2022 International Conference on Innovations and Development of Information Technologies and Robotics (IDITR) | 978-1-6654-0932-2/22/$31.00 ©2022 IEEE | DOI: 10.1109/IDITR54676.2022.9796495

Autonomous Mobile Robot Navigation using Adaptive Neuro Fuzzy Inference System

1st Muhammad Husnain Haider
[a]University of Electronic Science and Technology of China, Chengdu, China
[b]Yangtze Delta Region Institute, Huzhou, China
mhusnainhaider@outlook.com

2nd Hub Ali
State Key Laboratory for Management & Control of Complex Systems, CASIA
Beijing, China
hub@ia.ac.cn

3rd Abdullah Aman Khan
Sichuan Artificial Intelligence Research Institute,
Yibin, China
abdkhan@hotmail.com

4th Hao Zheng
University of Electronic Science and Technology of China, Chengdu, China
201821040136@std.uestc.edu.cn

5th M. Usman Maqbool Bhutta
Robotics Lab, MAE, The Chinese University of Hong Kong, Hong Kong
usmanmaqbool@outlook.com

6th Shaban Usman
University of Electronic Science and Technology of China, Chengdu, China
shabanusman@yahoo.com

7th Pengpeng Zhi
[a]Yangtze Delta Region Institute, Huzhou, China
[b]University of Electronic Science and Technology of China
zhipeng17@yeah.net

8th Zhonglai Wang*
[a]University of Electronic Science and Technology of China, Chengdu, China
[b]Yangtze Delta Region Institute, Huzhou, China
wzhonglai@uestc.edu.cn

***Abstract*—Navigation of autonomous robots in unknown and cluttered environments lies among the marked trends in robotics. Unlike animals and humans, the collision-free movement of a robot is challenging and requires processing complex information. An autonomous robot needs to cope with a large amount of uncertainty while navigating. The previous methods have limitations, such as lacking obstacle avoidance behaviour, having a large number of governing rules, designing a separate controller for each navigation and obstacle avoidance, not considering the robot's dynamics, computationally expensive training, and poor performance in a cluttered environment. This paper proposes a method that comprises a single adaptive neuro fuzzy inference system (ANFIS) based controller with 16 rules compared to hundred of rules used by previous methods to address such problems. Our method takes heading angle along with distance sensors data as input. All the inputs are fuzzified into linguistic variables such as near-far and left-right. Additionally, a fuzzy inference system (FIS) is designed and trained using the generated dataset for optimum performance of ANFIS. The proposed method efficiently provides collision-free navigation of the mobile robot in densely cluttered environments. Comprehensive experiments are performed to prove the robustness and potency of the proposed ANFIS controller. Moreover, the performance of the proposed method is compared with various previous methods. The results of these comparisons indicate our proposed method's superiority in finding a near-optimal path.**

***Index Terms*—ANFIS, obstacle avoidance, autonomous navigation, mobile robot, CoppeliaSim**

I. Introduction

Over the past decades, autonomous robots have played an essential role in agriculture, industrial applications, space exploration and road inspection, etc., [1–4] . Other than these, there is a vast application domain for autonomous robots, especially in some situations and environments that are harmful to human existence. For example, such robots played a vital role in minimizing the effect of the Fukushima nuclear power plant during the meltdown [5]. An autonomous robot must be able to analyze its surroundings, avoid collisions by detecting obstacles, and be able to plan the optimal trajectory path on its own while keeping in view the safety of the robot and its surroundings.

Global navigation algorithms exploit prior knowledge of the obstacles and environment, such as the location and sizes of the obstacles and the moving trajectory of the obstacles. Navigation algorithms must compute an optimal and collision-free path to reach a target destination [6]. Conventional global navigation systems are primarily based on potential field, visibility graphs, Voronoi graphs, and Dijkstra algorithm, etc. [7]. Local and global navigation algorithms can be realized using deterministic approaches such as neural networks, fuzzy, and neuro-fuzzy. Non-deterministic approaches such as genetic algorithm and particle swarm optimization [8] can also contribute to realizing such algorithms.

Neuro-fuzzy-based methods have been widely used for mobile robot navigation. Neuro-fuzzy algorithms are deterministic and intelligent enough to model reasoning and uncertainty of autonomous navigation of robots in unknown environments [9]. An autonomous mobile robot navigation model can be defined as a set of rules or behavior of a fuzzy system. For example, the obstacle avoidance and navigation strategy in [10] is defined using a set of 48 fuzzy rules. Similarly, a fuzzy controller [11] with consequences optimized using a gradient-based method is utilized to navigate a robot in a collision-free manner. Moreover, the study in [12] suggests a controller based on a fuzzy system that seeks a target, avoids obstacles and resolves potential deadlocks.

