

Adaptive Cruise Control using Fuzzy Logic

Ankita Singh
M.Tech. Scholar
Medicaps Institute of Technology and
Management Indore (India)
ankitasingh.srcem@gmail.com

C. S. Satsangi
H.O.D., Dept. of Computer Science
Medicaps Institute of Technology
and Management Indore (India)
cssatsangi108@gmail.com

Prashant Panse
Associate Prof., Dept. of Information
Technology
Medicaps Institute of Technology
and Management Indore (India)
prashant@medicaps.ac.in

Abstract –In recent years many studies on intelligent vehicles have been devoted to solve problem such as accident prevention, traffic flow smoothing. Adaptive Cruise Control (ACC) is used to maintain a constant safe distance between the host vehicle and the leading vehicle to avoid rear end collisions. It is an automotive feature that allows the speed of the vehicle to adapt to the traffic environment. ACC operates in distance control mode and velocity control mode. The method by which the ACC vehicle's speed is controlled is via engine throttle control and limited brake operation. The inter-vehicular distance between the vehicles is measured. Desired speed is obtained from the distance measured. Neural Network and fuzzy logic Controller is trained to produce the desired acceleration and braking. In this research, ACC is implemented using the comparative analysis of Neural Network and Fuzzy Algorithm. The results demonstrate that for every parameter the proposed architecture outrages the conventional Neural Networks. The model is developed on MATLAB platform and comparisons were made based on evaluation parameters.

Keywords – Adaptive Cruise Control (ACC), Fuzzy Logic Controller, Neural Network.

I. INTRODUCTION

Collision-avoidance system is the computer controlled architecture assembled for motor vehicles. These systems were developed to aid security for the driver and accompanying passengers. The mechanical version of these systems (Brakes) is pre-installed in the driving units and is also a mandatory benchmark for manufacturing companies. Automated systems include the monitoring devices that observe the behaviour of driver into two factors: 1) driver's behaviour to the 2) surrounding environment. These observations based on certain collision probability detection warn the person about the event.

Importance: The purpose of these systems is to minimize the probability of collision at any cost and is also termed as automated preventative strategy. In 1969, Director of National Highway Safety Bureau (NHSB) in United States created "Haddon Matrix". According to Emergency Medical

Services (EMS), this matrix is a "Public Health Model to the 'Epidemic' of Traffic-Related Injury". The matrix is a three stage process related to crash events known as: pre-event, event and post event. Collision avoidance is useful only at pre-event stage of incident to avoid the occurrence of other two stages (or at least minimize the damage followed by them). Every year over the globe, around 1.2 million people lose their life in road accidents. Also additional 50 million people get injured in severe or lax manner [1].

Collision Avoidance Systems (CAS) offers braking feature or self-directing the vehicle by evasive steering manoeuvre if it is prone to collide. An important aspect of such systems is the automated capability of vehicle control that can be self-activated at early stage of intervention. The significant difference between CMS and CAS is that the latter is authorized to activate evasive actions at an earlier stage compared to the CMS. Early brake intervention is needed in order for the CAS to totally avoid the accident. In both cases of CMS and CAS, efficient and reliable threat assessment algorithms are mandatory. The algorithms based on data are required to generate an appropriate response in minimal computational time. The overall response time and accuracy of output determines the efficiency and reliability of assessment algorithms. In comparison with CMS, CAS is quicker in response time as intervention is performed much earlier in this case.

Objective

When two cars (for implementation purpose) run on road, the possibility of collision is divided equally on the consciousness of both drivers. To prevent the collision and following damage (where human life is most costly) automated system is developed to prevent collision. This system monitors the speed of vehicles (The ACC is applied in rear car) and automated brakes are applied depending on the factors: speed and distance. Driver's state condition is not considered in this research. Further, the speed of cars is regulated to keep relative distance for active monitoring of speeds.

II. LITERATURE REVIEW

Prior Work

Figure 1 depicts the block representation of CAS. The CAS sources its data from various sensors. In this example, CAS consists of radar and vision data as input. Supporting sensors facilitate the parallel information that is required for assessment of collision. A collision is probability is determined based on the speed, yaw rate and acceleration of vehicle.

