Path Planning Strategy for Mobile Robot Navigation Using MANFIS Controller

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Abstract. Nowadays intelligent techniques such as fuzzy inference system (FIS), artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) are mainly considered as effective and suitable methods for modeling an engineering system. The hallmark of this paper presents a new intelligent hybrid technique (Multiple Adaptive Neuro-Fuzzy Inference System) based on the combination of fuzzy inference system and artificial neural network for solving path planning problem of autonomous mobile robot. First we develop an adaptive fuzzy controller with four input parameters, two output parameters and five parameters each. Afterwards each adaptive fuzzy controller acts as a single takagi-sugeno type fuzzy inference system, where inputs are front obstacle distance (FOD), left obstacle distance (LOD), right obstacle distance (ROD) (from robot), Heading angle (HA) (angle to target) and output corresponds to the wheel velocities (Left wheel and right wheel) of the mobile robot. The effectiveness, feasibility and robustness of the proposed navigational controller have been tested by means of simulation results. It has been observed that the proposed path planning strategy is capable of avoiding obstacles and effectively guiding the mobile robot moving from the start point to the desired target point with shortest path length.

Keywords: ANFIS, obstacle avoidance, mobile robot, path planning.

1 Introduction

Path planning strategy and navigation of mobile robot has acquired considerable attention in recent years. The major issue in autonomous mobile robot is its navigational problem in uncertain and complex environment. If robot wants to travel among the unknown obstacles to reach a specified goal without collisions, then various sensors must be needed to identify and recognize the obstacles present in the real world environment. The sensor based motion planning approaches uses either global or local path planning depending upon the surrounding environment. Global path planning requires the environment to be completely known and the terrain should be static, on other side local path planning means the environment is completely or partially unknown for the mobile robot. Many exertions have been paid in the past to improve various robot navigation techniques.

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Recently there have been found many interesting research work have been developed by many researchers for path planning of mobile robots. Many authors have considered a controller with complete information of the environment [1-2].Due to the complexity and uncertainty of the path planning problem, classical path planning methods, such as road map approaches (Visibility Graph [3], Voronoi diagrams [4]), Grids [5], Cell decomposition [6] and artificial potential field [7] are not appropriate for path planning in dynamic environments. The artificial potential field method provides a simple yet effective technique to plan paths for robot. The major drawback is that robots are often trapped into a local minimum before reaching to the target. Among the soft intelligent techniques ANFIS is a hybrid model which combines the adaptability capability of artificial neural network and knowledge representation of fuzzy inference system [8]. There are many fuzzy logic methods using various implementation or in combination with other techniques [9-12]. Mobile robot path planning based on neural network approaches presented by many researchers [13-16]. Navigation of multiple mobile robots using Neuro-fuzzy technique addressed by Pradhan et al. [17]. In this navigational controller, 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 discussed by Nefti et al. [18]. In this paper different sensor based information given as input 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 completely or partially unknown environment. To determine collision-free path of mobile robot navigating in a dynamic environment using Neuro-fuzzy technique presented by Hui et al. [19]. The performances of Neuro-fuzzy approaches are compared with other approaches (GA, Mamdani) and it was found that Neuro-fuzzy approaches are found to perform better than the other approaches. Control of mobile robot based on Neuro-fuzzy technique discussed by Godjevac and Steele [20]. 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.

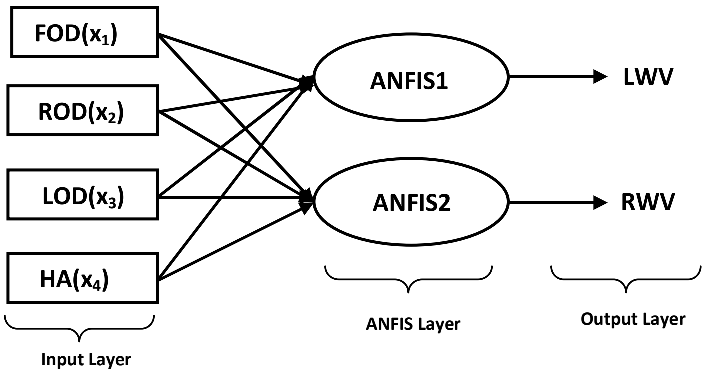

Fig. 1. Multiple ANFIS (MANFIS) Controller for Mobile Robot Navigation

In this paper, a new intelligent controller (MANFIS) has been designed for solving the path planning problem of mobile robot. Finally, simulation results are demonstrated to prove the authenticity of the proposed technique in various environments populated by variety of static obstacles.