ANFIS is a neuro-fuzzy-based controller that has shown potential in the navigation of mobile robots in unknown environments [13]. ANFIS combines the learning from experience and knowledge representation ability of the fuzzy system altogether [14]. ANFIS based study in [15] solved the path collision-free navigation problem for a nonholonomic wheeled robot. This study utilized gradient descent to optimize the ANFIS membership function parameters. Another technique that utilizes multiple ANFIS for tackling dynamic and static obstacles was proposed in [16]. A method that utilizes two ANFIS controllers for regulating left and right velocities and two ANFIS controllers for optimizing the heading adjustment was presented in [17].

Comparatively, real-time navigation is more challenging for robots as compared to humans. Despite the efforts, there are still some flaws and compromises associated with the previously proposed methods. Moreover, optimal and collision-free autonomous navigation of robots is still a big challenge. The previous methods' limitations include large numbers of rules for simple navigation tasks, additional controllers for obstacle avoidance behaviour, less adaptability to new environments, low performance in clutter environments and so on. It must be noticed that neural networks alone cannot represent knowledge and fuzzy systems are incapable of learning. A robust method based on sensor data is proposed to overcome such problems for the path planning of a mobile robot.

In this paper, we propose a method that overcomes all the mentioned shortcomings. The proposed method is easy to train as it only uses 16 rules (as compared to hundreds of rules) while optimally and efficiently reaching the target. All the experiments are carried out using MATLAB, while the visualization of the robot is conducted using CoppeliaSim, also known as V-REP. The contributions of this paper can be summarized as follows:

- This paper proposes a method to optimally plan a trajectory while avoiding all the obstacles. Moreover, the proposed method is computationally less expensive as it introduces 16 rules compared to hundreds of rules proposed by previous methods.
- A single ANFIS controller is proposed to simultaneously ply the mobile robot's obstacle avoidance and target navigation.
- We conducted comprehensive experiments in order to validate the supremacy of the proposed method. The results of the experiments support the performance claims.

II. Proposed method

The proposed ANFIS controller for the robot's autonomous navigation is discussed in depth in this section. A single controller is designed to handle the obstacle avoidance and navigate it to the target with minimal input fuzzy linguistic variables. The obstacle avoidance behavior has priority over the target navigation behavior. The mobile robot only follows the target direction when no obstacle exists within the robot's proximity. For the target navigation behavior, it is assumed that the desired heading h, i.e., the difference between the robots' current heading and target heading, is provided throughout the navigation process. At the same time, the obstacle location and environment are unknown to the robot. It contradicts the conventional design presented in various methods. Previously designed methods utilize multiple ANFIS controllers to handle these tasks separately. Additionally, there is a need to design a switching block for the robot steering governance, i.e., which ANFIS controller output will be selected, and under which circumstance (as all of them are giving an output of the same nature).

The overview of the proposed ANFIS based navigation method is presented in Fig. 1. In Fig. 1, it can be seen that the proposed ANFIS based method receives four sensor data from the robot. Further, this data is processed to approximate the turning angle.

A. Target navigation behaviour

Target navigation behavior only executes when the robot is free of obstacles, i.e., all the distance sensors read off a far signal. The main element for target navigation behavior is the heading angle h. The heading angle h is comprised of two gaussian bells (gbell) membership functions, namely left and right, ranging from -45 to 45 degrees as shown in Fig. 2. If the target does not lie in this range, the robot will turn 45 degrees to the right and seek again for the target; if the target is found, it will continue to move toward the target. Otherwise, it will repeat the 45-degree turn unless it finds the target in its range.

There is no need to feed heading angle h if both the destination points and the mobile robot are regarded to be point entities. The robot can be programmed to move straight towards the goal in such a case. Whereas the robot usually needs to address the two-dimensional scenarios which require a heading angle. However, the ultimate goal of this paper is to solve the path planning problem for a two-dimensional body rather than only point entities.

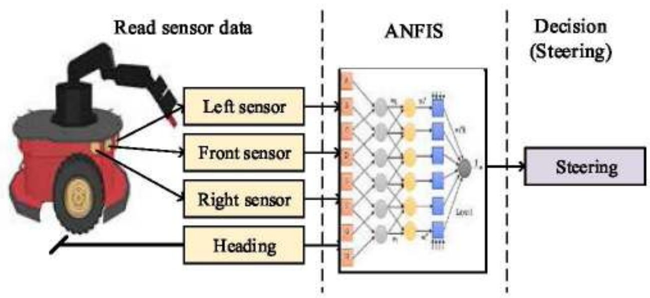

Fig. 1: Overview of the proposed ANFIS based autonomous navigation method.The mobile robot takes the heading angle along with distance sensors readings. ANFIS processes this information to find the suitable steering angle to achieve the target while averting obstructions under the current scenario.

