Unmanned Vehicle Trajectory Tracking by Neural Networks

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Abstract: *This paper, deals with a path planning and intelligent control of an autonomous vehicle which should move safely in its road partially structured. This road, involves a number of obstacles like donkey, traffic lights and other vehicles. In this paper, the Neural Networks (NN)-based technique Artificial Neural Network (ANN) is described to solve the motion-planning problem in Unmanned Vehicle (UV) control. This is accomplished by choosing the appropriate inputs/outputs and by carefully training the ANN. The network is supplied with distances of the closest obstacles around the vehicle to imitate what a human driver would see. The output is the acceleration and steering of the vehicle. The network has been trained with a set of strategic input-output. The results show the effectiveness of the technique used, the UV drives around avoiding obstacles.*

Keywords: *UV, NN, control.*

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1. Introduction

Modern systems are becoming increasingly more complex, making conventional control algorithms that utilize mathematical models insufficient. This resulted in the evolution of soft computing techniques [5] based on biological processes such as learning and evolutionary development. Soft computing techniques model human intelligence, providing decisions given imprecise and uncertain information [1]. The three most commonly employed soft computing tools are fuzzy logic, Neural Networks (NN) and genetic algorithms [4, 6, 8].

One of the most widely researched topics in the soft computing community is autonomous vehicles. The term autonomous represents the elimination of human control. Thus, autonomous vehicles generally refer to vehicular systems capable of performing navigation tasks without human guidance.

Autonomous vehicles are a promising technology with the ability for reduced traffic congestion and decreased accidental rates. Common tasks which require automation include lane-following, parking, collision avoidance, vehicle following, traffic signal detection and navigation at intersections.

Unmanned Vehicle (UV) has the ability of a mobile robot to reach the set targets by avoiding obstacles in its way. Thus, essential behaviors for UV navigation are obstacle avoidance and goal reaching [3]. Conventional control techniques can be used to build controllers for these behaviors; however, the environment uncertainty imposes a serious problem in developing the complete mathematical model of the system resulting in limited usability of these controllers. Amongst the various artificial intelligence techniques available in literature, NN offer promising solution to autonomous navigation problem because of their ability to learn complex non linear relationships between input values and output control variables. This ability of NN has attracted many researchers across the globe in developing NN based controllers for reactive navigation of mobile robots or vehicles in its environments.

This paper, investigates the possibility of applying NN predictive control to mobile vehicle in its road. The main objective is to have a vehicle that drives by itself and avoids obstacles in a virtual world. Every instant, the vehicle decides by itself how to modify its speed and direction according to its environment. In order to make it more real, the NN should only see what a person would see if it was driving, so the UV decision is only based on obstacles that are in front of the vehicle. By having a realistic input, the NN could possibly be used in a real vehicle and work just as well.

The organization of the paper is as follows: Section 2 brings out the research method which describes the navigation system developed section 3 give the briefly description of the NN. Section 4 describes the implementation of the NN controller. Simulation results and discussions are given in section 5. Section 6 will summarize our conclusions and gives the notes for our further research in this area.

2. The Research Method

The objective of the navigation system developed in this work consists of driving the vehicle to follow a reference path from an initial point to a final one in a partially structured environment as shown in Figure 1. Unexpected fixed obstacles are considered, shown in Figure 2.

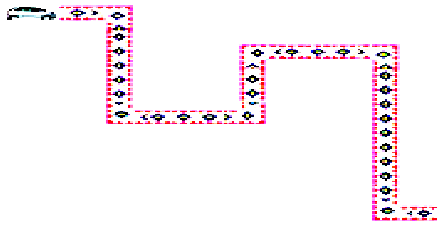

Figure 1. Reference path.

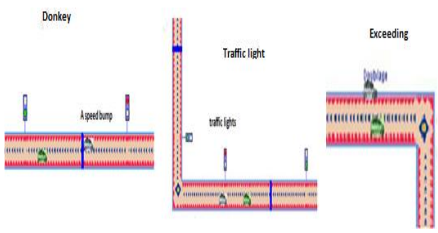

Figure 2. Obstacles avoidance (speed bump, traffic lights and vehicles exceeding).

3. Neural Networks

NN [2] are powerful tool for the identification of systems typically encountered in the structural dynamics fields. NN were originally developed to simulate the function of the human brain or neural system. Artificial Neural Network (ANN) is basically a massive parallel computational model that imitates the human brain. This method does not really solve problems in a strictly mathematical sense, but they are one method of relaxation that gives an approximate solution to problems. A number of NN techniques have been used in system identification such as backpropagation network [8], Hopfield network and Kohonen network. In the present paper, the most widely used technique; the back propagation NN is adapted for the identification of a structural dynamic model. The principles of the back propagation NN are shown in the following.