In this example, the radar data is processed together with the vision data in a sensor fusion algorithm where information from the two sensors is fused into confirmed target tracks. There is a wide area of technical publications handling sensor fusion, such as [2]. Sensor fusion is a separate and complex topic; this implies that a target matching algorithm could be designed in numerous ways.

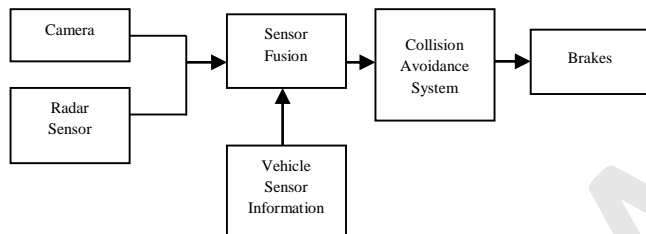


Figure 1: Functional Overview of a Collision Avoidance System

In this example, the radar data is processed together with the vision data in a sensor fusion algorithm where information from the two sensors is fused into confirmed target tracks. There is a wide area of technical publications handling sensor fusion, such as [2]. Sensor fusion is a separate and complex topic; this implies that a target matching algorithm could be designed in numerous ways.

Review of Recent Papers

The braking system of cars was evolved as the first measure of computer-controlled collision avoidance technology. The anti-lock braking system (ABS) was first attempt from an engineer to compensate with immature driver. This system was first introduced at the end of 1960s on two cars: Ford Thunderbird and Lincoln Continental Mark IIIs. This was termed as Sure-Track Braking [3] and prevented vehicle from slipping during emergency brakes as they allowed constrained rotation by not locking the wheels. The braking force was immensely enhanced as the wheels possessed better traction compared to previous ones that skidded across the surface. The ABS was further modified and a computer unit was installed in integration with vehicle that obtained its related input from electronic wheel sensors.

A Traction Control System provides the wheels of cars a better contract with the surface of track. This

mechanical system later was supplemented with computer technology and was implanted in vehicles along with ABS. The system is designed to deal with lateral (front-to-back) loss of friction only under acceleration [4]. For example, if the roadway surface has turned to ice and becomes slick then the friction between the vehicle's tires and the road is almost non-existent. In this case, TCS's computer will take over and regulate the engine speed and the power that your wheels are receiving not allowing you to spin out. One way to envision TCS is realizing it is the opposite of ABS; concerned with acceleration and not deceleration (ABS). Traction control started to gain momentum as an offered safety option, but it was not until a technology package, called Electronic Stability Control (ESC), that such a system was mandatory for new vehicles in the United States. The later version of FMVSS also known as ESC mandates a computer to progressively observe the reduced traction.

ECS is a unified approach of ABS and TCS technologies and if the driver is found to have diverted attention, the system takes over the control and applies brakes to degrade the speed of vehicle.

NHTSA mandated ESC once its effectiveness was proven, and by model year 2012 100 percent of vehicles were to be outfitted with this ground-breaking semi-autonomous vehicle technology [5].

Woll [6] discussed the use of radar technology for collision warning and other vehicular applications. Grosch [7] observed that radars are valuable sensors for all weather operation, and that experiments with automotive radar sensors have been conducted for over 40 years. Radar design difficulties and trade-offs regarding operating frequencies, frequency bandwidth requirements, transmitted power and the use of existing low cost production components are presented by the author.

A commercial production radar system is discussed, and the theory of operation of this radar system is described. A discussion of existing FCC regulations as related to intentional radar radiators and future FCC considerations is provided as well as some insight into international regulatory considerations.

The collusion warning radar is a potentially significant application of radar technology to the automotive market. Thus other researchers Esteve [8] proposed using a LIDAR system to detect range, and a RADAR system to measure distance, and a Doppler system to find velocity. Hisccke [9] observed that radar systems do not function properly in the presence of signals from other radiators. He anticipated that, as the number of radars increases, systems designed without consideration of the interference problem will exhibit poor or degraded performance. He identified the fundamental design parameters useful for maximizing operation in the presence of interference.

Kenue [10] developed an algorithm for specifying range and azimuth angular coverage of a radar sensor. The algorithm combines geometric and accident data analysis of straight and curved roads with worst-case horizontal curvature.