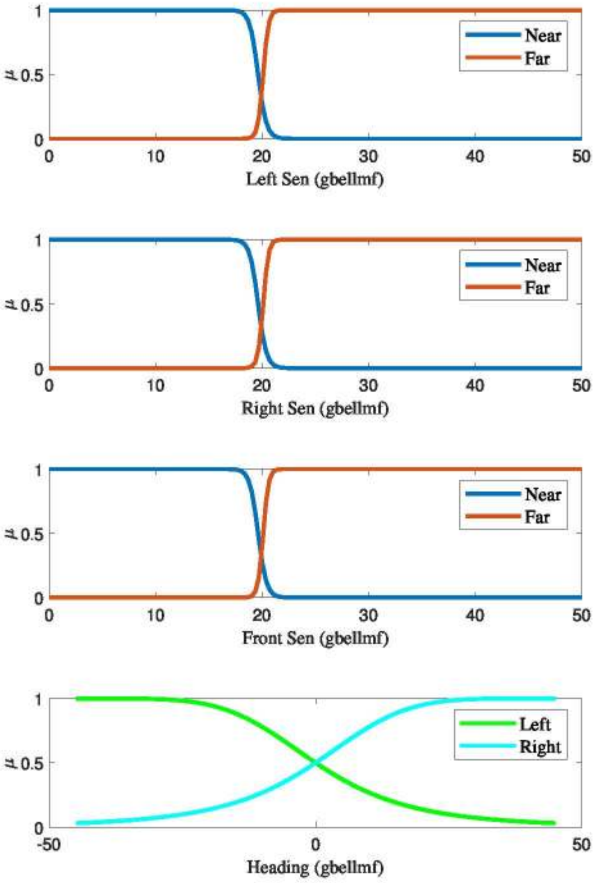

Fig. 2: Left, front, and right sensor data before training. The blue and red curves represent the membership functions of near and far linguistic variables, whereas aqua blue and green curves indicate left and right heading directions, respectively.

B. Obstacle avoidance behaviour

While keeping safety in view, collision avoidance is the principal aim of the robot. The ANFIS controller steers the robot away whenever there lies an obstacle nearby. ANFIS takes input data from three sensors: left, front, and right. Each input is further divided into two fuzzy linguistic variables near and far. The mobile robot takes the decision using an ANFIS controller as soon as it reads "near" to avoid the collision. Sensors' fuzzy membership functions (before training) are presented in Fig. 2.

C. ANFIS controller design

This section discusses ANFIS design in detail for target navigation and obstacle avoidance. Jang [18] proposed an ANFIS technique, which combines the neural network and fuzzy logic theory. It maps the relationship of fuzzy logic and neural network between input and output of the feed-forward network. The main idea of this method does not require to set parameters manually. The deep learning model automatically tunes the parameters, as shown in Fig. 3.

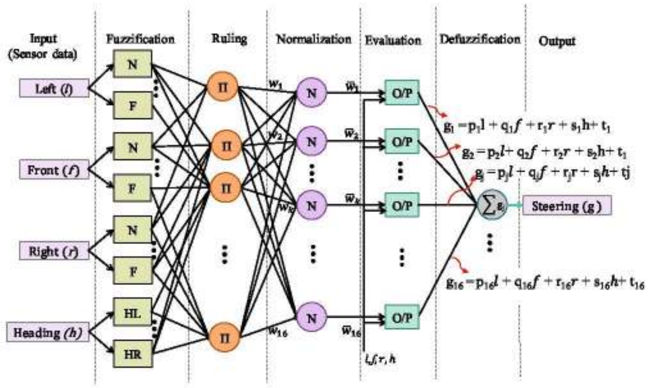

Fig. 3: The working mechanism of the proposed ANFIS model. Here, N, F, HL, and HR represent near, far, left heading, and right heading, respectively, while p, q, r, s, t stand for consequent parameters.

The architecture of ANFIS in Fig. 3 is divided into five layers. We take four inputs l, f, r, and h. The output is steering angle 'g'. There are two types of nodes in the ANFIS architecture, i.e., adaptive and fixed nodes.

1) Adaptive nodes: represented by squares in Fig. 3 and have adjustable parameters.
2) Fixed nodes: shown by circles and have fixed parameters.