2 Architecture of Multiple Adaptive Neuro-Fuzzy Inference System (MANFIS) for Mobile Robot Navigation

Adaptive network-based fuzzy inference system (ANFIS) is one of hybrid intelligent neuro-fuzzy system and it functioning under Takagi-Sugeno-type FIS, which was developed by Jang [8] in 1993. ANFIS has a similar configuration to a multilayer feed forward neural network but links in this hybrid structure only specify the flow direction of signals between nodes and no weights are connected with the links. There are two learning techniques are used in ANFIS to show the mapping between input and output data and to compute optimized of fuzzy membership functions. These learning methods are back propagation and hybrid. Parameters associated with fuzzy membership functions will modify through the learning process.

As for the prediction of left wheel velocity (LWV) and right wheel velocity (RWV) for mobile robot we assume that each adaptive neuro-fuzzy controller under consideration of four inputs i.e. Front obstacle distance (FOD) (x_1), Right obstacle distance (ROD) (x_2), Left obstacle distance (LOD) (x_3), Heading angle (HA) (x_4), and each input variable has five bell membership functions (MF) such as A_1(Very Near), A_2(Near), A_3(Medium), A_4(Far) and A_5(Very Far), B_1(Very Near), B_2(Near), B_3(Medium), B_4(Far) and B_5(Very Far), C_1(Very Near), C_2(Near), C_3(Medium), C_4(Far), and C_5(Very Far), D_1(Very Negative), D_2(Negative), D_3(Zero), D_4(Positive) and D_5(Very positive) respectively, then a Takagi-Sugeno-type fuzzy inference system if-then rules are 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 (wheel velocity) = $p_n x_1 + q_n x_2 + r_n x_3 + s_n x_4 + u_n$

A, B, C, and D are the fuzzy membership sets for the input variables x_1,x_2,x_3 and x_4 respectively.

where, i=1-5 and p_n,q_n,r_n,s_n and u_n are the linear parameters of function f_n and changing these parameters we can modify the output of ANFIS controller.

The function of each layer in ANFIS structure is discussed as follows:

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

$$\left.\begin{aligned} O_{0,FOD} &= X_1 \\ O_{0,ROD} &= X_2 \\ O_{0,LOD} &= X_3 \\ O_{0,TA} &= X_4 \end{aligned}\right\} \tag{2.1}$$

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

$$\left.\begin{aligned} O_{1,i} &= \mu_{A_i}(X_1) \\ O_{1,i} &= \mu_{B_i}(X_2) \\ O_{1,i} &= \mu_{C_i}(X_3) \\ O_{1,i} &= \mu_{D_i}(X_4) \end{aligned}\right\} \quad (2.2)$$

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 computing 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;

$$\mu_{A_i}(x) = \frac{1}{1+\left[\left(\frac{x_1 - c_i}{a_i}\right)^2\right]^{b_i}} \quad 2.2(i)$$

$$\mu_{B_i}(x) = \frac{1}{1+\left[\left(\frac{x_2 - c_i}{a_i}\right)^2\right]^{b_i}} \quad 2.2(ii)$$

$$\mu_{C_i}(x) = \frac{1}{1+\left[\left(\frac{x_3 - c_i}{a_i}\right)^2\right]^{b_i}} \quad 2.2(iii)$$

$$\mu_{D_i}(x) = \frac{1}{1+\left[\left(\frac{x_4 - c_i}{a_i}\right)^2\right]^{b_i}} \quad 2.2(iv)$$

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.

