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Adaptive network fuzzy inference system based navigation controller for mobile robot*

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Abstract: Autonomous navigation of a mobile robot in an unknown environment with highly cluttered obstacles is a fundamental issue in mobile robotics research. We propose an adaptive network fuzzy inference system (ANFIS) based navigation controller for a differential drive mobile robot in an unknown environment with cluttered obstacles. Ultrasonic sensors are used to capture the environmental information around the mobile robot. A training data set required to train the ANFIS controller has been obtained by designing a fuzzy logic based navigation controller. Additive white Gaussian noise has been added to the sensor readings and fed to the trained ANFIS controller during mobile robot navigation, to account for the effect of environmental noise on sensor readings. The robustness of the proposed navigation controller has been evaluated by navigating the mobile robot in three different environments. The performance of the proposed controller has been verified by comparing the travelled path length/efficiency and bending energy obtained by the proposed method with reference mobile robot navigation controllers, such as neural network, fuzzy logic, and ANFIS. Simulation results presented in this paper show that the proposed controller has better performance compared with reference controllers and can successfully navigate in different environments without any collision with obstacles.

Key words: Adaptive network fuzzy inference system; Additive white Gaussian noise; Autonomous navigation; Mobile robot
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1 Introduction

Autonomous mobile robots have enormous applications in industrial and automotive domains, such as surveillance, inspection of hazardous sites, and autonomous navigating cars. Autonomous navigation is an important trait in mobile robot navigation. The ability of a mobile robot to navigate by avoiding collisions with obstacles and to safely move towards a goal is of prime importance. Numerous algorithms have been developed in the past three decades to achieve mobile robot navigation. The use of artificial intelligence techniques for mobile robot navigation has gained prominence in the past decade.

Artificial intelligence techniques, such as fuzzy logic, neural network, and genetic algorithm, can express the subjective uncertainties in human mind and enable a machine to perform tasks in the same manner as humans do. Fuzzy logic and neural network are two prominently used artificial intelligence techniques for mobile robot navigation. Fuzzy logic can express the subjective uncertainties in human mind and represent any crisp (real world) data into natural linguistic variables. Neural network can learn from data sets. A fusion of fuzzy logic and neural network is called the "adaptive network fuzzy inference system (ANFIS)." It combines the positives of both fuzzy logic and neural network to form a robust algorithm which can learn the data sets, modify

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various parameters in membership functions, and process linguistic variables. The aforementioned characteristics of the ANFIS network illustrate its suitability for autonomous navigation.

Artificial intelligence methods have been used in mobile robot navigation by various researchers. Li and Choi (2013) focused on the development of a simple fuzzy logic based obstacle avoidance controller for mobile robot navigation in a static environment. Luo et al. (2014) proposed a sensor based, biologically inspired neural network algorithm to achieve real-time collision-free navigation and mapping of an autonomous mobile robot. Faisal et al. (2013) proposed an online navigation technique for a wheeled mobile robot in an unknown environment based on fuzzy logic. Kyrarini et al. (2014) proposed an inverse kinematics based fuzzy control algorithm for joystick control of the mobile robot—assisted gait rehabilitation system. Kim and Chwa (2015) proposed an obstacle avoidance method for position stabilization of the wheeled mobile robot using the interval type-2 fuzzy neural network controller. Ali et al. (2014) proposed a dynamic fuzzy logic controller for intrusion detection in network deployment. Al-Sagban and Dhaouadi (2016) proposed a reactive navigation algorithm for wheeled mobile robots under non-holonomic constraints and in unknown environments. Gudarzi (2016) proposed a robust control strategy for a half-car active suspension system based on human body dynamics. Muñoz et al. (2007) proposed a framework for the evaluation of navigation of autonomous mobile robot using different performance metrics. Badii et al. (2014) proposed a novel generic situation assessment architecture for robotic systems directly assisting humans. Oveisi and Nestorović (2014) proposed a multi-objective robust control strategy for vibration suppression of a clamped-free smart beam. Algabri et al. (2015) proposed a comparison study of artificial intelligence algorithms, such as fuzzy logic, particle swarm optimization (PSO) fuzzy logic, and neuro-fuzzy for mobile robot navigation. Kundu et al. (2012) proposed a perceptive controller for an autonomous mobile robot with a combination of neural network and fuzzy logic. Petković et al. (2016) proposed an adaptive neuro-fuzzy computing mechanism for estimation of precipitation. Mohanty and Parhi (2014) proposed a motion planning algorithm for mobile robot navigation using multiple adaptive neuro-fuzzy inference systems.

We present an implementation of ANFIS for a two-wheel differential drive mobile robot. Motivated by the abovementioned works, our main goals are to achieve autonomous navigation of mobile robots in an unknown environment with cluttered obstacles based on the inputs from three ultrasonic sensors mounted on the robot, and to account for the effect of environmental noise on the sensor data during mobile robot navigation. The 25-dB additive white Gaussian noise (AWGN) is added to the sensor data and fed to the trained ANFIS network.