The ANFIS controller is designed using first-order Sugeno fuzzy inference IF-THEN rules:

Rule 1: **If** l is L_n & f is F_n & r is R_n & h is H_l, **then** $g_1 = p_1 l + q_1 f + r_1 r + s_1 h + t_1$,

Rule 2: **If** l is L_n & f is F_n & r is R_n & h is H_r, **then** $g_2 = p_2 l + q_2 f + r_2 r + s_2 h + t_2$,

Rule j: **If** l is L_j AND f is F_j AND r is R_j AND h is H_j, **then** $g_j = p_j l + q_j f + r_j r + s_j h + t_j$,

where L_j, F_j R_j, and H_j are the fuzzy sets and j is the index $j = 1, 2, 3, ...n$ of fuzzy rules, g is the output of these rules and n represents total number of rules. We have 4 inputs each having two membership functions, 16 rules are defined to efficaciously handle the ANFIS steering angle 'g'. Likewise, p_j, q_j, r_j s_j and t_j are adaptive parameters during the training process. The fuzzification layer is the initial layer, and all of the nodes in this layer are adaptive nodes. The fuzzy membership grades of inputs are represented by the outputs $\varnothing_j^1$, which can be expressed as:

$$\varnothing_j^1 = \mu_{L_i}(l), \forall i \in \{1, 2\} \tag{1}$$

$$\varnothing_j^1 = \mu_{F_{i-2}}(f), \forall i \in \{3, 4\} \tag{2}$$

$$\varnothing_j^1 = \mu_{R_{i-4}}(r), \forall i \in \{5, 6\} \tag{3}$$

$$\varnothing_j^1 = \mu_{H_{i-6}}(h), \forall i \in \{7, 8\} \tag{4}$$

Where j represents the index node of the current layer. Additionally, μ_{L_j}, μ_{F_j}, μ_{R_j}, and μ_{H_j} are membership functions to represent the degree of belongingness of each corresponding sensor data:

$$\mu_{Li}(\mathrm{l}) = \frac{1}{1+\left(\frac{\mathrm{l}-a_i}{c_i}\right)^{2b_i}}, \forall i \in \{1,2\} \tag{5}$$

$$\mu_{Fi-2}(\mathrm{f}) = \frac{1}{1+\left(\frac{\mathrm{l}-a_i}{c_i}\right)^{2b_i}}, \forall i \in \{3,4\} \tag{6}$$

$$\mu_{Ri-4}(\mathrm{r}) = \frac{1}{1+\left(\frac{\mathrm{l}-a_i}{c_i}\right)^{2b_i}}, \forall i \in \{5,6\} \tag{7}$$

$$\mu_{Hi-6}(\mathrm{h}) = \frac{1}{1+\left(\frac{\mathrm{l}-a_i}{c_i}\right)^{2b_i}}, \forall i \in \{7,8\} \tag{8}$$

Where a_i, b_i, and c_i are the premise parameters of the gaussian bell (gbell) membership functions. In this layer, we find the premise parameters.

A circular node label represents AND operator, which is used to fuzzify the input signals in the second layer. The nodes in this layer are all fixed, and each node computes the rules' strength (i.e., firing strength). w_j output is the sum of the signals it receives:

$$\O_j^2 = w_j = \mu_{L_i}(l)\mu_{F_{i-2}}(f)\mu_{R_{i-4}}(r)\mu_{H_{i-6}}(h) \tag{9}$$

The main purpose of the third layer is to compute the normalization of the filtering strength. The output of this layer is $\bar{w}_j$. The normalization equation is given as follows:

$$\O_j^3 = \bar{w}_j = \frac{w_j}{\sum_{16}^{j=1} w_j} \tag{10}$$

The fourth layer adjusts the weights using the polynomials input and the output is the product of the normalized firing strength given as:

$$\O_j^4 = \bar{w}_j g_j = \bar{w}_j\left(p_j l + q_j f + r_j r + s_j h + t_j\right) \tag{11}$$

Nodes in the last layer sum up all of the incoming signals. This node's output is depicted by:

$$\O_j^5 = g = \sum_{j=1}^{16} \bar{w}_j g_j \tag{12}$$

The hybrid-learning approach for ANFIS is a blend of gradient descent and least-squares methods. The hybrid learning algorithm utilizes a forward pass and a backward pass approach for each epoch. Premise parameters (i.e., a_i, b_i, and c_i in the second layer) are held constant in the forward pass, while subsequent parameters (i.e., p_j, q_j, r_j s_j and t_j in the fourth layer) are computed using the least-squares approach. The gradient descent approach updates premise parameters in a backward pass while the subsequent values are determined in the prior step (held constant). In comparison to the gradient descent approach, the hybrid learning algorithm provides faster convergence and eliminates the problem of local minima. Further details can be found in [19].

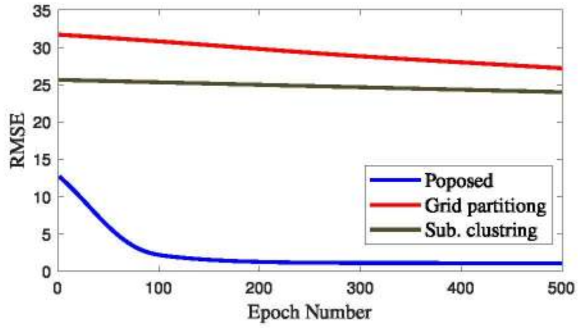

Fig. 4: RMSE of proposed ANFIS controller, sub. clustering, and grid partition over the same generated data set.

