensors which are positioned at 0°, 90°, and -90° to detect the FOD, ROD, and the LOD respectively. Another sensor is employed to determine the TA.

3.1.2. Implementation and simulation platform

In this work, we used the MATLAB R2021b platform to implement all phases of the proposed strategy. These include data generation, the creation of fuzzy inference systems, the simplification of the fuzzy rule base, and the training of the resulting ANFIS models. These capabilities make MATLAB an effective tool for optimizing and validating intelligent navigation systems.

3.1.3. Dataset generation

To collect the data pairs needed for the fuzzy rule-base modeling and training phase, we used our expertise-based guidance technique recently published in [29]. It consists in designing basic navigation scenarios in which paths are expertly planned to avoid obstacles and reach the target. A path-following algorithm is developed to enable the robot to collect data as it moves. In each state of the robot in the workspace, the ROD, FOD, LOD, and TA inputs are provided by the sensors, and the SA output is computed. Thus, we generated a dataset of 18,748 data pairs, of which 80% are for training and 20% for validation, to improve generalization and minimize overfitting. Figure 6 shows the distribution of the generated data points in a three-dimensional space (FOD, TA, SA). From this representation, we can distinguish three controller behaviors depending on the steering angle output: left deviation when the steering angle is greater than zero, right deviation when the steering angle is less than zero, and no deviation when the steering angle is equal to zero.

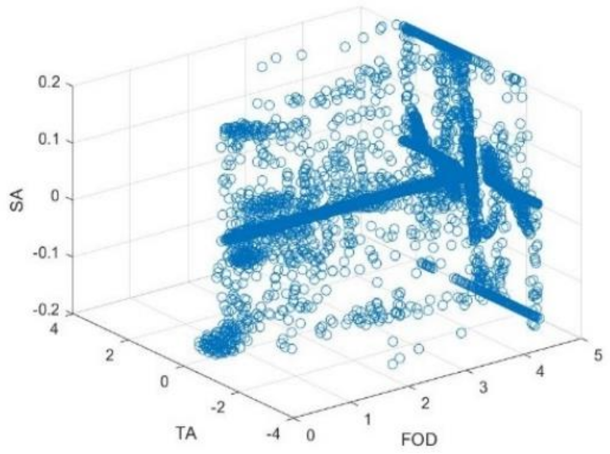

Figure 6. Distribution of the data points in a three-dimensional space (FOD, TA, SA)

3.2. Experimental study of the proposed strategy

As explained in the previous section, a strategy is proposed for optimizing a navigation controller based on a TS-FIS which will be trained by an ANFIS model. This strategy aims to balance the accuracy/complexity of the system. It consists in simplifying the fuzzy rule base using the following procedure: Modeling the fuzzy rule base using the subtractive clustering algorithm, merging fuzzy sets based on a similarity technique, and merging redundant fuzzy rules and training parameters using the ANFIS model.

3.2.1. Data-driven fuzzy rule base modeling

To generate an initial TS-FIS that corresponds to the distribution of data points, the subtractive clustering algorithm is applied to the dataset. the cluster radius value determines the number of clusters and subsequently affects the rule base size within the resulting system. In other words, specifying a small value for this parameter generally generates many small clusters, providing a TS-FIS with numerous fuzzy rules, and vice versa. According to the proposed strategy, the choice of this parameter must respect the accuracy/complexity trade-off after execution of the two phases: Simplification of the fuzzy rules and parameter learning using the ANFIS model. Table 3 shows the characteristics of the FISs obtained using the subtractive clustering algorithm with various radius values.

Table 3. Characteristics of the FISs obtained using the subtractive clustering algorithm with various radius values

	Number of rules	Number of fuzzy sets of variables (ROD, FOD, LOD, TA)
FIS (r=0.3)	9	(9, 9, 9, 9)
FIS (r=0.4)	7	(7, 7, 7, 7)
FIS (r=0.5)	6	(6, 6, 6, 6)
FIS (r=0.6)	5	(5, 5, 5, 5)

3.2.2. Rules base simplification

After generating FISs based on the data by applying the subtractive clustering algorithm with several cluster radius values, the rule base simplification phase is carried out. First, we applied the fuzzy set merging technique to the generated FISs. This step involves merging fuzzy sets whose membership functions have a high degree of overlapping for each input variable, based on a similarity threshold (ST). Several values of this parameter are used to balance the accuracy/complexity of the system. Next, we applied the rule merging technique to reduce the base when there are redundant rules, since the fuzzy set merging operation may produce a base with rules that have the same premise part. Table 4 details the experimental results obtained for each FIS depending on the cluster radius and similarity threshold.

