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Neuro-Fuzzy Based Adaptive Navigation for Truck like Mobile Robot

K. Sudhagar, A. Noorul Haq and T. Selvaraj
Department of Production Engineering, National Institute of Technology, Tiruchirapalli, India

Abstract: An important problem that faces manufacturers in the industry is how automatically backs up a truck like mobile robot to a specified point on a loading dock while loading or unloading. An intelligent approach is desirable for automatically backing up truck. In this study, ANFIS technique is used for obtain the control architecture to control the backward movement of a mobile robot with back propagation learning algorithm. The procedure using neuro fuzzy hybrid logic is described. The truck is trained with three inputs, five-layer neural network and 125 fuzzy rules sets. The controller is able to guide the truck to the dock from almost any initial position in the loading zone.

Key words: Neuro fuzzy, autonomous navigation, mobile robot, ANFIS

INTRODUCTION

Backing a truck to a loading dock in the loading zone is difficult exercise for all but the most skilled truck drivers. Anyone who has tried to back up a house truck trailer will realize this. A great deal of practice is required to develop the requisite skills. When watching a truck driver backing towards a loading dock, one can observes the driver backing, going forward, backing again, going forward etc. and finally backing up to the desired position in the zone. The forward and backward movements help to position the truck for successful backing up to the dock.

A more difficult backing up sequence would only allow backing, with no forward movements permitted. Design of a nonlinear controller by self learning to control the steering of a truck like robot while backing up to a loading duck from any initial position is developed by Nguyen and Widrow (1989) using two layer neural controller containing twenty five adaptive neural elements in the first layer and one element in the second layer.

In the recent years fuzzy logic control has emerged as one of the practical solution when the process is too complex and non linear for analysis by conventional quantitative techniques. However, the development of a fuzzy controller has to rely on the experience of the experts for deriving effective fuzzy control rules. Recently there has been an increasing use of Artificial Neural Networks (ANN) for various applications particularly because of their capability of learning from examples and adaptation. In the proposed system, both the FLC and ANN have been employed together and an Adaptive Neuro Fuzzy Inference System (ANFIS) is developed.

Many trails are made based on the intelligent control techniques like fuzzy logic control system and artificial neural networks to backing up the truck.Widrow and Nguyen (1989, 1990) extended the use of neural networks to solve highly nonlinear control problems. A two layer neural network containing 26 elements has learned to back up a simulated truck in a loading zone. A neural network controller steering a truck while backing up to a loading dock is demonstrated. Freeman (1994) developed a fuzzy control system that automatically back up a truck to a specified point on a loading dock. They have produced animation of the moving truck by mapping the function. A fuzzy logic implementation of a control system is often a better choice when a model of the system is not available or the model is too complex to simulate.

Another group effort based on intelligence techniques is made by Kosko (1992) and Kong and Kosko (1990). They developed fuzzy and neural system to back up a simulated truck and trailer to a loading dock in a planar parking lot from training data taken from the fuzzy and neural simulation. They generated FAM (Fuzzy Associative Memory) rules to control the truck-trailer. They have trained the neural truck systems with the back propagation algorithm. Bentalba designed a fuzzy control method for the purpose of generates the deceleration forces from the generated steering angle and the speed of the truck. In the design proposed by Nguyen and Widrow (1989), a nonlinear control system based on Neural Networks (NNs) ‘Neuro interface’ serves as a coupler between a human operator and a nonlinear system. Widrow and Malini (2002) apply the ideas to backing a truck with two trailers under human direction. Majority of

Corresponding Author: K. Sudhagar, Department of Production Engineering, National Institute of Technology, Tiruchirapalli, India

the published articles on backward motion of truck like robot is based on the time consuming and block box natured neural network and in some cases fuzzy logic technique is individually used.

In this research, the novel approach is implemented; the Neuro-Fuzzy technique (ANFIS) (Althoete, 1996) is developed to control the backward movement of the truck like robot in the loading zone.