III. Training, Testing, and Simulation Settings

This section provides details regarding the experiments, training, testing, and other related settings.

A. Data Set

The initial step in developing an ANFIS utilizing a fuzzy inference system is to supply a suitable dataset of input-output parameters. It is necessary to have information about the robot's target location and sensors data to measure heading and distances to design a path planning algorithm. The robot's left, right, and front sensors are used in simulations to measure the distance between the robot and obstacles. However, these prerequisites enable the fuzzy logic system to have a data set that must be created to emulate the most frequently faced obstacles scenario in the real world. A dataset with an ample amount of samples representing these scenarios is generated inspired from [14].

B. Training and testing

The ANFIS model is built and trained using MATLAB as the development tool in this work. An ANFIS model is trained using the Fuzzy logic Matlab toolbox, with training settings such as membership function, epoch numbers, and training methods all are customizable. After loading the training data into the MATLAB *workspace*, the *genfis* function creates the primary ANFIS network. This function provides membership functions that uniformly contain all discourse of the universe for every input. Training occurs when the basic ANFIS model is generated. The ANFIS program in MATLAB takes input/output data and builds an ANFIS architecture that matches inputs to desired outputs. It feeds a deep neural network with input variables tuned to decrease training mistakes. The training errors are computed using the root mean square error (RMSE) function, which is written as:

$$RMSE = \sqrt{\frac{1}{Samples}\sum_{j=1}^{Samples}\left(ANFIS_j - Actual_j\right)^2} \tag{13}$$

Where $Samples$ represents the size of training data and $ANFIS_j$ shows the output of the current ANFIS model, and

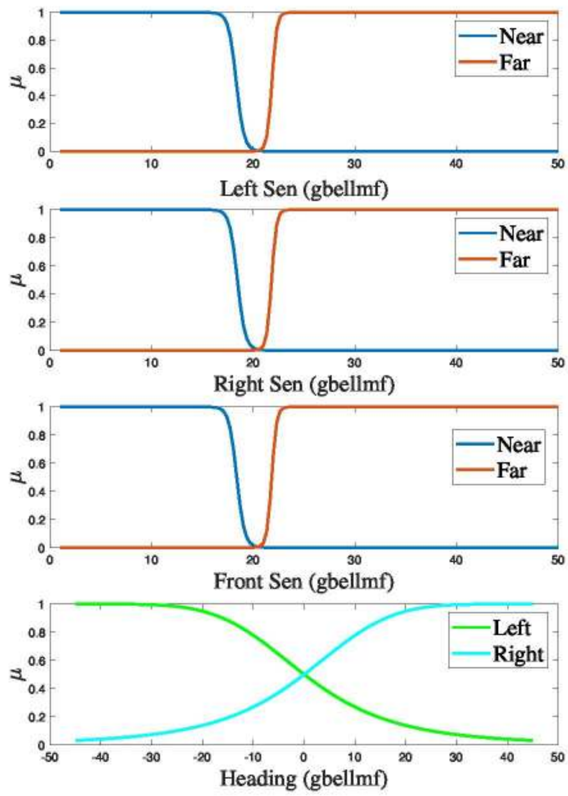

Fig. 5: Left, front, and right sensor data after training. Clour scheme is same as mentioned in Fig. 2

$Actual_j$ is defined as the actual output from the training data. Fig. 4 shows the RMSE of the proposed ANFIS controller, sub. clustering, and grid partition. The change in the membership functions of the left sensor, right sensor, front sensor, and heading angle after training the ANFIS controller using generated data is presented in Fig. 5. Moreover, Fig 6 provides the visual comparison among the 2500 testing data samples and ANFIS controller outputs for the steering angle. The average testing error is around 1 degree in the ANFIS after 500 epochs. The average testing error can be further reduced if data is trained for a larger number of epochs. However, further training does not play any significant role in the obstacle avoidance task, so we consider the model is ideally trained.

