Path Generation and Obstacle Avoidance of an Autonomous Mobile Robot Using Intelligent Hybrid Controller

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Abstract. Intelligent soft computing techniques such as artificial neural network and fuzzy logic approaches are verified to be efficient and appropriate when implemented to a variety of systems. Recent years both techniques has been rising interest and as a result Neuro-Fuzzy techniques have been developed. It has also taken the advantages of neural network and fuzzy inference system. This paper presents the application of an adaptive neuro-fuzzy inference system (ANFIS) to path generation and obstacle avoidance of an autonomous mobile robot in an unknown static and dynamic environment. In this architecture different sensor based information such as front obstacle distance (FOD), left obstacle distance (LOD), right obstacle distance (ROD) and target angle (TA) are given as input to the adaptive controller and output from the controller is steering angle of the mobile robot. Outcome from the simulation results using MATLAB demonstrated that the ANFIS model could be used as a suitable and effective technique to navigate the mobile robot safely both in static and dynamic environment, find and reach to target objects.

Keywords: ANFIS, Mobile robot, navigation.

1 Introduction

Mobile robots are extensively used in various fields of engineering such as aerospace research, nuclear industry, mining industries and also in military operations. Path planning of an autonomous mobile robot in an unknown cluttered environment is the most important aspects in a mobile robots research area. But the mobile robot should have learning capability to navigate safely in complex, unknown environment. In path planning, the objective of the mobile robot is to travel safely from source to target without hitting with obstacles that present in environment. In this paper an intelligent hybrid technique i.e. ANFIS (Adaptive Neuro-Fuzzy Inference System) is implemented for the path planning of a mobile robot. This technique gives the advantages of both fuzzy logic and neural network. Many researchers have been developed several efficient hybrid techniques in the navigation of mobile robots.

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Among these hybrid intelligent techniques, the adaptive Neuro-fuzzy system can learn only from its environment and then make decisions. A neural fuzzy system is based on fuzzy inference system, which is trained by a learning algorithm derived from neural network theory.

In literature survey, there can be found different approaches associated with motion control of the autonomous mobile robot. Sudhagar et al. [1] have presented ANFIS based navigation for truck like mobile robot.They have trained the truck with three inputs, five-layer neural network with back propagation learning algorithm for the control the movement of a mobile robot. Neuro-fuzzy motion planners for intelligent robots have been discussed by Tsoukalas et al. [2]. The robot is supported with sensors to acquire local environmental input and a neuro-fuzzy model processing predictable aspects of its environment. The method is verified through a robot learning to navigate from start point to goal point without colliding with obstacles present in its path. Navigation of multiple mobile robots using Neuro-fuzzy technique has been addressed by pradhan et al. [3]. In this design, output from the neural network given as input to the fuzzy controller to navigate the mobile robot successfully in the clutter environment. Experimental verifications also have been done with the simulation results to prove the validity of the developed technique. Navigation of mobile robots using adaptive neural-fuzzy system have discussed by Nefti et al. [4]. Different sensor based information they have given to the Sugeno–Takagi fuzzy controller and output from the controller is the robot orientation. Experimental results settle the importance of the methodology when dealing with navigation of a mobile robot in unknown or partially unknown environment. To determine collision-free path of mobile robot navigating in a dynamic environment using Neuro-fuzzy technique has been presented by Hui et al. [5]. The performances of Neuro-fuzzy approaches are compared other approaches (GA, Mamdani) and it is found that Neuro-fuzzy approaches are found to perform better than the other approaches. Control of mobile robot based on Neuro-fuzzy technique has been discussed by Godjevac and Steele [6]. In this paper they have shown how Neuro-fuzzy controllers can be achieved using a controller based on the Takagi-Sugeno design and a radial basis function neural network for its implementation. Neuro-fuzzy based mobile robot navigation has been presented by Rusu et al. [7]. In this paper they discussed a Neuro-fuzzy controller for sensor based navigation in indoor environments. A Neuro-Fuzzy Controller for mobile robot navigation has been addressed by Kim and Trivedi [8]. In this paper they have applied Neural integrated fuzzy controller to control the robot motion—steering angle, heading direction, and speed. Navigation of an autonomous mobile robot using neuro-fuzzy approach has been design by Crestani et al. [9]. They have developed a fuzzy-neural network based technique that considers the direction velocity of navigation as controllable terms.

The objective of the study in this paper is to open up a path planning layout for a mobile robot to navigate safely towards the destination while avoiding various obstacles present in the environment. Hybrid learning algorithm which combines the gradient descent method and least square estimate (LSE) is used to adjust the parameters in ANFIS.

