A New Intelligent Approach for Mobile Robot Navigation

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Abstract. In recent times computational 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 optimization methods for modeling an engineering system. In this paper an efficient hybrid technique has been applied for mobile robot navigation using multiple adaptive neuro-fuzzy inference system (MANFIS). ANFIS has taken the advantages of both fuzzy inference system and artificial neural network. First, we design an adaptive fuzzy controller with four input parameters, two types of output parameters and three parameters each. Next each adaptive fuzzy controller acts as a single Sugeno-Takagi type fuzzy inference system where inputs are the different sensor based information and output corresponds to the velocity of the mobile robot. The implementation of the proposed navigational controller is discussed via numerous simulation examples. It is found that such an adaptive neuro-fuzzy controller is successfully and quickly finding targets in an unknown or partially unknown environment.

Keywords: Mobile robot, Navigation, Neuro-fuzzy, Obstacle avoidance.

1 Introduction

At present mobile robots have been successfully used in various areas of engineering such as aerospace research, nuclear research, production engineering etc. The major objective in the current robotic research field is to find a collision free path from a given start position to predefined destination point. In general path planning algorithms are classified as local and global depending upon the surrounding environment. In global path planning the surrounding environment is completely known to the mobile robot so the path travelled by the mobile robot is predefined, where as in local path planning the environment is completely unknown or partially known to the mobile robot so various sensors are used to perceive the information about the surrounding environment and plan the motion accordingly. Many exertions have been paid in the past to improve various robot navigation algorithms.

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In literature survey, there can be found several researchers have been addressed on many intelligent techniques for mobile robot navigation. 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 Visibility Graph [3], Voronoi diagrams [4], Grids [5], Cell decomposition [6], artificial potential field [7], Rule based methods [8], and Rules learning techniques [9] are not appropriate for path planning in dynamic environments. The use of the above algorithms for path finding for mobile robot requires more time and the finding of this path will not completely feasible for real-time movement. There are many fuzzy logic methods using various implementations or in combination with other techniques [10-14]. Mobile robot path planning based on neural network approaches presented by many researchers [15-18].Among the intelligent techniques ANFIS is a hybrid model which combines the adaptability capability of artificial neural network and knowledge representation of fuzzy inference system [19].Song and Sheen [20] developed a pattern recognition method based on fuzzy-neuro network for reactive navigation of a car-like robot. Li et al. [21] suggested a neuro-fuzzy technique for behavior based control of a car-like robot that navigates among static obstacles. Navigation of multiple mobile robots using Neuro-fuzzy technique addressed by Pradhan et al. [22]. 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 discussed by Nefti et al. [23]. Different sensor based information they have given to the SugenoTakagi 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. A Neuro-Fuzzy Controller based mobile robot navigation presented by Kim and Trivedi [24]. In this study they have implemented neural integrated fuzzy controller to control the mobile robot motion in terms of steering angle, heading direction, and speed. To determine collision-free path of mobile robot navigating in a dynamic environment using Neuro-fuzzy technique presented by Hui et al. [25]. In this paper 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 [26]. 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.

We propose in this paper to develop an intelligent navigational controller for solving navigation problem for mobile robot in an unknown or partially unknown environment. A new MANFIS (Multiple Adaptive Neuro-Fuzzy Inference System) controller has been designed to solve the optimization problem. Finally,

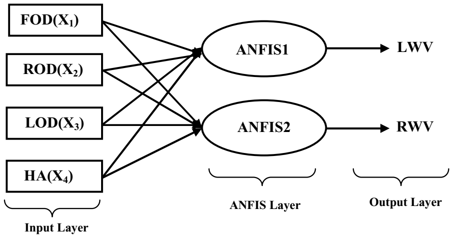


Fig. 1. Multiple ANFIS (MANFIS) Controller for Mobile Robot Navigation

simulation results are presented to verify the effectiveness of the proposed controller in various scenarios populated by stationary obstacles.

2 Architecture of Multiple Adaptive Neuro-Fuzzy Inference System (MANFIS) for Current Analysis

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 [19] in 1993. 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 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(x_4) (TA) and each input variable has three bell membership functions(MF) A_1 (Far), A_2 (Medium) and A_3 (Near) , B_1 (Far), B_2 (Medium) and B_3 (Near), C_1 (Far), C_2 (Medium) and C_3 (Near), D_1 (Negative), D_2 (Zero) and D_3 (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) $= p_n x_1 +\ q_n x_2\ +\ r_n x_3\ +\ s_n x_4\ +\ u_n$

where, i=1,2,3 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 structure. The function of each layer in ANFIS model is discussed as follows:

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

$$O_{0,FOD} = x_1, O_{0,ROD} = x_2, O_{0,LOD} = x_3, O_{0,HA} = x_4 \tag{2.1}$$

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

$$O_{1,i} = \mu_{A_i}(x_1), O_{1,i} = \mu_{B_i}(x_2), O_{1,i} = \mu_{C_i}(x_3), O_{1,i} = \mu_{D_i}(x_4) \tag{2.2}$$