3.2.3. ANFIS-based parameter training

In this step, we adjusted the parameters of all FISs resulting in previous steps using the ANFIS model to increase the accuracy. This architecture is based on hybrid learning. The gradient descent method is used to adjust the non-linear parameters, while the LSE method is used to tune the linear parameters. For this, we used the data pairs generated by the method explained previously. Indeed, we used 80% of the data for training and 20% for validation to improve generalization and avoid overfitting. Figures 7 and 8 show respectively the curves of the training RMSE and the validation RMSE in 3,000 epochs for the case of the FIS with $r = 0.5$ and $ST = 0.85$.

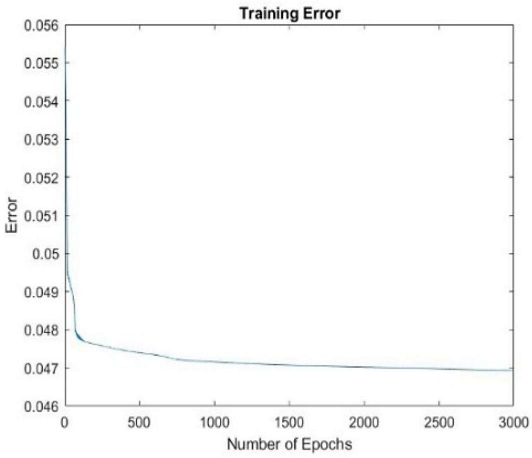

Figure 7. Training RMSE curve in 3000 epochs for the case of the FIS with $r = 0.5$ and $ST = 0.85$

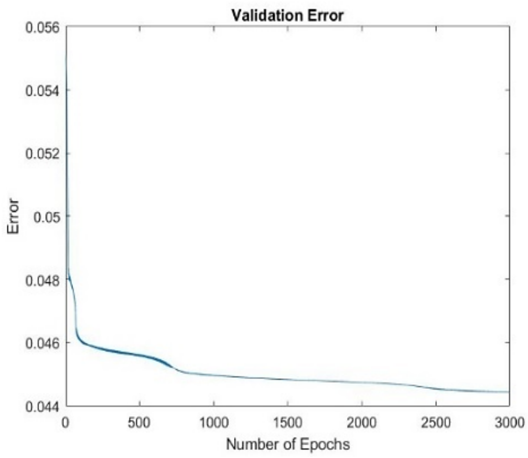

Figure 8. Validation RMSE curve in 3000 epochs for the case of the FIS with $r = 0.5$ and $ST = 0.85$

To evaluate the resulting FISs, we took into consideration the accuracy/complexity trade-off. The complexity depends on the number of fuzzy rules and the number of fuzzy sets. Whereas, the accuracy of the system can be determined based on the RMSE evaluation metric. Table 4 details the experimental results obtained for each FIS after the full execution of the strategy depending on the cluster radius and similarity threshold. According to this table, the controller based on the FIS designed with the parameters ($r = 0.5$ and $ST = 0.85$) provides an acceptable number of fuzzy sets of (3, 2, 3, 3) representing the input variables (ROD, FOD, LOD, TA) respectively, and a minimum value of 0.0442 for RMSE. Hence, it is the controller that best respects the accuracy/complexity trade-off. To demonstrate its efficiency in reactive navigation, an evaluation through simulations is carried out. It consists in testing the quality of navigation by considering three criteria: target reaching, obstacle avoidance, and path smoothness.