C. Experiment settings and environment

The performance of the proposed method is analyzed using MATLAB 2021a and CoppeliaSim Edu 4.2.0. A three-wheeled mobile robot 'Pioneer 3dx' with two front wheels having independent motor control and a roller wheel at the rear is used to perform simulations. All the training and testing of FIS are executed in MATLAB. An API connection is necessary for both platforms to communicate while performing simulations. MATLAB is responsible for mobile control, while obstacles prone environment is designed in CoppeliaSim. Mobile robot speed is considered constant during the experiments. All the obstacles are shown in black color, and the target position is

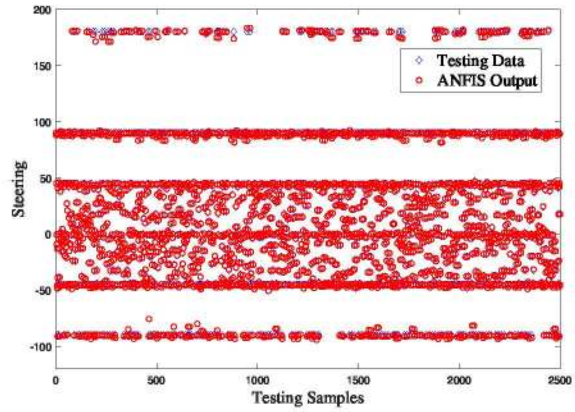

Fig. 6: ANFIS steering output and the testing sample results show coherence in nature. The blue diamond represents the samples for the testing data, and red circles indicate the corresponding ANFIS output (Zoom in for a better view).

defined as a small red square on the floor. The path followed by the robot is shown with a magenta curve.

IV. Results and Discussions

Fig. 7 depicts robots path in various cluttered obstacle prone environments. Fig. 7-(a) and Fig. 7-(d) shows that robot successfully avoids all the obstacles coming in its way and achieves the goal position in an optimal way. Fig. 7-(a) and Fig. 7-(d) represents top view and 3D view respectively. Similarly, to test the repeatability in performance and autonomous navigation behavior without collision the robot is tested in another cluttered environment Fig. 7-(b) the top view of the same environment is presented in Fig. 7-(e). It can be seen from Fig. 7-(c) that the mobile robot follows an ideal path from starting position to the final position with a safe margin from the obstacle. The top view of the Fig. 7-(c) is presented vertically below in Fig. 7-(f). The results of simulation studies show that the proposed ANFIS controller effectively guides the mobile robot to navigate toward the target without any collision while following an ideal path.

Several cluttered environments with obstacles are designed and used to test the supremacy of the proposed ANFIS controller over other various controllers. Fig. 8-(a) illustrates a comparison between proposed ANFIS controller and fuzzy logic based controller [20]. A single fuzzy logic-based controller [20] is designed to navigate the robot from an initial position to the target. However, there exist challenges as two controller designs have been presented. Firstly, a fuzzy navigational controller is designed with 35 rules, but it can only perform the target navigation task. Secondly, an improved controller design with 62 rules is also discussed. Nevertheless, it can only navigate in very simple environments with a few obstacles, as presented in Fig. 8-(a). It is worth noting that increasing the number of rules adds up more parameters to be evaluated and optimized that drastically heightens the