Second Layer: It is also known as rule layer. Every node in this layer is a fixed node and labeled as π_n. Every node in this stage corresponds to a single Sugeno-Takagi fuzzy rule. A rule node receives inputs from the respective nodes of layer-1 and determines the firing strength of the each rule. Output from each node is the product of all incoming signals.

$$O_{2,n} = W_n = \mu_{A_i}(X_1).\mu_{B_i}(X_2).\mu_{C_i}(X_3).\mu_{D_i}(X_4) \quad (2.3)$$

where W_n represents the firing strength or the truth value, of nth rule and n=1, 2, 3…636 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 nth rule's firing strength to sum of all rules's firing strength.

$$O_{3,n} = \overline{W}_n = \frac{W_n}{\sum_{n=1}^{625} W_n} \tag{2.4}$$

The number of nodes in this layer is the same the number of nodes in the previous layer that is 625 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,

$$O_{4,n} = \overline{W}_n f_n = \overline{W}_n \left[p_n(X_1) + q_n(X_2) + r_n(X_3) + s_n(X_4) + u_n \right] \tag{2.5}$$

Where $\overline{W}_n$ is a normalized firing strength from layer-3 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.

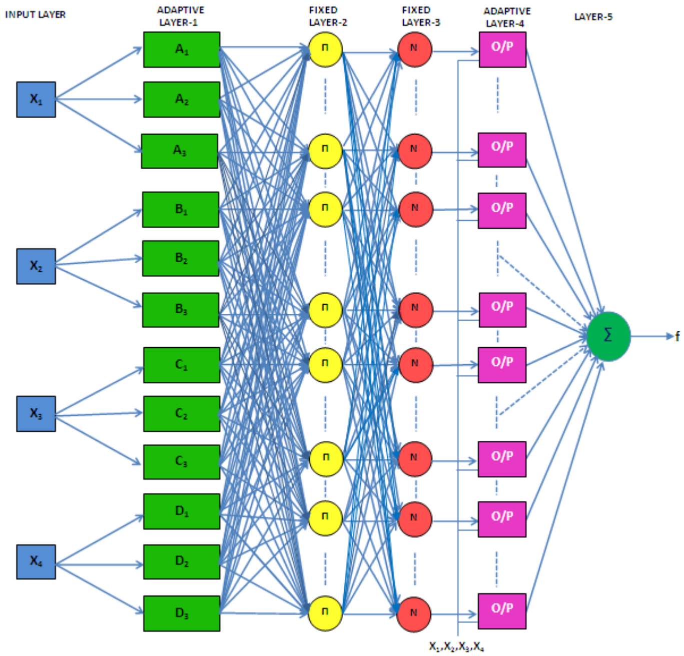

Fig. 2. The structure of ANFIS 1 network

Fifth Layer: It is represented by a single summation node. This single node is a fixed node and labeled as ∑. This node determines the sum of outputs of all defuzzification nodes and gives the overall system output that is wheel velocity.

$$O_{5,1} = \sum_{n=1}^{625} \overline{W} f_n = \frac{\sum_{n=1}^{625} W_n f_n}{\sum_{n=1}^{625} W_n} \tag{2.6}$$

3 Simulation Results and Discussion

We have been verified our proposed hybrid technique in two dimensional path planning through series of simulation experiments under completely or partially unknown environment. Our implementation was compiled using MATLABR2008a processing under Windows XP. All the simulation results were applied on PC with Intel core2 processor running at 3.0GHz, 4Gb of RAM and a hard drive of 160Gb.

The coordinates of the sides of the paths as well as coordinates of any static obstacles were known to the MANFIS controller. Knowing the coordinates of the robot, the current navigational controller can thus calculate the distances and heading angle of the robot, as if it was sensor. In current navigation model, we have been developed two main reactive behaviors: one to reach the target and the other avoiding obstacles. The simulated robot path planning algorithm has been developed and set obstacles at different position of the environment. When a robot is close to an obstacle, it must change its speed to avoid the obstacle. If a target is sensed by a