Table 4. Experimental results obtained for each FIS after the execution of the proposed strategy depending on the cluster radius (r) and similarity threshold (ST)

	Similarity threshold (ST)	Number of fuzzy sets per variable after fuzzy set merging	Number of rules after rule base simplification	Number of parameters	RMSE after training
FIS (r =0.3)	0.75	3, 2, 3, 3	8	62	0.0459
	0.80	4, 2, 4, 3	8	66	0.0457
	0.85	4, 2, 4, 3	8	66	0.0457
FIS (r =0.4)	0.75	3, 2, 3, 3	6	52	0.0456
	0.80	3, 2, 3, 3	6	52	0.0456
	0.85	3, 3, 3, 3	6	54	0.0454
FIS (r =0.5)	0.75	3, 2, 2, 3	5	47	0.0444
	0.80	3, 2, 2, 3	5	47	0.0444
	0.85	3, 2, 3, 3	5	47	0.0442
FIS (r =0.6)	0.75	2, 2, 2, 2	4	36	0.0463
	0.80	2, 3, 2, 3	4	40	0.0479
	0.85	2, 3, 2, 3	4	40	0.0479

3.3. Simulation result

In mobile robotics, experimentation remains the key to evaluating the efficiency of a controller. For this reason, using the robot configuration provided previously and the proposed controller based on the FIS ($r = 0.5$ and $ST = 0.85$), we have carried out simulation experiments in several environments designed with different degrees of clutter. The simulation scenario in Figure 9 is performed to explain the robot's behavior according to the controller's prediction. Based on the path followed by the robot in this simulation experiment, we can conclude that the robot respected the three types of reactive navigation behaviors: target-seeking, obstacle-avoidance, and wall-following. The representative curve in Figure 10 illustrates the variation of the steering angle depending on navigation time in this simulation.

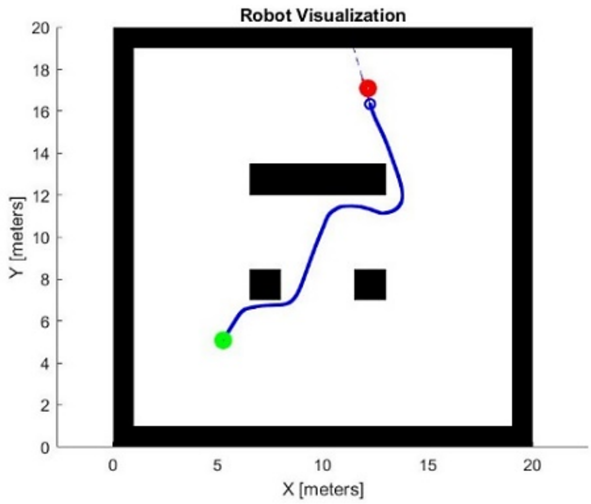

Figure 9. Simulation experiment to illustrate the robot's behaviors: target-seeking, obstacle-avoidance, and wall-following

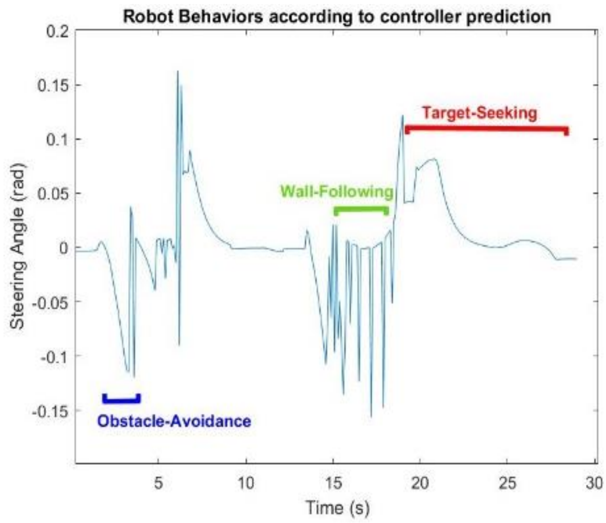

Figure 10. Variation of the steering angle (system output) according to the robot's behaviors