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 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;

$$\mu_{A_i}(x) = \frac{1}{1 + [(\frac{x_1 - c_i}{a_i})^2]^{b_i}}, \tag{2.2a}$$

$$\mu_{B_i}(x) = \frac{1}{1 + [(\frac{x_2 - c_i}{a_i})^2]^{b_i}} \tag{2.2b}$$

$$\mu_{C_i}(x) = \frac{1}{1 + [(\frac{x_3 - c_i}{a_i})^2]^{b_i}} \tag{2.2c}$$

$$\mu_{D_i}(x) = \frac{1}{1 + [(\frac{x_4 - c_i}{a_i})^2]^{b_i}} \tag{2.2d}$$

$a_i, b_i$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. Each rule point receives inputs from the respective points of layer-2 and calculates the firing strength of the each fuzzy rule. Output from each node is the product of all incoming signals.

$$O_{2,n} = W_n = \mu_{A_i}(x_1).\mu_{B_i}(x_2).\mu_{C_i}(x_3).\mu_{D_i}(x_4) \tag{2.3}$$

Where W_n represents the firing strength or the truth value, of nth 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 point in this layer receives inputs from all points in the adaptive fuzzy rule layer and calculates the normalized firing strength of a given rule. The normalized firing strength of the nth point of the nth rules firing strength to sum of all ruless firing strength.

$$O_{3,n} = \overline{W}_n = \frac{W_n}{\sum_{n=1}^{81} W_n} \tag{2.4}$$

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

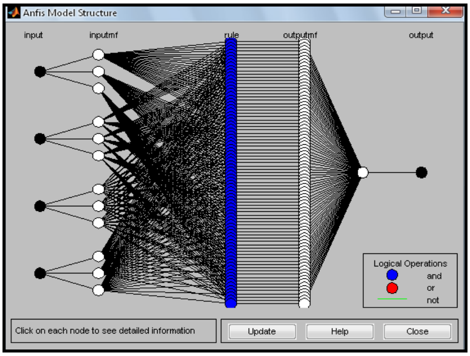


Fig. 2. The structure of ANFIS 1 network

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,

$$O_{4,n} = \overline{W}_n f_n = \overline{W}_n [p_n(x_1) + q_n(x_2) + r_n(x_3) + s_n(x_4) + u_n] \tag{2.5}$$

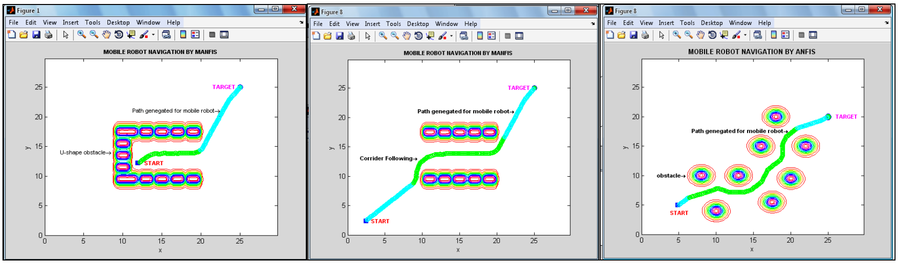
Where $\overline{W}_n$ is a normalized firing strength from layer-3 and are the parameters set of this node. These parameters are also called consequent parameters.

Fifth Layer: It is represented by a single summation node. This single point is a fixed point and labeled as $\sum$. This point determines the sum of outputs of all defuzzification points and gives the overall model output that is velocity of wheels.

$$O_{5,n} = \sum_{n=1}^{81} \overline{W}_n f_n = \frac{\sum_{n=1}^{81} W_n f_n}{\sum_{n=1}^{81} W_n} \tag{2.6}$$

3 Simulation Results and Discussion

In this part MATLAB simulations of the proposed algorithm are presented. In order to verify the validity and performance of the current navigational controller, we have performed the simulation results to verify robot trajectory under the various environmental scenarios according to the robot motion rule. When a robot is close to an obstacle, it must change its speed to avoid the obstacle shown by green color line in simulation figure. If a target is sensed by a 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 target is clear, the robot will turn and proceed towards the target shown by cyan line. In Fig. 3a-3c shows the path created for mobile robot motion in various environments with considering different start and goal positions. It was clearly



(a) Single mobile robot escaping from dead end (b) Single mobile robot escaping from corridor (c) Single mobile robot in maze environment

Fig. 3. Mobile robot navigation using MANFIS controller

observed, through MATLAB simulations, that the proposed hybrid controller technique performs favorably over each individual reactive behavior. By using this technique the mobile robot can reach successfully at the target object.

4 Conclusion

It has been shown that the proposed navigational controller can be successfully implemented for a single target with unknown or partially unknown environment .The main emphasis of the model was placed on flexibility in adaption to various complex environments and robustness to perception uncertainty. The obtained results from above technique were analyzed in a number of simulated experiments and it was clearly observed that the current navigational controller is an effective approach for the obstacle avoidance and moving towards the goal by the mobile robot. Future work involves extending this research work to multiple mobile robots with dynamic obstacles instead of single robot with static obstacles.

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