PROBLEM DESCRIPTION AND MODELING

The task of the truck-backer-upper problem to be outlined as follows: A truck is positioned at an arbitrary position (x, y) on a yard with an arbitrary angle of the truck with horizontal (φ). The truck moves at constant speed backwards. Figure 1 shows the simulated truck and loading zone.

The truck corresponding to the cab part of the neural truck in the Nguyen and Widrow (1989) neural truck backer-upper system. The three state variables φ, x and y exactly determine the truck position. 'φ' specifies the angle of the truck with the horizontal. The coordinate pair (x, y) specifies position of the rear center of the truck in the loading zone. The goal is to make the truck arrive at the loading dock at a right angle middle position of loading zone and to align the position (x, y) of the truck with the desired loading dock (0,0). We considered only backing up. The truck moved backward by some fixed distance at every stage (Kosko, 1992; Kong and Kosko, 1990).

At every stage the neuro-fuzzy controller should produce the steering angle 'θ' that backs up the truck to the loading dock from any initial position and from any angle in the loading zone.

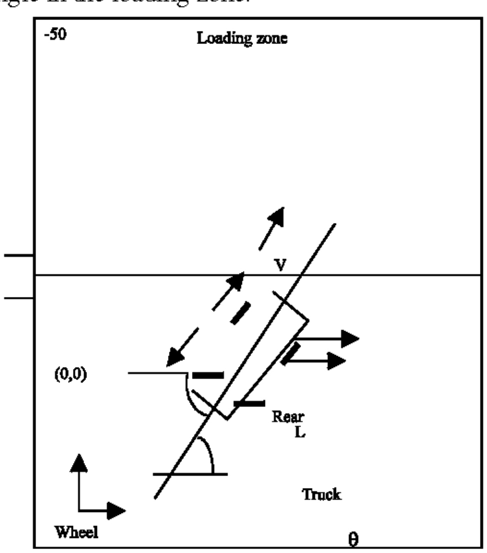

Fig. 1: Simulated truck and loading zone

TRUCK LIKE MOBILE ROBOT DYNAMICS MODEL

Consider the dynamic equations describing the truck like robot vehicle, as introduced in Nguyen and Widrow (1989); the system equations for the motion of truck have been derived from the geometric considerations and are described as:

$$\frac{d\theta}{dt} = \frac{v \tan \varphi}{L} \tag{1}$$

$$x' = x + r \cos \varphi' \tag{2}$$

$$y' = y + r \sin \phi' \tag{3}$$

$$\phi' = \phi + \theta \tag{4}$$

r = Fixed driving distance of the truck for all backing movements.
v = Constant backing speed.
L = Length of the truck.

Where (x, y) is the starting point and (x^1y^1) is the final point of the truck on its motion. φ = Truck angle with horizontal, θ = Steering angle, φ' = New truck angle with horizontal. The variable ranges were as follows:

$$-50 \le x \le +50$$
$$-90 \le \varphi \le 270$$
$$-30 \le \theta \le 30$$

Positive values of è represented clockwise rotations of the steering wheel. Negative values represented counter clockwise rotations. The resolution of φ and θ was one degree each.

ADAPTIVE NEURO-FUZZY BASED TRAINING

In this study, a class of adaptive network is proposed that are functionally equivalent to fuzzy inference systems. The proposed architecture is referred to as ANFIS, which stands for adaptive neuro fuzzy inference system.