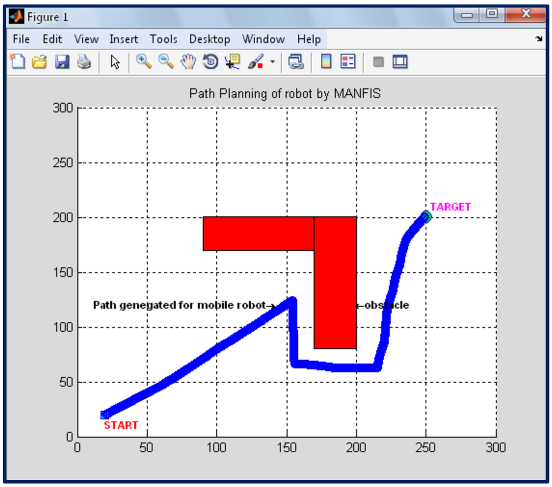

Fig. 3. Single robot escaping from corner end using MANFIS Controller

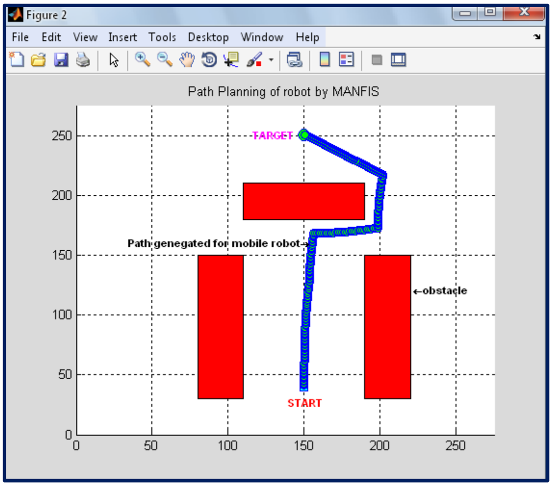

Fig. 4. Single robot escaping from corridor using MANFIS Controller

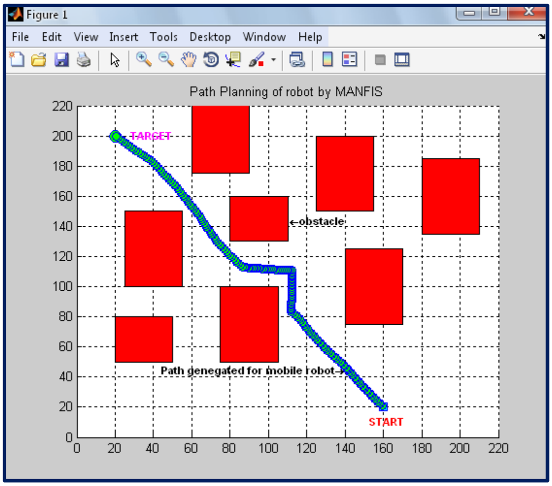

Fig. 5. Single robot escaping from maze environment using MANFIS Controller

mobile robot, it will decide whether it can reach that target, i.e. it will judge whether there are obstacles that will obstruct its path. If the path leading to the source is clear, the robot will turn and proceed towards the source. In Fig .3 to Fig. 5 shows the path created for mobile robot motion in various environments with considering different start and goal positions. It can be observed that, using sensory information, the mobile robot can reach successfully at the target object by efficiently using multiple types of reactive behaviors with proposed navigation algorithm. The simulation experiments were also compared with fuzzy logic and Neural Network and it is verified that using proposed technique the robot reached to the specified target in optimum path length (Table-1).

Table 1.

SL No.	Path length cover by the robot in pixels		
	Fig.3	Fig.4	Fig.5
MANFIS	178	136	150
FUZZY	201	158	188
NN	199	164	186

4 Conclusion and Future Work

In this research paper, a new intelligent hybrid algorithm (MANFIS) has been designed for path planning problem of autonomous mobile robot in an unknown or partially unknown environment populated by variety of static obstacles. It has been observed that the proposed navigational controller is capable of avoiding obstacles and effectively reached at target with optimum/shortest path length. The authenticity of the proposed technique has been verified and proven by simulation experiments using MATLAB. The proposed method has been also compared with other intelligent techniques (Fuzzy logic, Neural network) and the settlement in results show the efficiency of the technique. In future work, the real time implementation is to be carried out using robot and multiple robots are to be considered instead of a single mobile robot.

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