A typical three-layer back propagation NN is shown in Figure 3 and consisted of the next: The input layer with *a* nodes, the hidden layer with *b* nodes and output layer with *c* nodes. Between layers there are weights W_{ha} and W_{ch} representing the strength of connections of the nodes in the network. The first type of operation of back propagation NN is called feed forward and is shown as solid lines with arrow in Figure 3. For this operation, the output vector $C(t)$ is calculated by feeding the input vector $A(t)$ through the hidden layer of the neural network. The output of the node *h* in the hidden layer $H_{h(t)}$ for the given input layer $A(t)$ is:

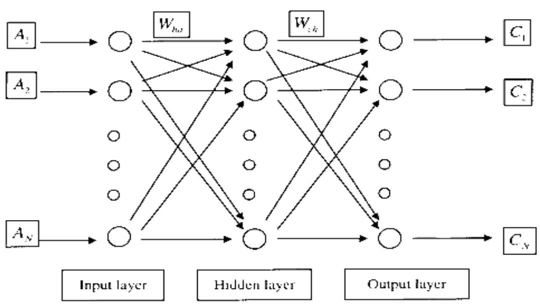

Figure 3. Three layer back propagation NN.

$$H_h(t) = F(Net_h(t)) \tag{1}$$

$$H_h(t) = F\sum_i (W_{hi} A_i(t)) \tag{2}$$

Where Net_h represents the total input to the node *h* in the hidden layer and $F(x)$ is the activation function, which has to be differentiable. In this paper, the activation function is the sigmoid function.

$$F(x) = \frac{e^{x_j}}{e^x + 1} = \frac{1}{1+e^{-x}} \tag{3}$$

The output of the node *c* in the output layer $C_c(t)$ is:

$$C_c(t) = F(Net_c(t)) \tag{4}$$

$$H_h(t) = F\sum_h (W_{ch} F(W_{hi} A_i(t))) \tag{5}$$

Where Net_c represents the total input to the node *C* in the output layer.

The second type of operation of the back propagation NN is called error back propagation, which is marked by dashed lines in Figure 3. The sum of the square of the differences between the desired output $Lc(t)$ and NN outputs $C(t)$ is:

$$E = \frac{1}{2}\sum_h (L_c(\mathrm{t}) - C_c(\mathrm{t}))^2$$

The adaptive rule for the weight W_{ch} as the connections between the hidden layer and output layer, can be determined as:

$$W_{ch}(t+\Delta t) = W_{ch}(\mathrm{t}) + \Delta W_{ch} \tag{7}$$

$$\Delta W_{ch} = -\eta \frac{\partial E}{\partial W_{ch}} \tag{8}$$

$$\Delta W_{ch} = -\eta \sum_i \Delta_c(t) H_h(t) \tag{9}$$

$$\Delta_c(t) = \frac{dF(Net_c)}{dNet_c}(L_c(t) - C_c(t)) \tag{10}$$

The adaptive rule for connections between the input layer and the hidden layer W_{hc} as:

$$\Delta W_{ha} = -\eta \frac{\partial E}{\partial W_{ha}} \tag{11}$$

$$\Delta W_{ha} = -\eta \sum_i \Delta_h(t) A_a(t) \tag{12}$$

$$\Delta_h(t) = \frac{dF(Net_h)}{dNet_h} \sum_c W_{hc} \Delta_{c(t)} \tag{13}$$

The coefficient η is called the learning rate. The error back propagation rules shown in Equations 8 and 13 with applying the differentiation process successively can be expanded to the networks with any number of hidden layers. The weights in the network are continuously adjusted until the inputs and outputs reach the desired relationship.

4. The System Model

The neural system to control the vehicle in its road is modelled as shown in Figure 4.

As input of the neural system the vector of positions (X, Y) which characterize four positions: The position of every object, the position of the road, the position of the vehicle and also, the position of obstacles. The second information is the velocity V of the vehicle and finally the Obstacle O.

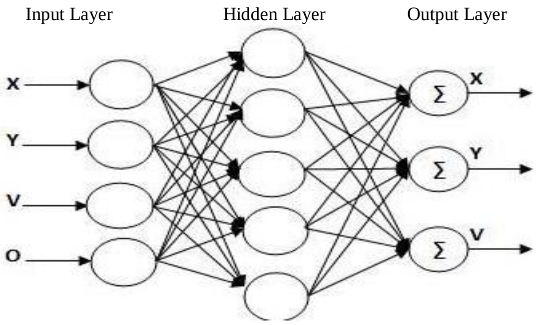

Figure 4. NN Architecture.

The output needs to control the vehicle's speed and direction. That would be the acceleration, the brake and the steering wheel. So, three outputs are needed, one will be the acceleration/brake since the brake is just a negative acceleration and the others will be the positions.

In Table 1 different arrangements of obstacle relative to the vehicle, velocity and the desired reaction from the UV are visualized.

Table 1. Vehicle situations on the road.