2 Kinematic Analysis of Mobile Robot

The Kinematic analysis of differentially steered wheeled mobile robots in a two-dimensional plane can be done in one of two ways: either by Cartesian or polar coordinates. It is assumed that the mobile robot moves without slipping on a plane, i.e., there is a pure rolling contact between the wheels and the ground and also there is no lateral slip between the wheel and the plane. The modeling in Cartesian coordinates is the most common use and the discussion will be limited to modeling in Cartesian coordinates. The robot has two fixed standard wheels and one caster wheel and is differentially driven by skid steer motion. The two driving wheels are independently driven by two motors to acquire the motion and orientation. Both the wheels have same diameter '2r' (Fig.1). The driving wheels are separated by distance 'W'.The position of the robot in the 2-D plane at any instant is defined by the situation in Cartesian coordinates and the heading with respect to a global frame of reference. The tangential velocity of mobile robot is given by [11].

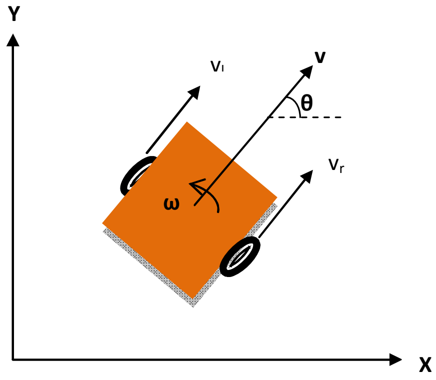

Fig. 1. Mobile Robot kinematic parameters

$$v_t = \frac{1}{2}(v_r + v_l) \tag{2.1}$$

$$\omega_t = \frac{1}{W}(v_r - v_l) \tag{2.2}$$

$$v_r = r\omega_r \ \text{ and } \ v_l = r\omega_l \tag{2.3}$$

Where v is the linear velocity and ω is the angular velocity of the mobile robot. Suffixes r,l,t stand for right wheel, left wheel and tangential directions of motion respectively.

3 Architecture of the Adaptive Neuro-Fuzzy Inference System (ANFIS) for Current Analysis

Adaptive Network-Based Fuzzy Inference System (ANFIS) is one of hybrid intelligent neuro-fuzzy inference system and it functioning under Takagi-Sugeno-type fuzzy inference system, which was developed by Jang [1993]. ANFIS has a similar structure to a multilayer feed forward neural network but the links in an ANFIS only indicate the flow direction of signals between nodes and no weights are associated with the links.

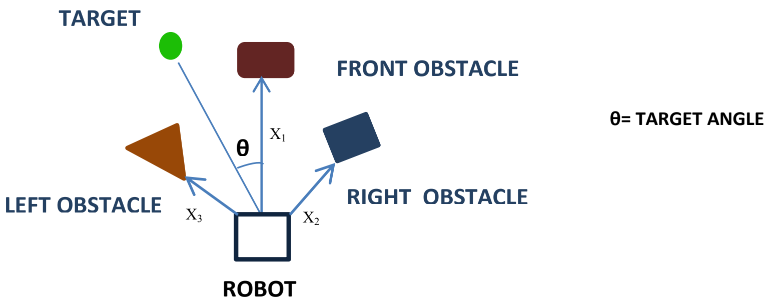

Fig. 2. Schematic Diagram for Robot Initial Position

As for the prediction of steering angle for mobile robot we assume the fuzzy inference system under consideration of four inputs i.e Front obstacle distance (X_1), Right obstacle distance (X_2), Left obstacle distance(X_3) , target angle(X_4) and each input variable has three membership functions(MF) A_1,A_2,andA_3,B_1,$B_2$and B_3,C_1,C_2andC_3, and D_1,D_2andD_3 respectively, then a Takagi-Sugeno-type fuzzy inference system if-then rules is set up as follows;

Rule: if X_1 is A_i and X_2 is B_i and X_3 is C_i and X_4 is D_i, then
f_n(steering Angle) = $p_nX_1+q_nX_2+r_nX_3+s_nX_4+u_n$

where,i=1,2,3 and p_n,q_n,r_n,s_n and u_n are the linear parameters of function fn. In ANFIS architecture nodes of the same layer have similar functions. The output signals from previous layers are the input to the next layer.