The simulation scenarios shown in Figure 11 are performed in a previously unknown environment with a high degree of clutter to demonstrate the efficiency of the proposed controller. Each scenario is characterized by a target position and a robot starting point. According to these simulation experiments, the controller ensured the three criteria of autonomous navigation quality which are robot safety by avoiding obstacles, smoothness by planning a near-optimal path without zigzags, and effectiveness by reaching the target. To compare the proposed controller with other state-of-the-art controllers, we designed a benchmark environment with the same configuration as in the papers [11], [14], [23]. Figure 12 shows the paths planned by the proposed controller and the state-of-the-art ANFIS-based controllers in this environment. The ANFIS-based controller in [23] planned a collision-free path with three segments (dotted green path), which increased the path length. The hybrid-ANFIS-based controller in [11] planned a collision-free path that unnecessarily moved away from the right obstacle (dashed yellow path), which slightly increased the path length. The GPS-ANFIS-based controller in [14] planned a collision-free path with zigzags (red path with circles), which delayed reaching the destination. In contrast, the proposed controller planned an almost straight collision-free path without zigzags (continuous blue path), which ensured optimality and smoothness. This result is due to the accuracy of the proposed controller, which establishes a balance between the two constraints: obstacle-avoidance and target-seeking.

3.4. Discussion

In this article, we have proposed a strategy to model an ANFIS-based controller for reactive mobile robot navigation. It aims to balance the accuracy/complexity of the system to ensure safe, smooth, and effective navigation. First, we used the subtractive clustering algorithm to model many FISs that reflect the distribution of data points using several cluster radius values. Next, we merged the fuzzy sets of input variables using several similarity thresholds. We then merged the redundant rules of each FIS. Finally, we used the ANFIS model to train the FIS parameters. To satisfy the accuracy/complexity trade-off, we kept the most accurate and least complex FIS. That is, the FIS with the lowest test RMSE value and a reduced rule base (few rules and few fuzzy sets). This approach resulted in a fuzzy controller with satisfactory accuracy since simulation experiments confirmed the navigation quality in cluttered environments in Figure 11 and superiority over state-of-the-art methods when comparing planned paths in Figure 12. In addition, this controller is based on a less complex fuzzy system of 22 premise parameters and 25 consequent parameters, since the resulting architecture comprises just 5 fuzzy rules and (3, 2, 3, 3) fuzzy sets associated respectively with the input variables (ROD, FOD, LOD, TA). Table 5 shows the superiority of the proposed controller over the state-of-the-art ANFIS-based controllers in terms of model complexity. As a result, the fuzzy controller obtained by following the proposed strategy responded well to the accuracy/complexity problem. This will contribute enormously to the improvement of reactive navigation, which is demanded in real-time applications requiring high precision and very short execution time.