ANFIS is a multi-input single-output architecture based on Takagi-Sugeno fuzzy inference system. Therefore, a cascaded configuration of two ANFIS controllers has been employed in the proposed method to achieve mobile robot navigation in a static environment. A data set to train the ANFIS network has been obtained by designing a fuzzy logic controller and navigating the mobile robot using a fuzzy logic controller in different environments. The obtained data set is used to train the ANFIS network. ANFIS controller-1 processes the input sensor distances including left obstacle distance (LOD), front obstacle distance (FOD), and right obstacle distance (ROD), and produces output left wheel velocity (LWV). ANFIS controller-2 processes three input sensor data (LOD, FOD, and ROD) and produces output right wheel velocity (RWV). During mobile robot navigation, to account for the corruption of sensory data by environmental noise, the 25-dB AWGN has been added to the sensor data and fed to the trained ANFIS network. The robustness of the proposed ANFIS controller is tested by navigating the mobile robot in three different environments. The performance of the proposed controller is evaluated using parameters, such as travelled path length (TPL), travelled path efficiency (TPE), and bending energy (BE), and has been compared with the reference controllers, such as neural network controller, fuzzy logic controller, and ANFIS controller. The simulation results demonstrate that the proposed ANFIS controller provides better performance compared with reference controllers, and can process the noise corrupted sensor data to enable the mobile robot to autonomously navigate in an unknown environment with cluttered obstacles.

2 Mobile robot kinematics

A two-wheel differential drive mobile robot is used in this study. The geometrical description of the mobile robot is shown in Fig. 1.

The accelerations of the left and right wheels are ω_L and ω_R, respectively. The contact between wheels and ground is assumed to be pure rolling and non-slipping (Rusu and Birou, 2010). The relationship between the left and right wheel velocities is expressed as

$$V_L = r\omega_L, \tag{1}$$

$$V_R = r\omega_R, \tag{2}$$

where r is the radius of the wheels. V_L and V_R are the linear velocities of the left and right wheels of a mobile robot, respectively.

The total linear velocity V and angular velocity ω of the robot can be expressed as

$$V = \frac{1}{2}(V_R + V_L) = \frac{r}{2}(\omega_R + \omega_L), \tag{3}$$

$$\omega = \frac{1}{L}(V_R - V_L) = \frac{r}{L}(\omega_R - \omega_L). \tag{4}$$

The dynamic model for the mobile robot can be expressed as

$$\begin{pmatrix} x' \\ y' \\ \theta' \end{pmatrix} = \begin{pmatrix} \cos\theta & 0 \\ \sin\theta & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} V \\ \omega \end{pmatrix}. \tag{5}$$

3 Adaptive network fuzzy inference system architecture

ANFIS integrates the features of artificial neural network (ANN) and fuzzy logic controller. ANFIS, which works on the Takagi-Sugeno FIS model, was developed by Jang (1993). The proposed ANFIS controller consists of three inputs (sensor readings) and two outputs (wheel velocities). The Takagi-Sugeno based ANFIS model is a multi-input single-output model. Therefore, to realize the proposed controller two ANFIS controllers have been cascaded. Each ANFIS model will receive three inputs and produce one output. The block diagram of the proposed ANFIS controller architecture is shown in Fig. 2.

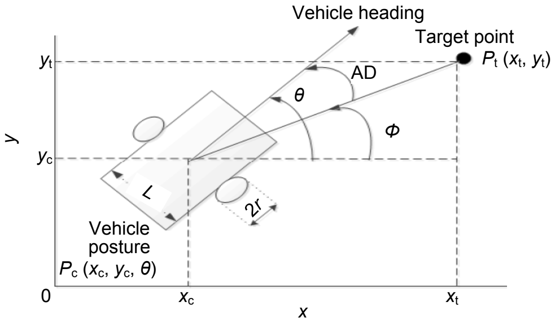

Fig. 1 Geometric description of a mobile robot

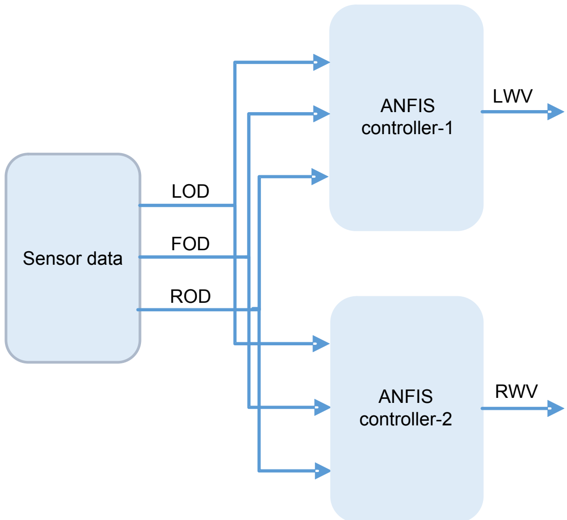

Fig. 2 Adaptive network fuzzy inference system (ANFIS) controller architecture

The three inputs to the ANFIS controllers are LOD (x), FOD (y), and ROD (z). Each input variable is represented by three trapezoidal membership functions, such as A_1 (close), A_2 (near), A_3 (far), B_1 (close), B_2 (near), B_3 (far), C_1 (close), C_2 (near), and C_3 (far), as shown in Fig. 3.