A frequency modulated /continuous wave (FM/cw) radar was developed [11] for automotive applications. The objective of this effort was to design low-cost automotive collision warning radar that could be operated under Part 15 of the U.S. Federal Communications Commission regulations regarding intentional radiators including proximity sensors. Data are presented showing radar measurements of a conducting sphere and test vehicle.

Li et al. [12] proposed a technique that they have tested for use in connection with collision avoidance radar to be used in automobiles. To this end a six-port microwave/millimetre wave digital phase/frequency discriminator is used to measure Doppler frequency shifts. They explained that this arrangement allows the determination of relative speed and the direction of travel of the target vehicle. Ranging is implemented by the measurement of phase difference at two adjacent frequencies.

III. ADAPTIVE CRUISE CONTROL (ACC)

The future within cruise control systems development is likely to be aimed towards adaptive systems. Adaptive cruise control systems can autonomously control the range between the host vehicle and the vehicle ahead of the ego vehicle. When the road ahead is clear the system automatically adjusts the velocity up to the user defined level. These kinds of systems can be very useful for maintaining a safe distance to the closest vehicle ahead and enable the driver to concentrate on other important aspects of driving. It is common that the user has the ability of controlling the system by specifying a preferred distance up to the closest vehicle ahead, as well as a preferred speed level when the road is clear.

Patterson [13] studied ACC's impacts on capacity and safety. His thesis compared ACC with conventional cruise control and manual driving in both macroscopic and microscopic level. In macroscopic level, it is found that ACC was used more in similar trips and the number of brake interventions in ACC vehicles is larger than that in CCC vehicles. In the microscopic level, it is found that manual driving results in larger headway. But ACC and CCC have similar speed-headway profiles. Because of some advantages to fuzzy logic models, Wu et al. [14] gave a complete description of the fuzzy sets for both car following and lane changing in FLOWSIM which offers a user defined update rate and applies accelerations. The fuzzy inference model for car following is based divergence of the ratio of vehicle distance to desired vehicle distance and the relative

speed of two vehicles. Holve et al. [15] suggested that ACC system has to meet the expectations of the human driver to a certain degree. They proposed an adaptive fuzzy logic controller that is flexible in different driving situations and comprehensible for the driver. Holve et al. [16] also proposed a scheme to generate fuzzy rules of ACC controller, in which the driver is a component of the ACC control loop. Their Fuzzy-ACC has been tested in normal road traffic. Similar work can be found in Chakroborty et al. [17], in which relative speed, distance headway and acceleration/deceleration rate of leading vehicle are the inputs to a fuzzy logic model.

Hybrid systems have captured the attention of the research community in the past few years. Indeed, interesting theoretical results, as well as control applications have been reported in the literature in recent years. Automotive control has been the first field where hybrid systems have revealed their potential.

IV. PROPOSED METHODOLOGY

This research has adopted BPNN, RBNN and Fuzzy logic for controlling of ACC parameters. This algorithm is designed with parameters for safety of transportation only. In this section, algorithms are discussed based on mathematical quotations as implemented. Further the results are studied for comparison and to identify the nobility of proposed architecture.

Back Propagation Neural Network

Back Propagation Neural Network (BPNN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well.

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyse. This expert can then be used to provide projections given new situations of interest and answer "what if" questions.

Feedback Networks

Feedback networks (figure 2) can have signals travelling in both directions by introducing loops in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic; their 'state' is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found. Feedback architectures are also referred to as interactive or recurrent, although the latter term is often used to denote feedback connections in single-layer organisations.

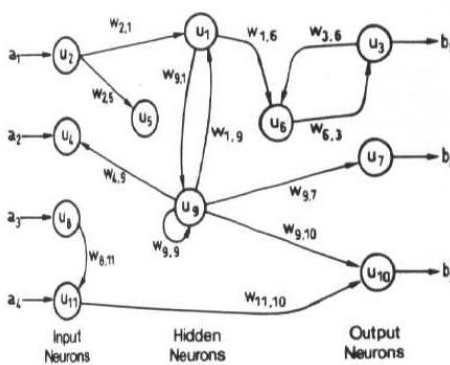


Figure 2: An Example of a Complicated Network

- STEP 1: Creating a training set of input speed error and targets throttle command and brake command [18].
- STEP 2: Creating a feedforward network, with 2 layers. Hidden layer-3 Neurons, Tansig transfer function Output layer-1 Neuron, Purelin transfer function
- STEP 3: Training function: Levenberg-Marquardt
- STEP 4: Setting of training parameters Learning rate=0.05 Error goal=0
- STEP 5: Training the network.
- STEP 6: Finally, outputs are simulated.