The function of each layer in ANFIS is discussed as follows;

Input Layer: In this layer nodes simply pass the incoming signal to layer-1. That is

$$\left.\begin{aligned} O_{0,FOD} &= X_1 \\ O_{0,ROD} &= X_2 \\ O_{0,LOD} &= X_3 \\ O_{0,TA} &= X_4 \end{aligned}\right\} \qquad (3.1)$$

First Layer: This layer is the fuzzification layer. Neurons in this layer complete fuzzification process. Every node in this layer is an adaptive node and computing the membership function value. The output of nodes in this layer are presented as

$$\left.\begin{aligned} O_{1,i} &= \mu_{A_i}(X_1) \\ O_{1,i} &= \mu_{B_i}(X_2) \\ O_{1,i} &= \mu_{C_i}(X_3) \\ O_{1,i} &= \mu_{D_i}(X_4) \end{aligned}\right\} \qquad (3.2)$$

i=1,2,3

Here $O_{1,i}$ is the bell shape membership grade of a fuzzy set S (A_i , B_i ,C_i and D_i) and it computes the degree to which the given inputs (X_1,X_2,$X_3$and X_4) satisfies the quantifier S. Membership functions defined as follows;

$$\mu_{A_i}(x) = \frac{1}{1+\left[\left(\frac{X_1-C_i}{a_i}\right)^2\right]^{b_i}} \tag{3.2(i)}$$

$$\mu_{B_i}(x) = \frac{1}{1+\left[\left(\frac{X_2-C_i}{a_i}\right)^2\right]^{b_i}} \tag{3.2(ii)}$$

$$\mu_{C_i}(x) = \frac{1}{1+\left[\left(\frac{X_3-C_i}{a_i}\right)^2\right]^{b_i}} \tag{3.2(iii)}$$

$$\mu_{D_i}(x) = \frac{1}{1+\left[\left(\frac{X_4-C_i}{a_i}\right)^2\right]^{b_i}} \tag{3.2(iv)}$$

a_i , b_i and c_i are parameters that control the Centre, width and slope of the Bell-shaped function of node 'i' respectively. These are also known as premise parameters.

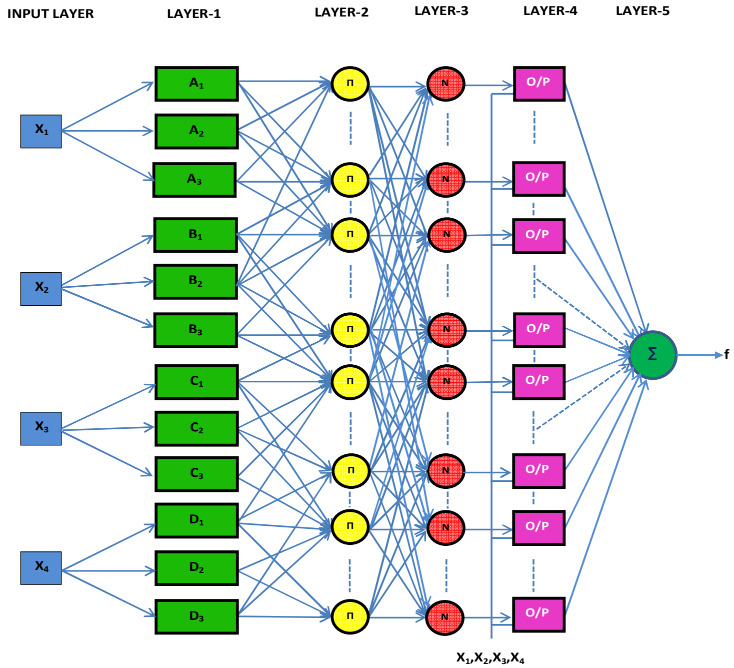

Fig. 3. Schematic Diagram for ANFIS Structure

Second Layer: It is also known as rule layer. Every node in this layer is a fixed node and labeled as π_n. Each node in this layer corresponds to a single Sugeno-Takagi fuzzy rule. A rule node receives inputs from the respective nodes of layer-2 and determines the firing strength of the each rule. Output from each node is the product of all incoming signals.

$$O_{2,n} = w_n = \mu_{A_i}(X_1) \cdot \mu_{B_i}(X_2) \cdot \mu_{C_i}(X_3) \cdot \mu_{D_i}(X_4) \quad (3.3)$$

Where 'W_n' represents the firing strength or the truth value, of n^{th} rule and n=1, 2, 3…81 is the number of Sugeno-Takagi fuzzy rules.

Third Layer: It is 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 layer and determines the normalized firing strength of a given rule. The normalized firing strength of the nth node of the n^{th} rule's firing strength to sum of all rules's firing strength.

$$O_{3,n} = \overline{w}_n = \frac{\overline{w}}{\sum_{n=1}^{81} w_n} \quad (3.4)$$

The number of nodes in this layer is the same the number of nodes in the previous layer that is 81 nodes. The output of this layer is called normalized firing strength.