Input Neurons Relative to Obstacle and Velocity			Output Neurons Relative to Velocity	
Obstacle	**Velocity**	**Antecedent**	**Acceleration**	**Consequent**
No Obstacle	Full Acceleration		Full Acceleration	No Action
No Obstacle	Low Acceleration		Accelerate	
Donkey	Full Acceleration	Distance donkey is D	Slow down	
Traffics Lights	Full Acceleration	Color traffic lights is Green	Slow down	
Traffics Lights	Full Acceleration	Color traffic lights is Red	Stop	
Vehicle	Full Acceleration	Our vehicle speed is greater than the vehicle on the road	Full Acceleration	Change of position and exceeding
Vehicle	Full Acceleration	Speed of your vehicle is smaller than that of vehicle in road	Full Acceleration	No Action

5. Simulation Results and Discussions

In this section, to show the contribution of the control by NN approach, simulation was approved on an UV.

First, Figure 5 shows the path followed by the UV controlled by the proposed NN including obstacles described in the above sections.

Figure 6 shows the vehicle's path obtained after controlling with the NN and Figure 7 gives the error calculated between the reference paths and obtained one after application of control.

As it can be seen from Figures 6 and 7 the path obtained from simulation setup is more close to the reference path which validates the proposed method. Figure 8 shows the generations of rules.

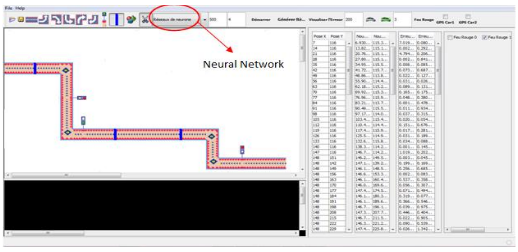

Figure 5. Learning about sample reference path.

Figure 6. The path found by the NN.

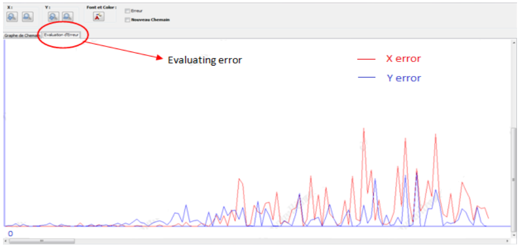

Figure 7. The error between the reference path and the path calculated.

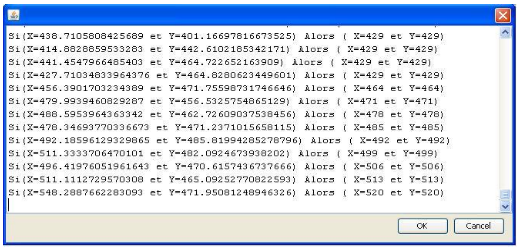

Figure 8. Generation of rules.

The function of the speed controller subsystem is to achieve the desired speed that is to say the increase and decrease in speed on the road and especially in front of obstacles, so the accelerator control. Figure 9 shows the variation of the UV speed in function of obstacles come across the road.

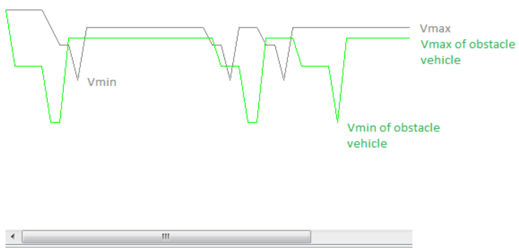

Figure 9. Vehicle speed variations at obstacles.

From Figure 9, it can be seen that the UV can indeed avoid obstacles and reach the targets. To verify the feasibility of proposed method Table 2 shows results of NN controller.

Table 2. NN best simulations results.

Datasets	**Statistical Results**	
Rate Accuracy (%)	**Total Classification Accuracy (%)**	
Set X	98.43	98.77
Set Y	99.11	

Therefore, it can be concluded that the NN controller have a good potential to effect fast response to obstacles and reduce errors.

To show the performance of the results obtained by our approach, an approach based on type-2 fuzzy logic theory and genetic algorithm.

Algorithms [7] have been selected for comparison because of its high capacity of prediction and control in non linear dynamical systems.

Table 3. Comparison of the NN results with GA-FL.

Approach	**Average Error**
NN	1.23
GA-FL	3.81

The average error obtained with fuzzy logic combined with the genetic algorithm (GA-FL) is mentioned in Table 3 and by comparing with the results obtained by the NN algorithm, it is demonstrated that neural networks can be used effectively for the identification and control of nonlinear dynamical systems precisely in autonomous vehicle path planning.

6. Conclusions

Automatic motion planning and navigation is the primary task of an automated guided vehicle or mobile robots. All such navigation systems consist of a data collection system, a decision making system and a hardware control system. In this research, our artificial intelligence system is based on NN model for navigation of an UV in unpredictable and imprecise environment.

We have designed a trajectory tracking controller taking into account the obstacles using NN and we have demonstrated that soft computing approaches are more preferable over conventional methods of problem solving, for problems that are difficult to describe by analytical or mathematical models. Autonomous robotics is such a domain in which knowledge about the environment is inherently imprecise, unpredictable and incomplete. Therefore, the features of NNs are of particular benefit to the type of problems emerging in behaviour based robotics. Soft computing techniques contribute to one of the long term goal in autonomous robotics, to solve the problems that are unpredictable and imprecise namely in unstructured real-world environments.

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