Radial Basis Neural Network

Radial basis networks can require more neurons than standard feed forward back propagation networks, but often they can be designed in a fraction of the time it takes to train standard feed forward networks. They work best when many training vectors are available. A Radial Basis Function (RBF) neural network has an input layer, a hidden layer and an output layer. The neurons in the hidden layer contain Gaussian transfer functions whose outputs are inversely proportional to the distance from the centre of the neuron.

- STEP 1: Creating a training set of input speed error and targets throttle command [19] and brake command.
- STEP 2: Plotting of training vectors.

STEP 3: Finding a function which fits the data points [20], done by Radial Basis network.

- Number of layers: 2
- Hidden layer-Radial Basis neurons.
- Output layer-Linear neurons.

STEP 4: Radial Basis transfer function is defined and plotted.

STEP 5: Three Radial Basis functions are scaled and summed to produce a function.

STEP 6: Creating a Radial Basis network with function newrb.

- eg=0.02
- Spread=0.1

STEP 7: Finally, simulating the network response.

Fuzzy Adaptation

The first step performed in the fuzzy mechanism is scaling the input variables into the domain between and. The second step is the calculation of membership value of the fuzzy input variable in each fuzzy set. Five fuzzy set (NL, NS, ZO, PS, PL) are used for both input variables (error and error derivative). Here NL, NS, ZO, PS and PL stand for negative large, negative small, zero, positive small and positive large.

The third step of the fuzzy adaptation mechanism is mapping of input variables to output variables. The membership functions of outputs are shown in Figure 3. Four fuzzy sets (ZO, S, H, and BH) are used for output variables. Here ZO, S, H, BH stand for zero, small, high and big high.

Here we designed fuzzy structure based on two input and two output variables. The first input is the error (which is the difference between the required and current speeds of car) and second input is change in error (which is the differentiation of first input error with respect to time). Both the input are ranged -200 to 200 km/hr as the 200 km/hr is the highest speed of modelled car.

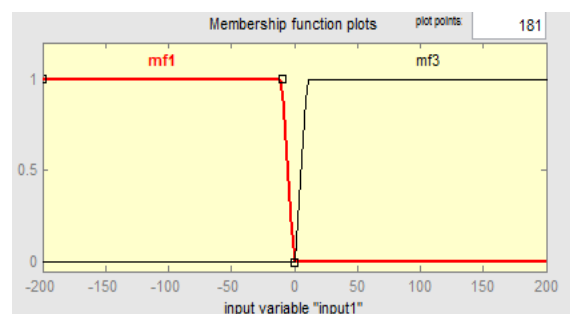


Figure 3: input variable "Error"

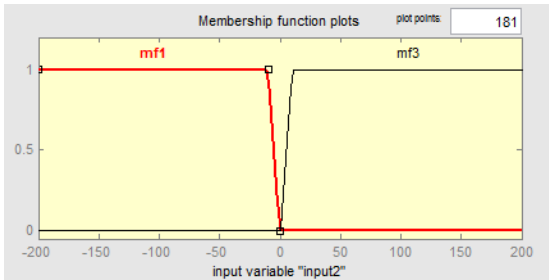


Figure 4: input variable 2 “Change in Error”

Based on these two inputs two outputs are modelled, first is throttle (which is responsible for increment in speed) and second one is break (which is to decrease the speed). Both variable are modelled on scale of 0 and 1 as shown below:

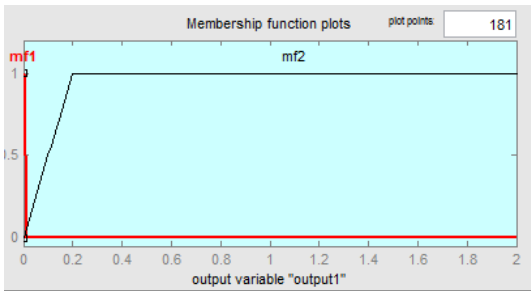


Figure 5: output variable 1 “Throttle”