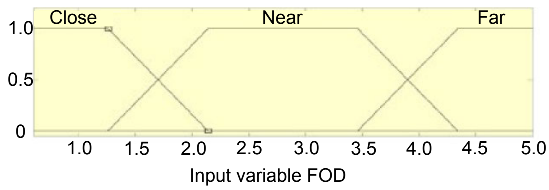

Fig. 3 Membership functions for input variable (FOD)

The rule of the proposed ANFIS controller can be set as follows:

If x is A_i, y is B_i, and z is C_i, then
$f_n=p_nx+q_ny+r_nz+s_n$,

where A_i, B_i, and C_i are the fuzzy membership sets for the input variables x, y, and z, respectively. i=1: 3 and p_n, q_n, r_n, and s_n are the linear parameters of wheel velocity function f_n; these parameters control the output of the ANFIS controller. The structure of the ANFIS controller for the proposed method is shown in Fig. 4.

The role of each layer in the ANFIS structure is described below.

Input layer transfers input data to layer-1.

$$O_{0,\,\mathrm{LOD}}=X,\ O_{0,\,\mathrm{FOD}}=Y,\ O_{0,\,\mathrm{ROD}}=Z. \tag{6}$$

1. Layer-1

This layer is called the "fuzzification layer." Neurons in this layer perform the fuzzification process. Every node in this layer is an adaptive node and calculates the membership function value in the fuzzy set. Outputs of the nodes in this layer are presented as

$$O_{1,i}=\mu_{A_i}(X), O_{1,i}=\mu_{B_i}(Y), O_{1,i}=\mu_{C_i}(Z), \tag{7}$$

where $O_{1,\,i}$ represents a trapezoidal membership grade of a fuzzy set S (A_i, B_i, and C_i) and computes the degree to which the given inputs (X, Y, and Z) quantify S. Membership functions are defined as

$$\mu_{A_i}(x:a_i,b_i,c_i,d_i)=\begin{cases} 0, & x<a_i, \\ \dfrac{x-a_i}{b_i-a_i}, & a_i\le x<b_i, \\ 1 & b_i\le x<c_i, \\ \dfrac{d_i-x}{d_i-c_i}, & c_i\le x<d_i, \\ 0, & x\ge d_i, \end{cases} \tag{8}$$

where a_i, b_i, c_i, and d_i are parameters that control the dimensions of the trapezoidal function of node i. These parameters are known as "premise parameters."

2. Layer-2

This layer is called the "rule layer." Every node in this layer is a fixed node labeled as π_n. Every node in this stage corresponds to a single Takagi-Sugeno fuzzy rule. The proposed ANFIS controller controls 27 rules; then, the rule layer contains 27 rule nodes. Each rule node receives inputs from the respective nodes of layer-1 and determines the firing strength of each rule. Rule layer uses logical operation "and" to represent the fuzzy rules; then the color of the rule nodes is blue. The output of each node in this layer is the product of all incoming signals expressed as

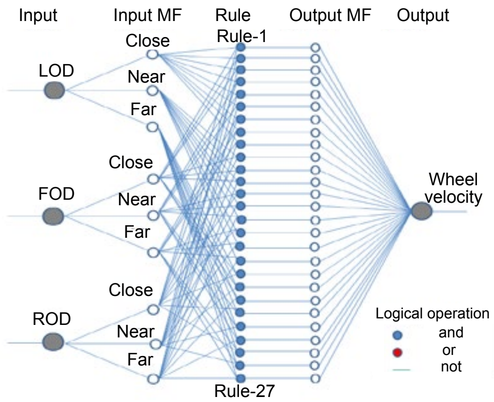

Fig. 4 Structure of the ANFIS controller
References to color refer to the online version of this figure

$$O_{2,n}=W_n=\mu_{A_i}(X)\cdot\mu_{B_i}(Y)\cdot\mu_{C_i}(Z), \tag{9}$$

where W_n represents the firing strength of the n^{th} rule and n is the number of Takagi-Sugeno fuzzy rules.