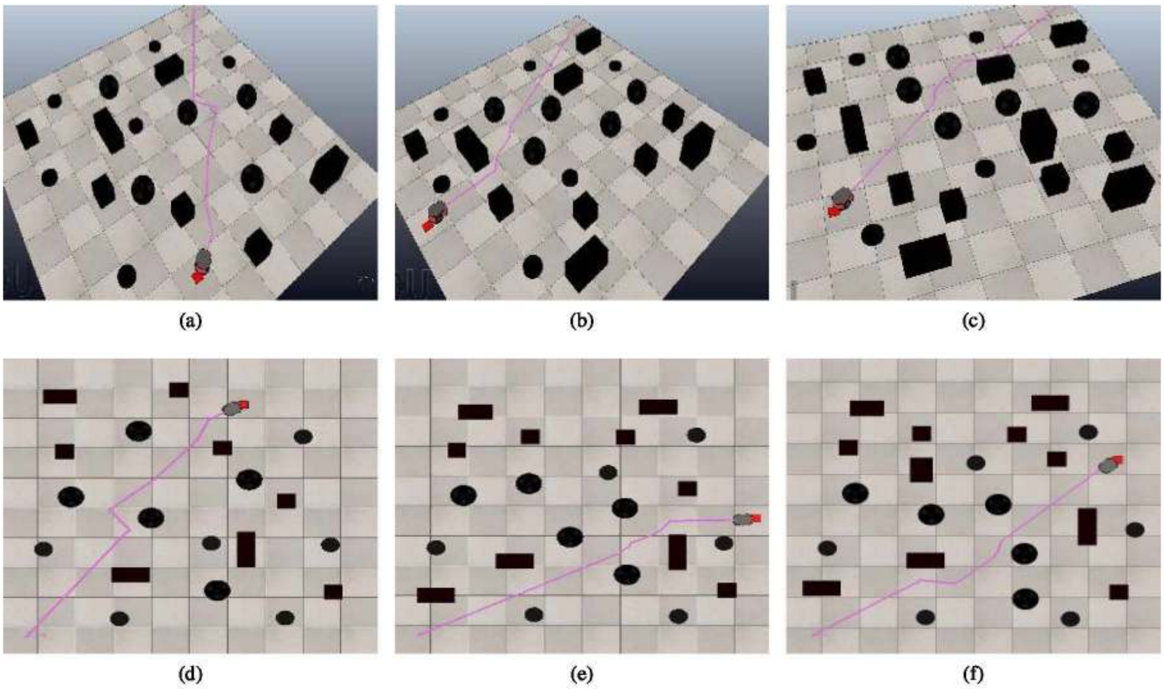

Fig. 7: 3D and 2D (top-view) of some selected simulation results. The top row i.e., (a)-(c) represents the cluttered environment in 3D view whereas the bottom row i.e., (d)-(f) represents the top views of the cluttered environment. From the images, it can be observed that the robot safely and successfully reaches the final destination even in cluttered environments.

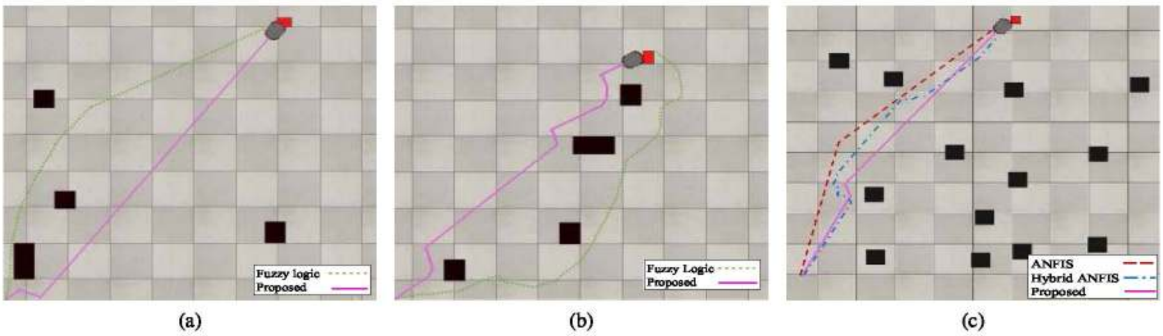

Fig. 8: Comparison of the proposed method with various methods. Subfigures (a) and (b) present a comparison with a fuzzy logic-based controller [20] over two different cluttered environments. Subfigure (c) presents a comparison of the proposed controller with the hybrid ANFIS [14] and ANFIS controller [21], respectively. It can be seen that the proposed method has outperformed all other methods.

complexity of the controller. Fig. 8-(b) represents another environment of the fuzzy navigational controller which is comparatively difficult than Fig. 8-(a) as there are multiple obstacles in the sight of the target. In both scenarios, fuzzy logic navigational controller [20] produce a very long path. The proposed ANFIS controller is designed with 16 rules that follow the optimal path to reach the target, keeping it in view that the obstacles and map are unknown to the robot. Comparison among hybrid ANFIS [14], ANFIS controller [21] and proposed method is shown in Fig.8-(c). From Fig. 8-(c), it is evident that the proposed controller moves straight with fewer turns, hence providing an optimal path comparatively.

In diverse environments, where the task of motion planning is particularly arduous by the presence of a variety of various shaped and sized barriers, the ANFIS controller guides the robot through a variety of obstacles, allowing it to determine efficient paths to the target. By navigating under unknown surroundings, achieving efficient performance in cluttered, complex environments, and generating near-optimal solutions, the ANFIS controller tackles the inadequacies of the proposed previous methods. To prove the efficacy various simulations studies have been presented in Fig. 7 and Fig. 8. The predominance of the proposed ANFIS controller is observed through the simulations results.

V. Conclusion

This paper proposes a single ANFIS controller for autonomous navigation in densely cluttered environments. The proposed strategy relies on a single controller (contrary to multiple controllers and hundreds of rules) for target navigation and obstacle avoidance behaviours. The proposed ANFIS takes heading angle information along with distance sensors data to evaluate the steering. ANFIS steering output purely relies on the faced scenarios. Training and testing of the ANFIS controller show it works efficiently to handle target navigation and obstacle avoidance behaviour concurrently. Finally, simulations studies verify the training and testing results in various densely saturated obstacle prone environments using CoppeliaSim. Notably, simulation results show that the proposed ANFIS controller outmatches various state of the art approaches. This work will be enhanced to avoid concave obstacles in future research work.

References

[1] F. Wang, C. Li, S. Niu, P. Wang, H. Wu, and B. Li, "Design and analysis of a spherical robot with rolling and jumping modes for deep space exploration," *Machines*, vol. 10, no. 2, p. 126, 2022.