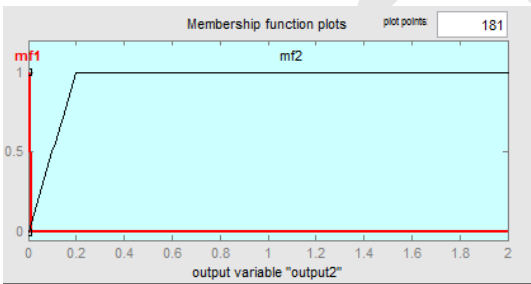


Figure 6: output variable 2 “Break”

These variables are associated with 2x2 rule base as show below:

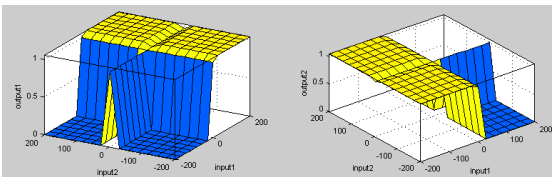


Figure 7: Fuzzy Surface for inputs and outputs

V. SIMULATION AND RESULTS

The Car is modelled under Simulink environment of MATLAB with maximum speed of 200. Car consist a gasoline in engine. The engine and transmission are coupled with a torque converter. Car is modelled as a subsystem with two inputs (throttle and brake) and one output (speed in Km/Hr) as shown below:

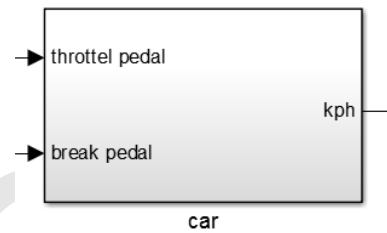


Figure 8: Simulink Subsystem showing Car

The system is first simulated with Neural Network as shown below:

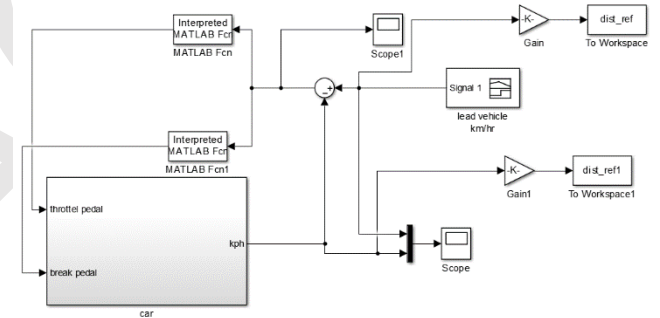


Figure 10: Simulink model with Neural Network

Above figure shows car connected with neural network controller, MATLAB Fcn blocks contain program for neural network, error is calculated by subtracting current speed of car from the lead vehicle speed and results are saved in workspace. Speed graph are as shown below for BPNN:

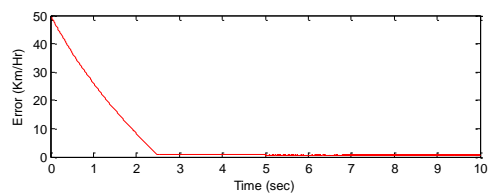
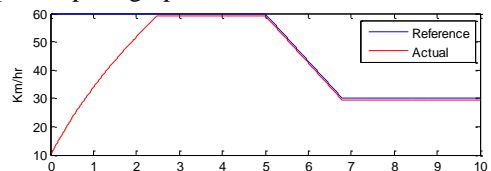


Figure 10: Response of Back propagation NN

Now we simulated same model for radial basis neural network and response is as follows:

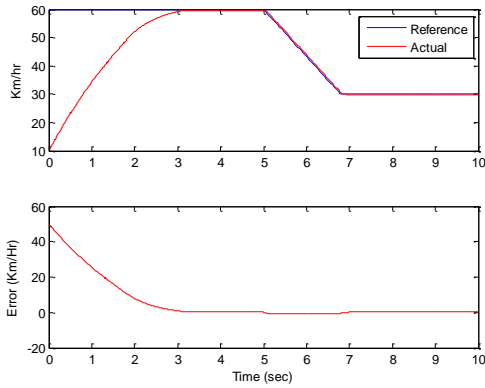


Figure 11: Response of RBNN

Neural network is replaced with Fuzzy Controller in next simulation as shown below:

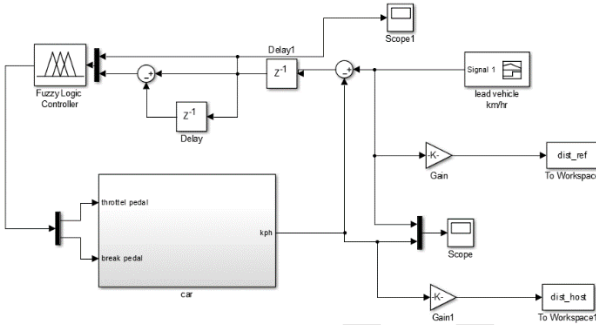


Figure 12: Simulink model for proposed research work with Fuzzy controller for cruise control

The speed responses for fuzzy is as shown below:

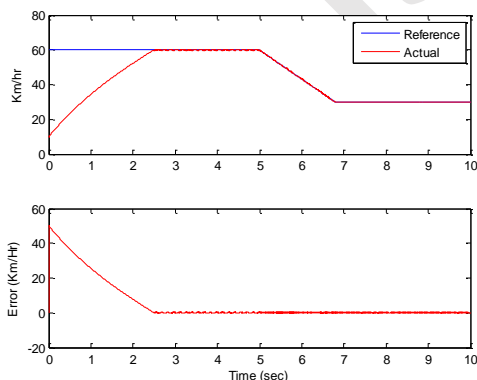


Figure 13: Response of Fuzzy Controller

All the results are compared as shown below:

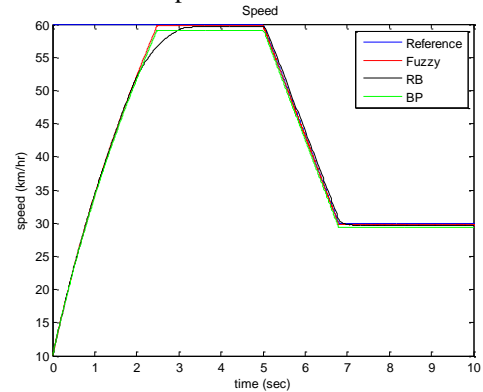


Figure 14: speed response for Fuzzy, BPNN and RBNN

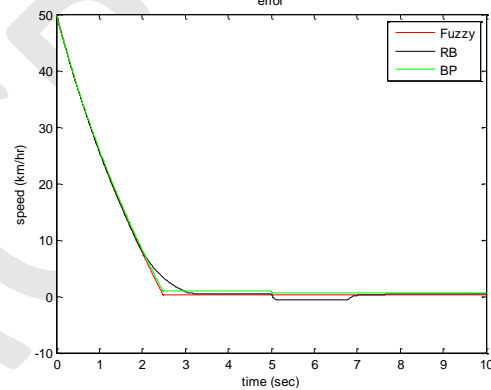


Figure 15: Error response for Fuzzy, BPNN and RBNN

To evaluate performance error can be summarize as mean square error as shown below:

Table 1: Performance comparison

| Method | MSE |
|--------|-----------------|
| BPNN | 447.92 |
| RBNN | 227.2373 |
| Fuzzy | 174.7672 |

VI. CONCLUSION AND FUTURE SCOPE

This paper presents the speed control of car with reference to lead vehicle for avoiding rear end collision. Host vehicle continuously monitors the speed of lead vehicle and its controller controls its speed in order to avoid collision. Here we presented neural networks (BPNN and RBNN) as reference of our work and proposed Fuzzy based controlling. All three methods are tested in SIMULINK environment of MATLAB as we model electrical and mechanical dynamics of car with controllers. Results clear shows that fuzzy based controller works better than neural networks as it got

minimum MSE of 174.76. Also Fuzzy based controller has much faster response than neural network and it is less complex than BPNN and RBNN.

This research work is focused on the avoidance of rear end collision using Adaptive Cruise Control optimized with Fuzzy logic. Future work may be directed in the avoidance of side end collision.