3. Layer-3

This layer is called the "normalization layer." Every node in this layer is a fixed node and labeled as N_n. Each node in this layer receives inputs from all nodes in the fuzzy rule layers and determines the normalized firing strength of a given rule. The n^{th} node calculates the ratio of the n^{th} rule's firing strength to the sum of all rules' firing strengths. Outputs of this layer are called the "normalized firing strengths," as follows:

$$O_{3,n}=\overline{W}_n=\frac{W_n}{\sum_{n=1}^{27}W_n}. \tag{10}$$

4. Layer-4

Every node in this layer is an adaptive node. Each node in this layer is connected to the corresponding normalization node and receives initial inputs X, Y, and Z. A defuzzification node determines the weighted consequent value of a given rule as follows:

$$O_{4,n} = \overline{W}_n f_n = \overline{W}_n (p_n X + q_n Y + r_n Z + s_n), \quad (11)$$

where $\overline{W}_n$ is a normalized firing strength value received from layer-3, and p_n, q_n, r_n, and s_n are the parameter sets of this node. These parameters are called "consequent parameters."

5. Layer-5

It is represented by a single summation node. This single node is a fixed node and labeled as Σ. This node determines the sum of the outputs of all defuzzification nodes and provides the overall system output, i.e., the wheel velocity:

$$O_{5,1} = \sum_{n=1}^{27} \overline{W} f_n = \frac{\sum_{n=1}^{27} W_n f_n}{\sum_{n=1}^{27} W_n}. \quad (12)$$

A hybrid learning algorithm has been used to update the network parameters of the ANFIS system. The hybrid learning algorithm divides the parameters into two parts as input (membership functions) and output parameters (weights). During the forward pass, the membership function parameters are kept constant. This enables the outputs of the network to be a linear combination of output parameters of the parameter set. Least square error based training is used in the forward pass.

During the backward pass, the output parameters are kept constant and the error is back propagated. The input parameter set is updated using the gradient descent algorithm.

4 Experimental results

The implementation process of the proposed ANFIS based navigation controller has been presented in the following subsections.

4.1 Data collection

Building a training data set is an important process in ANFIS training. Due to the non-availability of a mathematical relationship between sensor readings and wheel velocities, we need alternate methods to obtain training data samples to build an ANFIS controller. In this study, we built a simple fuzzy logic controller for mobile robot navigation to obtain the training data. The block diagram of the fuzzy logic controller is shown in Fig. 5.

The steps in the data extraction process are explained as follows:

1. Build a fuzzy logic controller for mobile robot navigation.

2. Build an environment for mobile robot navigation.

3. Navigate the mobile robot using the fuzzy logic controller in the environment.

4. After successful navigation, extract the sensor data and the corresponding wheel velocities.

5. The mobile robot has been made to navigate in three different environments. Therefore, certain sensor values, which are similar, have been deleted.

6. ANFIS is a multi-input single-output system. Therefore, the data set was divided into two: one data set was built with sensor data and corresponding left wheel velocity data, and the other data set contained sensor data and corresponding right wheel velocity data.

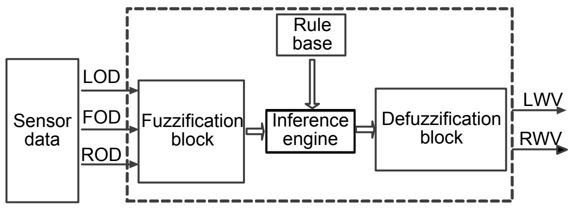

Fig. 5 Structure of the fuzzy logic controller

The total number of training data set samples used for training the ANFIS controller is 540. A sample of the data set used for training ANFIS controller-1 is presented in Table 1.

4.2 ANFIS controller design

The data set obtained in the previous steps is used to build an ANFIS controller. The training data set for ANFIS controller-1 is shown in Fig. 6.

A hybrid method has been used to train the data set. The root mean squared (RMS) training error obtained after training the data set of ANFIS controller-1 was 0.013. The RMS training data error vs. the number of training epochs is shown in Fig. 7. Three trapezoidal membership functions were used to represent each input of ANFIS controller-1. The membership functions after training ANFIS controller-1 are shown in Figs. 8–10.

Table 1 Sample data set for training ANFIS controller-1

Sample No.	LOD	FOD	ROD	LWV
1	5	5	5	0.5
2	5	4.8	2.7	0.48
3	5	5	1.9	0.36
4	3.5	5	2.1	0.41
5	3	5	2.9	0.7
…	…	…	…	…
539	5	2.1	2.5	0.1
540	2.8	5	5	0.79

LOD: left obstacle distance; FOD: front obstacle distance; ROD: right obstacle distance; LWV: left wheel velocity