[2] L. Chen, J. Cao, K. Wu, and Z. Zhang, "Application of generalized frequency response functions and improved convolutional neural network to fault diagnosis of heavy-duty industrial robot," *Robotics and Computer-Integrated Manufacturing*, vol. 73, p. 102228, 2022.

[3] M. Moraitis, K. Vaiopoulos, and A. T. Balafoutis, "Design and implementation of an urban farming robot," *Micromachines*, vol. 13, no. 2, p. 250, 2022.

[4] R. Wu, J. Fan, L. Guo, L. Qiao, M. U. M. Bhutta, B. Hosking, S. Vityazev, and R. Fan, "Scale-adaptive pothole detection and tracking from 3-d road point clouds," in *2021 IEEE International Conference on Imaging Systems and Techniques (IST)*, 2021, pp. 1–5.

[5] C. Rhodes, C. Liu, and W.-H. Chen, "Autonomous source term estimation in unknown environments: From a dual control concept to uav deployment," *IEEE Robotics and Automation Letters*, 2022.

[6] M. Alajlan, A. Koubaa, I. Chaari, H. Bennaceur, and A. Ammar, "Global path planning for mobile robots in large-scale grid environments using genetic algorithms," in *2013 International Conference on Individual and Collective Behaviors in Robotics (ICBR)*. IEEE, 2013, pp. 1–8.

[7] N. Sariff and N. Buniyamin, "An overview of autonomous mobile robot path planning algorithms," in *2006 4th student conference on research and development*. IEEE, 2006, pp. 183–188.

[8] A. Pandey, S. Pandey, and D. Parhi, "Mobile robot navigation and obstacle avoidance techniques: A review," *Int Rob Auto J*, vol. 2, no. 3, p. 00022, 2017.

[9] P. K. Mohanty and D. R. Parhi, "Path planning strategy for mobile robot navigation using manfis controller," in *Proceedings of the International Conference on Frontiers of Intelligent Computing: Theory and Applications (FICTA) 2013*. Springer, 2014, pp. 353–361.

[10] A. Zhu and S. X. Yang, "Neurofuzzy-based approach to mobile robot navigation in unknown environments," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 37, no. 4, pp. 610–621, 2007.

[11] N. Yousfi, C. Rekik, M. Jallouli, and N. Derbel, "Optimized fuzzy controller for mobile robot navigation in a cluttered environment," in *2010 7th International Multi-Conference on Systems, Signals and Devices*. IEEE, 2010, pp. 1–7.

[12] Q. Y. Bao, S. M. Li, W. Y. Shang, and M. J. An, "A fuzzy behavior-based architecture for mobile robot navigation in unknown environments," in *2009 International Conference on Artificial Intelligence and Computational Intelligence*, vol. 2. IEEE, 2009, pp. 257–261.

[13] H. Xue, Z. Zhang, M. Wu, and P. Chen, "Fuzzy controller for autonomous vehicle based on rough sets," *IEEE Access*, vol. 7, pp. 147 350–147 361, 2019.

[14] M. S. Gharajeh and H. B. Jond, "Hybrid global positioning system-adaptive neuro-fuzzy inference system based autonomous mobile robot navigation," *Robotics and Autonomous Systems*, vol. 134, p. 103669, 2020.

[15] M. Imen, M. Mansouri, and M. A. Shoorehdeli, "Tracking control of mobile robot using anfis," in *2011 IEEE International Conference on Mechatronics and Automation*. IEEE, 2011, pp. 422–427.

[16] A. Pandey, A. K. Kashyap, D. R. Parhi, and B. Patle, "Autonomous mobile robot navigation between static and dynamic obstacles using multiple anfis architecture," *World Journal of Engineering*, 2019.

[17] A. Al-Mayyahi, W. Wang, and P. Birch, "Adaptive neuro-fuzzy technique for autonomous ground vehicle navigation," *Robotics*, vol. 3, no. 4, pp. 349–370, 2014.

[18] J. Jang, "Anfis: adaptive-network-based fuzzy inference system," *IEEE transactions on systems, man, and cybernetics*, vol. 23, no. 3, pp. 665–685, 1993.

[19] L. Wang and S. Pang, "An implementation of the adaptive neuro-fuzzy inference system (anfis) for odor source localization," in *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2020, pp. 4551–4558.

[20] H. Omrane, M. S. Masmoudi, and M. Masmoudi, "Fuzzy logic based control for autonomous mobile robot navigation," *Computational intelligence and neuroscience*, vol. 2016, 2016.

[21] J. K. Pothal and D. R. Parhi, "Navigation of multiple mobile robots in a highly clutter terrains using adaptive neuro-fuzzy inference system," *Robotics and Autonomous Systems*, vol. 72, pp. 48–58, 2015.