The Adaptive neural networks based fuzzy logic controller is designed with three inputs, the position of rear center of the truck in the loading zone (x, y) and the truck angle with horizontal (φ). The training data is viewed to be very complex hence five linguistic variables for each input variable were used to get the desired performance. The linguistic variables are specified by Gaussian membership functions and as a result 125 rules are devised. The rule-base contains the fuzzy IF-THEN rules of Sugeno's first order type (Takagi and Sugeno, 1985) in which the output of each rule is a linear combination of input variables plus a constant term. The final output is the weighted average of each rules output. A specific rule set with fuzzy logic is as follows:

Rule 1: IF x is A_1 and y is B_1 and φ is C_1,
THEN $f_1 = p_1 x + q_1 y + r_1 \varphi + s_1$

Rule 2: IF x is A_2 and y is B_2 and φ is C_2
THEN $f_2 = p_2 x + q_2 y + r_2 \varphi + s_2$.

The architecture of the ANFIS (Rajendran and Sing, 2000) using inputs x, y and φ is shows in Fig. 2. Node functions in each layer are described.

Layer 1: Each node in this layer performs a Gaussian membership function.

$$O_{1,i} = \mu_{Ai}(x_i) = \exp(-(c_i - X_i)^2 / 2\sigma^2) \quad i = 1....5 \tag{5}$$

Where c_i and σ_i are the center and width of the i^{th} fuzzy set A_i respectively, X_i is the input to the node i.

Layer 2: Every node in this layer represents the firing strength of the rule

$$O_{2,i} = w_i = \mu_{Ai}(x_i).\mu_{Bi}(y_i).\mu(\varphi) \quad i = 1....5 \tag{6}$$

Eventually the nodes of this layer perform fuzzy and operation.

Layer 3: The nodes of this layer calculate the normalized fixing strength of each rule

$$O_{3,i} = \overline{w_i} = \frac{w_i}{\sum w_i} \quad i = 1....5 \tag{7}$$

Where w_i is the fixing strength of a rule.

Layer 4: The nodes in this layer output the weighted consequent part of the rule table.

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i \varphi + s_i) \quad i = 1....5 \tag{8}$$

Where $\{p_i, q_i, r_i, s_i\}$ is the parameter set of the node 'i'. It is also called as consequent parameter.

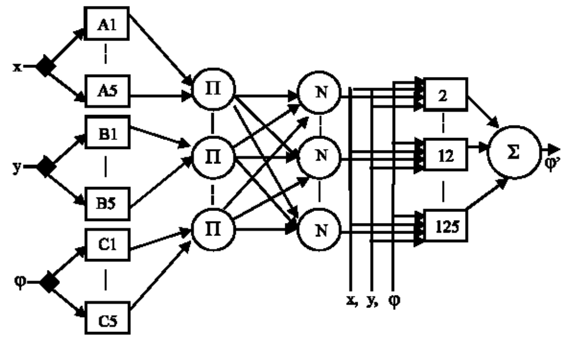

Fig. 2: ANFIS architecture

Layer 5: The single node in this layer computes the overall output as the summation of all the incoming signals.

$$O_{5,i} = \sum \overline{w_i} f_i = \frac{\sum w_i f_i}{\sum w_i} \quad i = 1....5 \tag{9}$$

Where $O_{1,i}$ denote the output of the i th node in layer 1.

Hybrid learning algorithm and training: The learning algorithm for the connectionist network structure consists of two separate stages of a learning strategy, which combines unsupervised learning and supervised gradient descent learning procedure. In phase one a self-organized learning scheme is used to locate initial membership functions and to find the presence of fuzzy logic rules. In phase two, a supervised learning scheme is used to optimally adjust the parameters of membership functions for desired output.

The back propagation algorithm (Jang *et al*., 2002) is used for the supervised learning. To initiate the learning scheme, training data and the desired or guessed coarse of fuzzy partition (i.e., the size of the term set of each input/output linguistic variable) must be provided from the outside world (Lin and Lee, 1991).

The ANFIS training is done assuming that there is no expert available and the initial values of the membership function parameters are equally distributed along the universe of discourse and all consequent parts of the rule table set to zero. The ANFIS starts from zero output and during training it gradually learns the rules and functions as close to the desired controller. Thus during training the network structure update membership functions and rule-base parameters according to the gradient descent update procedure. A total of 1500 input-output data pairs are created for the training of adoptive neuro fuzzy based truck like mobile robot system.