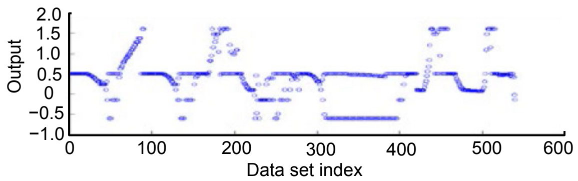

Fig. 6 Data set for training ANFIS controller-1

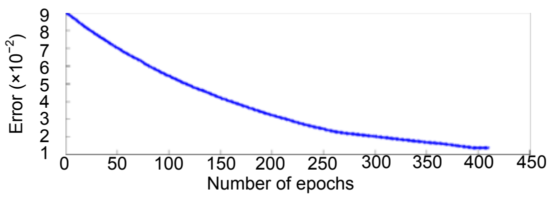

Fig. 7 RMS training data error ANFIS controller-1 vs. the number of training epochs

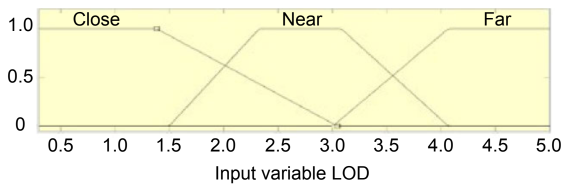

Fig. 8 LOD after training ANFIS controller-1

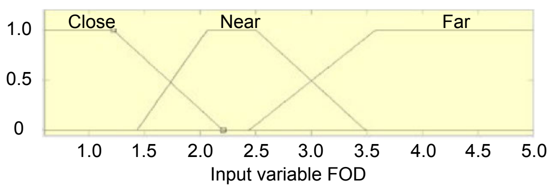

Fig. 9 FOD after training ANFIS controller-1

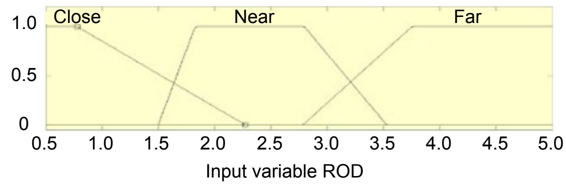

Fig. 10 ROD after training ANFIS controller-1

The training data set for ANFIS controller-2 is shown in Fig. 11.

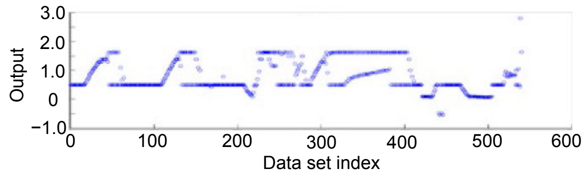

Fig. 11 Data set for training ANFIS controller-2

The RMS training error obtained after training the data set of ANFIS controller-2 was 0.039. The RMS error vs. the number of training epochs is shown in Fig. 12.

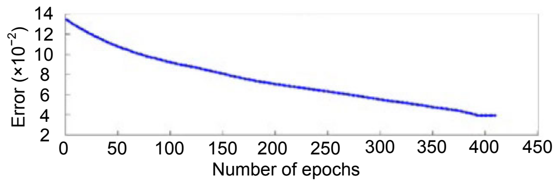

Fig. 12 RMS training data error ANFIS controller-2 vs. the number of training epochs

The membership functions after training ANFIS controller-2 are shown in Figs. 13–15.

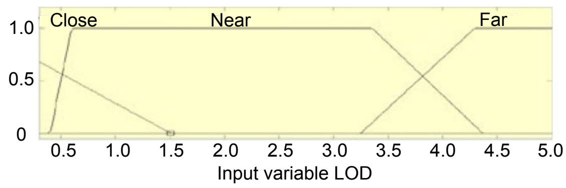

Fig. 13 LOD after training ANFIS controller-2

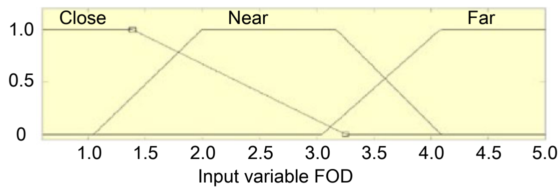

Fig. 14 FOD after training ANFIS controller-2

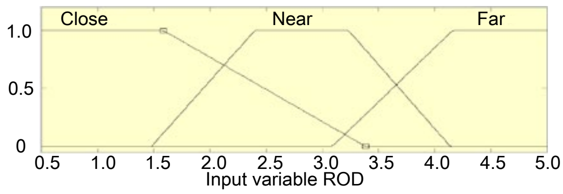

Fig. 15 ROD after training ANFIS controller-2

4.3 Mobile robot navigation using ANFIS simulation results

A two-wheel differential drive mobile robot was used for implementation of the proposed method. The mobile robot was equipped with three ultrasonic sensors which control the direction of mobile robot navigation by changing wheel velocities. To account for the environmental noise affecting sensor data, a 25-dB AWGN has been added to the sensor data before feeding to the ANFIS controllers during navigation. MATLAB software packages were used for the development of the ANFIS controller, mobile robot, and the environment. The block diagram of the proposed ANFIS controller used for mobile robot navigation is shown in Fig. 16.