Fourth Layer: Every node in this layer is an adaptive node. Each node in this layer is connected to the corresponding normalization node, and also receives initial inputs X_1, X_2, X_3 and X_4. A defuzzification node determines the weighted consequent value of a given rule define as,

$$O_{4,n} = \overline{w}_n f_n = \overline{w}_n [p_n(X_1) + q_n(X_2) + r_n(X_3) + s_n(X_4) + u_n] \quad (3.5)$$

Where $\overline{w}_n$ is a normalized firing strength from layer-2 and [p_n, q_n, r_n, s_n, u_n] are the parameters set of this node. These parameters are also called consequent parameters.

Fifth Layer: 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 outputs of all defuzzification nodes and gives the overall system output.

$$O_{5,1} = \sum_{n=1}^{81} \overline{w}\, f_n = \frac{\sum_{n=1}^{81} w_n f_n}{\sum_{n=1}^{81} w_n} \quad (3.6)$$

4 Simulation Results

The simulation results are obtained by using MATLAB software to show the performance and validity of the developed method in various environmental conditions. When a robot is closed to an obstacle, it avoids a hitting by moving away from it in opposite direction. When the data values from sensors are less than the threshold values then the obstacle avoidance behavior is activated. An advantage of ANFIS is to control velocity and direction of robot, if there are no obstacles on the robot path then it moves quickly towards the goal. Fig.4 shows the ability of the robot navigates safely and finds the target successfully in cluttered environment.Fig.5 shows avoidance behavior of a single mobile robot. In Fig.6. it can be noted that the robots stay well away from the obstacles as well as from each other. The simulation results also compared with fuzzy logic and neural network technique and it is verified that using the ANFIS controller the robot reached to the specified target in less time (Table-1).

Table 1.

Sl.No.	Figure	Fuzzy	NN	ANFIS
		Total travel time in Sec.		
1	4	13.6	12.1	11.2
2	5	10.9	10.1	8.9
3	6	17.5	16.4	14.9

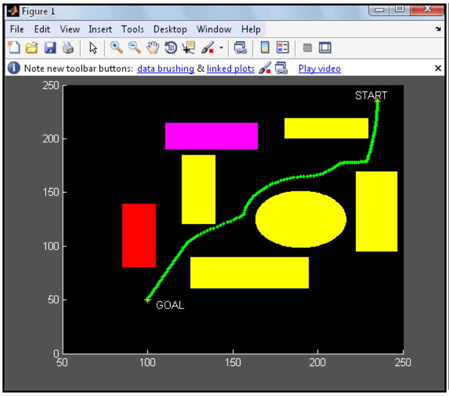

Fig. 4. Navigation path for one mobile robot to reach target using ANFIS controller

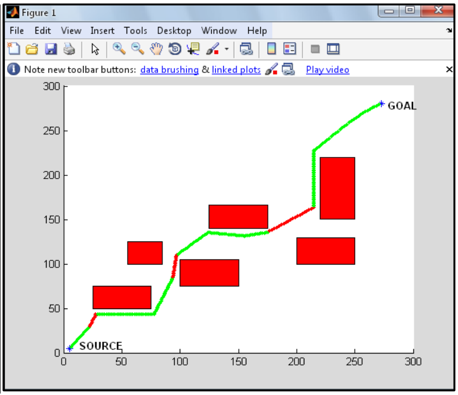

Fig. 5. Environment for one robot and one target using ANFIS controller

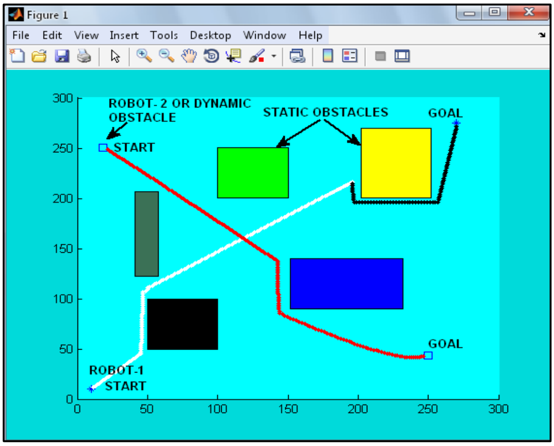

Fig. 6. Collision avoidance between two mobile robots using ANFIS

5 Concluding Remarks

In this paper, an adaptive neuro-fuzzy technique has been applied for navigation of an autonomous mobile robot in an unknown cluttered environment. The simulation experiments using Matlab in different environmental scenarios showing better performance to avoiding static as well as dynamic obstacles present on the robot path. The resulting architecture has also adaptable to any kinds of complex environment. The proposed method also compared with other intelligent techniques and the settlement in results show the efficiency of the technique. The future research is planned to implement the proposed design to multiple robots navigation instead of a single robot.

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