RESULTS AND DISCUSSION

Computer simulation was carried out to test the proposed method. The truck was placed in a variety of initial conditions and backing up was effected in each case. The results are illustrated in Fig. 3-6.

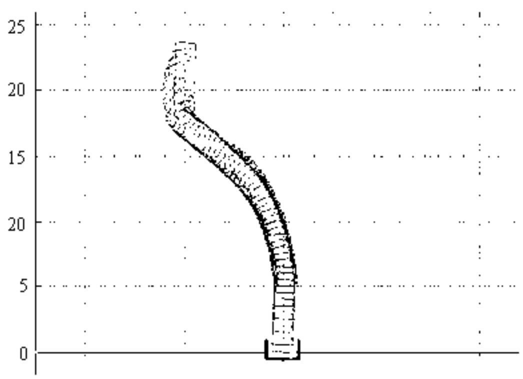

Fig. 3: Docking of truck from initial position (-20, 22)

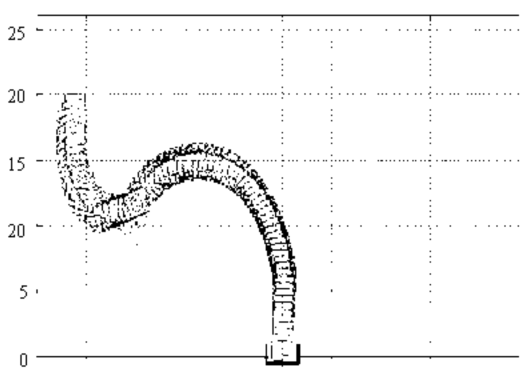

Fig. 4: Docking of truck from initial position (-42, 18)

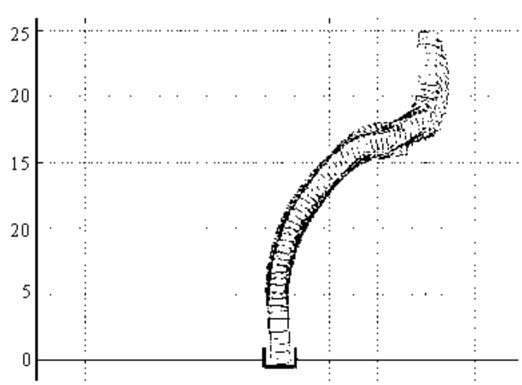

Fig. 5: Docking of truck from initial position (30, 23)

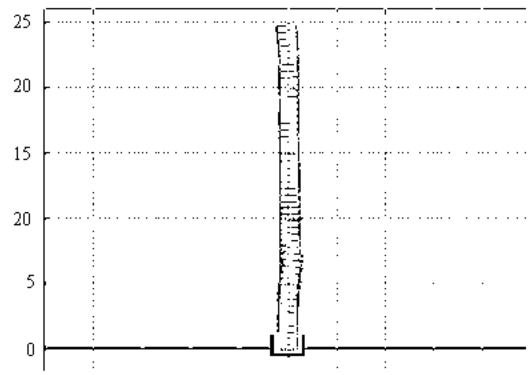

Fig. 6: Docking of truck from initial position (0, 18)

CONCLUSION

The major contribution of this research has been the application of neuro fuzzy logic in the design of a controller to navigate a truck like mobile robot. A neuro fuzzy logic controller steering a truck while backup to a loading dock is demonstrated. The fuzzy rules are derived from the training examples and the designed controller is adaptive. Simulation results show that the designed neuro fuzzy controller is able to guide the truck to dock from almost any initial position in the loading zone.

The conclusion drawn from the results of the proposed controller is:

- Lack of online complicated mathematical computations makes it more reliable for real time application.
- The controller is adaptive for various initial positions in the operating area and significantly improves the performance of the system.

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