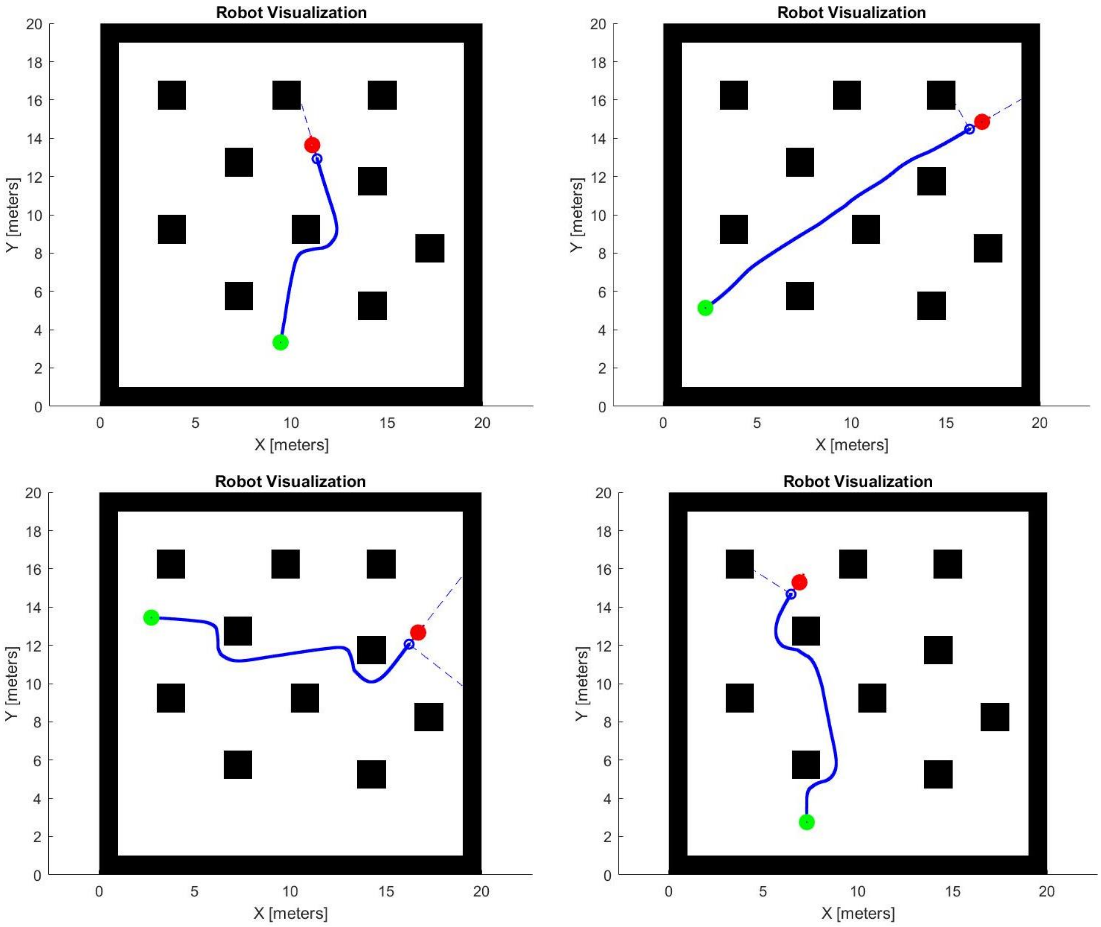

Figure 11. Simulation scenarios of navigation in a previously unknown environment

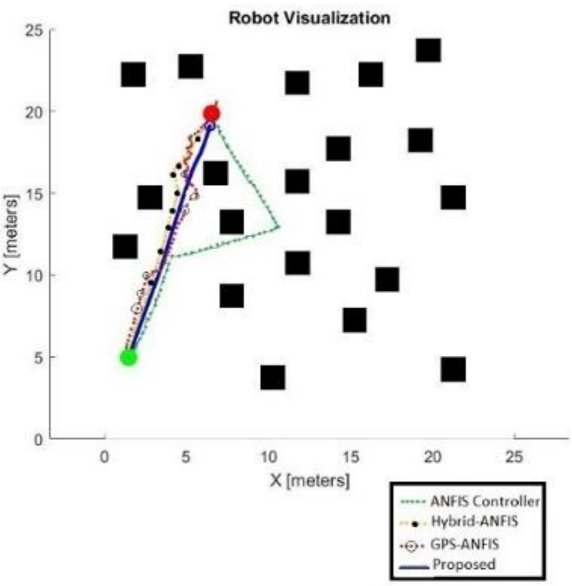

Figure 12. Comparison of the proposed controller with the state-of-the-art ANFIS-based controllers in terms of path planification

Table 5. Comparison of the proposed controller with the state-of-the-art ANFIS-based controllers in terms of model complexity

Navigation controller	Fuzzy set configuration	rules	Premise parameter	Consequent parameter	Total parameters
GPS-ANFIS [14]	3, 3, 3	27	27	108	135
Hybrid-ANFIS [11]	3, 3, 3	27	27	108	135
CS-ANFIS [22]	3, 3, 3, 3	81	36	405	441
IWO-ANFIS [20]	3, 3, 3, 3, 3, 3	729	54	5103	5157
Conventional ANFIS [23]	3, 3, 3, 3	81	36	405	441
Proposed method	3, 2, 3, 3	5	22	25	47

4. CONCLUSION

In this paper, we have proposed a strategy for modeling an ANFIS-based controller for mobile robot navigation from data generation to the model training phase. To address the accuracy/complexity trade-off, this approach combines a suite of methods, namely, data-driven modeling using a subtractive clustering algorithm, fuzzy set merging using similarity thresholds on the corresponding membership functions, redundant rule merging, and parameter training using the ANFIS architecture. The controller obtained using this strategy has demonstrated its performance in terms of accuracy and complexity through simulation experiments and comparison with state-of-the-art methods. However, the proposed controller is unable to plan collision-free paths in special environments such as U-shaped obstacles. We will therefore address this issue in future work by combining other methods. We will also adapt the proposed controller to a multi-robot system in environments where obstacles and targets are dynamic.

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