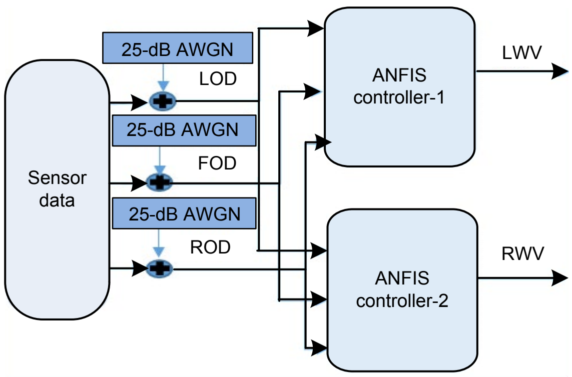

Fig. 16 Block diagram of the ANFIS controller for mobile robot navigation

To validate the robustness of the proposed ANFIS controller, the proposed mobile robot navigation controller was tested in three different environments. The performance of the proposed controller was evaluated with respect to the reference artificial intelligence based navigation controllers, such as neural network, fuzzy logic, and ANFIS. The performance of the proposed controller was validated based on two parameters: TPL and BE.

1. TPL

TPL is the length of the trajectory traced by the mobile robot from the initial position to the target position. For a trajectory in an x-y plane containing n points, assuming the initial point as $(x_1, f(x_1))$ and the target position $(x_n, f(x_n))$, TPL can be calculated as

$$\mathrm{TPL}=\sum_{i=1}^{n-1}\sqrt{(x_{i+1}-x_i)^2+\left(f(x_{i+1})-f(x_i)\right)^2}, \quad (13)$$

where $(x_i, f(x_i))$ (i=1, 2, …, n) are the n points of the trajectory in the Cartesian coordinates (Guo et al., 2003).

2. BE

BE is a function of curvature k, used to evaluate the smoothness of the robot's navigation. The smoothness of a trajectory shows the consistency between the decision-action relationship taken by the navigation system and the ability to anticipate and respond to events with a sufficient speed (Rosenblatt, 1997). BE can be calculated as the sum of the squares of the curvature at each point of line $k(x_i, y_i)$, along the length of line L. The BE of the trajectory of a robot is expressed as

$$\mathrm{BE}=\frac{1}{n}\sum_{i=1}^{n}k^2\left(x_i, f(x_i)\right), \quad (14)$$

where $k(x_i, y_i)$ is the curvature at each point of the trajectory of the robot, and n is the number of points in the trajectory.

4.3.1 Environment-1

A control algorithm based on the reactive behaviors, called the "adaptive fusion of reactive behaviors," has been used by Muñoz et al. (2007) to achieve mobile robot navigation. In this study, neural network has been designed to obtain few sets of behavioral combinations to enable the system to perform tasks, such as navigation towards a goal, while avoiding the obstacles in its path. This algorithm was tested in an environment with cluttered obstacles, and the mobile robot navigation was evaluated through six different scenarios. Each scenario contains different initial and target positions. The proposed ANFIS navigation controller was tested in the environment proposed by Muñoz et al. (2007).

Figs. 17–22 show that the mobile robot successfully navigates without any collision with obstacles.

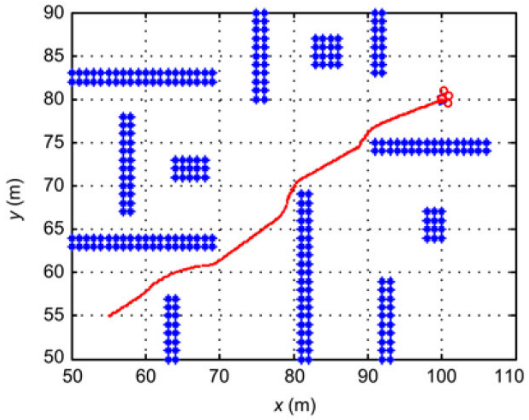

Fig. 17 Environment-1 (scenario-1) with obstacles: initial position (55, 55) and target position (100, 80)

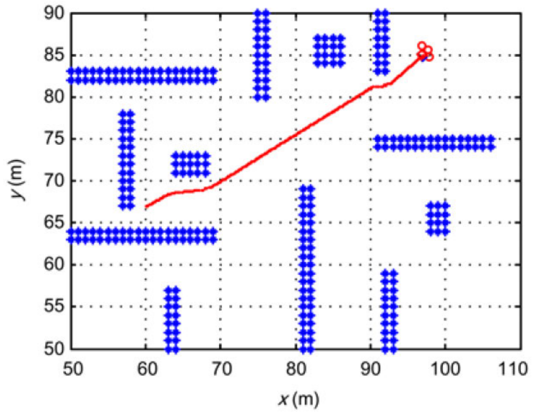

Fig. 18 Environment-1 (scenario-2) with obstacles: initial position (60, 67) and target position (97, 85)