REFERENCE

- [1] WHO, World report on road traffic injury prevention, 2010.
- [2] C. Lundquist, Automotive Sensor Fusion for Situation Awareness, Thesis for Degree of Licentiate, Linköping University, 2009.
- [3] Ibid.
- [4] Edmunds, Traction Control, Online available at: <http://www.edmunds.com/car-safety/traction-control.html>
- [5] Final Rule 49 CFR Parts 571 and 585 - [Docket No. NHTSA-2007-27662].
- [6] Woll, J.D., 1995, "VORAD collision warning Radar," IEEE National Radar Conference - Proc. 1995. IEEE, Piscataway, NJ, USA, 95CH3571-0. pp 369-372.
- [7] Grosch, T.O., Klimkiewicz, W., Moosbrugger, P., Carpenter, L., 1995, "24-GHz frequency modulated/continuous wave automotive radar designed for collision warning," Proc. of SPIE - The International Society for Optical Engineering v 2344 1995- Society of Photo-Optical Instrumentation Engineers, Bellingham, WA, USA. pp 146-158.
- [8] Esteve, D., Rolland, P.A.; Simonne, J.J.; Vialaret, G., 1995, "Prometheus-prochip status of sensor technology applied to automotive collision avoidance," Proc. of SPIE - The International Society for Optical Engineering, v 2470 1995- Society of Photo-Optical Instrumentation Engineers, Bellingham, WA, USA. pp 386-395.
- [9] Hischke, M., 1995, "Collision warning radar interference," Intelligent Vehicles Symposium, Proc., 1995. IEEE, Piscataway, NJ, USA, 95TH8132. pp 13-18.
- [10] Kenue, S.K., 1995, "Selection of range and azimuth angle parameters for a forward looking collision warning radar sensor," Intelligent Vehicles Symposium, Proceedings 1995. IEEE, Piscataway, NJ, USA, 95TH8132. pp 494-499.
- [11] Grosch, T., 1995, "Radar sensors for automotive warning and avoidance," Proc. of SPIE - the Intern Soc for Optical Engineering, v 2463, 1995, Society of Photo-Optical Instrumentation Engineers, Bellingham, WA, USA, pp 239-247.
- [12] Li, j., Bosisio, R.G. and Wu, K., 1994, "Collision Avoidance Radar Using Six-Port Phase/Frequency Discriminator (SPFD)," IEEE MTT-S Digest, pp. 1553-1556.
- [13] Patterson, A. K., (1998) Intelligent Cruise Control System Impact Analysis, Thesis of the Virginia Polytechnic Institute and State University, August 6.
- [14] Wu, J., McDonald, M., Brackstone, M., 1998. A fuzzy logic microscopic simulation model for interurban ATT assessment. In: Proceedings of the 10th European Simulation Symposium and Exhibition. Society for Computer Simulation International ISBN 1-56555-154-0, Nottingham, UK.
- [15] Holve, R., Protzel, P., Bernasch, J., Naab, K., (1995a) Adaptive Fuzzy Control for Driver Assistance in Car-Following, Proceedings of the 3rd European Congress on Intelligent Techniques and Soft Computing - EUFIT '95. Aachen, Germany, Aug., pp. 1149 – 1153.
- [16] Holve, R., Protzel, P., Naab, K., (1995b). Generating Fuzzy Rules for the Acceleration Control of an Adaptive Cruise Control System, Proceedings and at the NAFIPS conference, being held June 19th-22nd, 1995 in Berkeley, CA, USA.
- [17] Chakroborty, Partha, Kikuchi, Shinya, 1999. Evaluation of the General Motors based car following models and a fuzzy inference model, Transportation Research Part C 7 (1999) 209-235.
- [18] Sungwoo CHOI, Brigitte d'andr' ca-novel, Michel FLIESS, Hugues Mounier, Jorge VILLAGRA, "Model-free control of automotive engine and brake for Stop-and-Go scenarios," European control conference, 2009.
- [19] Luke Ng, Christopher M. Clark, and Jan P. Huissoon, "Reinforcement Learning of Adaptive Longitudinal Vehicle Control for Dynamic Collaborative Driving" proceedings of the IEEE Intelligent Vehicles Symposium, Eindhoven University of Technology Eindhoven, The Netherlands, June 4-6, 2008.
- [20] Yang Bin, Keqing Li, Xiaomin Lian Hiroshi Ukawa, Masatoshi Handa, Hideyuki Itonuma "Longitudinal Acceleration Tracking Control of Vehicular Stop-and-go Cruise Control System", Proceedings of the 2004 IEEE Int. Conf. Networking, Sensing & Control pp 607-612, Taiwan, March 21-23, 2004.