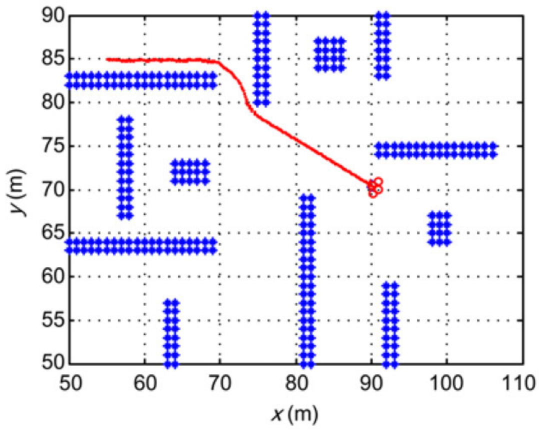

Fig. 19 Environment-1 (scenario-3) with obstacles: initial position (55, 85) and target position (90, 70.5)

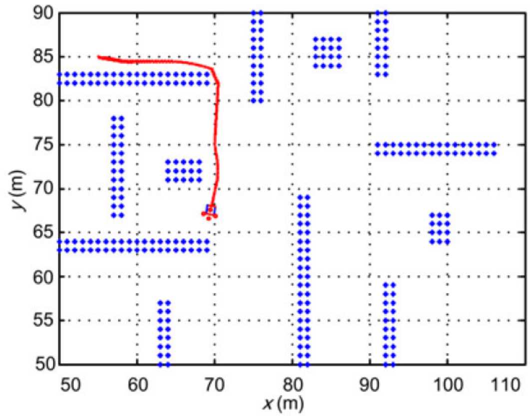

Fig. 20 Environment-1 (scenario-4) with obstacles: initial position (55, 85) and target position (69.5, 67.5)

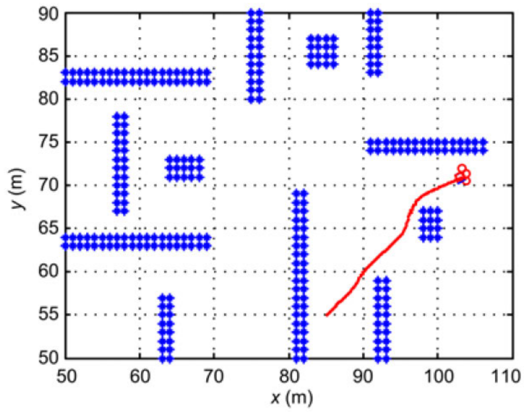

Fig. 21 Environment-1 (scenario-5) with obstacles: initial position (85, 55) and target position (103, 71)

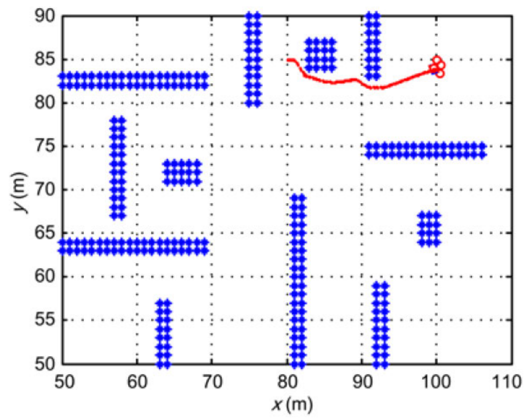

Fig. 22 Environment-1 (scenario-6) with obstacles: initial position (80, 85) and target position (100, 84)

The TPL and BE obtained during the navigation of the proposed ANFIS controller in each scenario were compared with the reference controller (Tables 2 and 3). Tables 2 and 3 show that the proposed controller provides better performance than the reference neural network based controller.

Table 2 ANFIS controller performance evaluation in environment-1 (travelled path length/efficiency)

Sample No.	Environment	Travelled path length/efficiency	
		Reference method	Proposed method
1	Scenario-1	58.19 m (88.45%)	54.01 m (95.30%)
2	Scenario-2	42.99 m (95.70%)	41.86 m (98.28%)
3	Scenario-3	46.29 m (81.83%)	42.95 m (88.20%)
4	Scenario-4	35.99 m (64.02%)	33.94 m (67.88%)
5	Scenario-5	25.99 m (92.65%)	25.29 m (95.22%)
6	Scenario-6	22.99 m (87.08%)	22.17 m (90.30%)

Table 3 ANFIS controller performance evaluation in environment-1 (bending energy)

Sample No.	Environment	Bending energy	
		Reference method	Proposed method
1	Scenario-1	0.084	0.016
2	Scenario-2	0.071	0.019
3	Scenario-3	0.012	0.023
4	Scenario-4	0.014	0.020
5	Scenario-5	0.039	0.017
6	Scenario-6	0.046	0.024

4.3.2 Environment-2

Li and Choi (2013) presented a simple fuzzy logic control for obstacle avoidance for mobile robot navigation in an unknown environment. The proposed ANFIS controller was used to navigate the mobile robot in the environment used by Li and Choi (2013). Fig. 23 shows that the mobile robot using the proposed controller can successfully navigate without any collision.

The TPL and BE obtained during the navigation of the proposed ANFIS controller were compared with the reference controller (Tables 4 and 5). Tables 4 and 5 show that the proposed controller provides better performance than the reference fuzzy based controller.

Table 4 ANFIS controller performance evaluation in environment-2 (travelled path length/efficiency)

Sample No.	Environment	Travelled path length/efficiency	
		Reference method	Proposed method
1	Environment-2	45.6 m (77.52%)	41.42 m (85.35%)

Table 5 ANFIS controller performance evaluation in environment-2 (bending energy)

Sample No.	Environment	Bending energy	
		Reference method	Proposed method
1	Environment-2	Not available	0.003

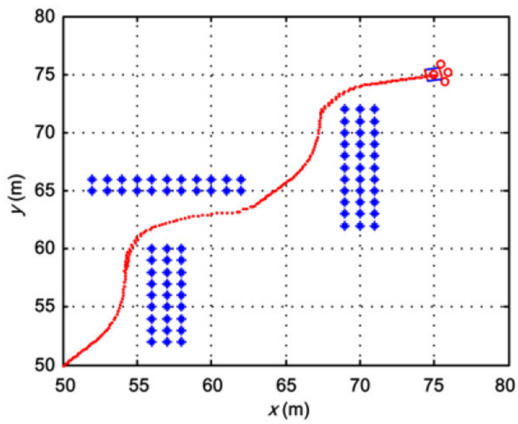

Fig. 23 Environment-2 with obstacles: initial position (50, 50) and target position (75, 75)

4.3.3 Environment-3

An adaptive neuro-fuzzy logic controller for obstacle avoidance for mobile robot navigation in an unknown environment was presented by Algabri et al. (2015). The proposed ANFIS controller was used to navigate the mobile robot in the environment used by Algabri et al. (2015). Fig. 24 shows that the mobile robot using the proposed controller can successfully navigate without any collision.

The TPL and BE obtained during the navigation of the proposed ANFIS controller were compared with the reference controller (Tables 6 and 7). In the reference paper, the travelled path length was mentioned in terms of mean and standard deviation. Tables 6 and 7 show that the proposed controller provides better BE than the reference ANFIS based controller.

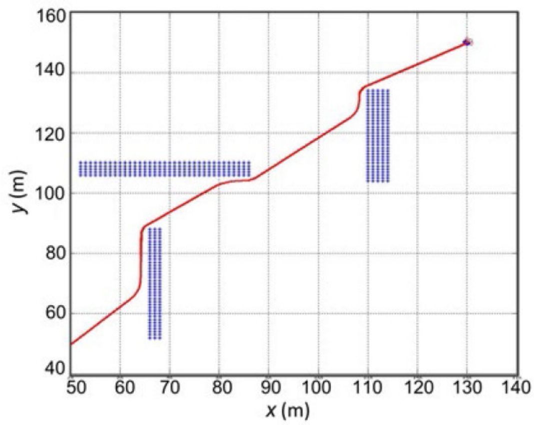

Fig. 24 Environment-3 with obstacles: initial position (50, 50) and target position (130, 150)

Table 6 ANFIS controller performance evaluation in environment-3 (travelled path length/efficiency)

Sample No.	Environment	Travelled path length/efficiency	
		Reference method	Proposed method
1	Environment-3	139.21 (mean) SD: 0.57 (91.99%)	140.26 (91.30%)

SD: standard deviation

Table 7 ANFIS controller performance evaluation in environment-3 (bending energy)

Sample No.	Environment	Bending energy	
		Reference method	Proposed method
1	Environment-3	0.006	0.001

5 Conclusions

In this study, a mobile robot navigation controller based on ANFIS has been presented. A cascaded configuration of two ANFIS controllers has been employed to achieve mobile robot navigation in an unknown environment with highly cluttered obstacles. The training data set to train the ANFIS controller has been obtained by building a fuzzy logic controller and post-training. To address the effect of environmental noise on sensor data, the 25-dB AWGN has been added to the sensor data during mobile robot navigation. To test the robustness of the proposed ANFIS controller, the mobile robot has been navigated in different environmental configurations, and the performance of the proposed controller has been evaluated based on TPL and BE, and has been compared with those of the reference controllers, such as neural network, fuzzy logic, and ANFIS. It has been observed that the proposed ANFIS controller can handle noisy sensor data and provide better performance, enabling the robot to successfully navigate in environments without any collision with cluttered obstacles.

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