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ANFIS Based Modeling and Prediction Car Following Behavior in Real Traffic Flow Based on Instantaneous Reaction Delay

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***Abstract*—Nowadays, car following models, as the most popular microscopic traffic flow modeling, are increasingly being used by transportation experts to evaluate new Intelligent Transportation System (ITS) applications. This paper presents a car-following model that was developed using an adaptive neuro fuzzy inference system (ANFIS) to simulate and predict the future behavior of a Driver-Vehicle-Unit (DVU). This model was developed based on new idea for calculate and estimate the instantaneous reaction of DVU. This idea was used in selection of inputs and outputs in train of ANFIS model. Integration of the driver's reaction time delay and omission of the necessity of regime classification are considered while developing the model. The model's performance was evaluated based on field data and compared to a number of existing car following models. The results showed that new model based on instantaneous reaction delay outperformed the other car-following models. The model was validated at the microscopic level, and the results showed very close agreement between field data and model outputs. The proposed model can be recruited in Drier Assistant devices, Safe Distance Keeping Observers, Collision Prevention systems and other ITS applications.**

I. INTRODUCTION

INTELLIGENT Transportation Systems (ITS) are being developed and deployed to improve the efficiency, productivity, and safety of existing transportation facilities and to alleviate the impact of transportation on the environment. These systems exploit currently available and emerging computer, communication, and vehicle-sensing technologies to monitor, manage, and control the highway transportation system. The success of ITS deployment depends on the availability of advanced traffic analysis tools to predict network conditions and to analyze network performance in the planning and operational stages. Many ITS sub-systems are heavily dependent on the availability of timely and accurate wide-area estimates of prevailing and emerging traffic conditions. Therefore, there is a strong need for a Traffic Estimation and Prediction System (*TrEPS*) to meet the information requirements of these subsystems and to aid in the evaluation of ITS traffic management and information strategies [1].

Microscopic models are increasingly being used by transportation experts to evaluate the applications of new ITS. A variety of applications including car navigation systems, adaptive cruise control systems, lanes keeping assistance systems and collision prevention systems directly use the microscopic traffic flow models [2]. Car following models are among the most popular microscopic traffic flow modeling approaches aiming to describe the process of following a leader car by a vehicle. As shown in Fig.1, car following describes the longitudinal action of a driver when he follows another car and tries to maintain a safe distance to the leading car. The majority of available car-following models assume that the driver of the follower vehicle (FV) responds to a set of variables like relative velocity and relative distance between the leader vehicle (LV) and the FV, velocity of the FV, and/or desired distance and/or velocity of the target driver. The response is typically considered to be as acceleration or velocity changes of the following vehicle [1].

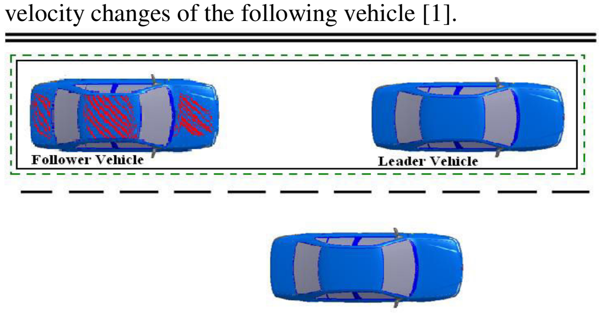

Figure 1. Car following behavior (LV and FV).

Highly nonlinear nature of car following behavior necessitates the development of intelligent algorithms to describe, model and predict this phenomenon. Fuzzy logic can be a potential method dealing with structural and parametric uncertainties in the car following behavior. Additionally, artificial neural networks can be favorable tools providing the possibility of exploiting real observed data while developing the models. Neuro-fuzzy models, such as ANFIS, are combinations of artificial neural networks and fuzzy inference systems, simultaneously using the advantages of both methods. Integration of human expert knowledge expressed by linguistic variables, and learning based on the data are powerful tools enabling neuro fuzzy models to deal with uncertainties and inaccuracies [3]. In this paper an innovative ANFIS model based instantaneous reaction delay is proposed for modeling and prediction of DVU behavior in car following scenarios.

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II. BRIEF REVIEW OF CAR-FOLLOWING MODELS

Humans play an essential role in the operation and control of human–machine systems such as driving a car. Modeling driver behavior has transferred human skills to intelligent systems, e.g., the adaptive cruise control (ACC) system, intelligent speed adaption (ISA) system, and autonomous vehicles. Human driving models are also indispensable for the performance evaluation of transportation systems. With advances in emerging vehicle-based ITS technologies, it becomes even more important to understand the normative behavior response of drivers and changes under new systems [1]. Based on Rasmussen's human–machine model as shown in Fig. 2 [4], driver behavior can also be separated into a hierarchical structure with three levels: the strategic, tactical, and operational level. At the highest or strategic level, goals of each driver are determined, and a route is planned based on these goals. The lowest operational level reflects the real actions of drivers, e.g., steering, pressing pedal, and gearing. In the middle tactical level, certain maneuvers are selected to achieve short-term objectives, e.g., interactions with other road users and road infrastructures. The behavior at this level is dominated by the most recent situations but is also influenced by drivers' goals at the higher level.

Figure 2. Rasmussen's human–machine model

To develop microscopic traffic simulation of high fidelity, researchers are often interested in imitating human's real driving behavior at a tactical level. That is, without describing the detailed driver actions, DVUs in the simulation are modeled to replicate their states in reality, i.e., the profiles of vehicle position, velocity, acceleration, and steering angle. Fig. 3 shows the model structure of a DVU in which the detailed driver actions become internal.

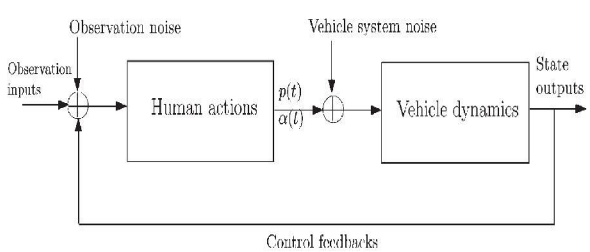

Figure 3. Structure of a DVU model [1]

Although more factors might be involved in the follower's decision in the real traffic environment, the variables above show strong correlation to the driver's decision and are relatively easy to observe using modern equipment.

Car following behavior, which describes how a pair of vehicles interacts with each other, is an important consideration in traffic simulation models. A number of factors have been found to influence car-following behavior, and these include individual differences of age, gender, and risk-taking behavior [2]. Regarding literatures, car-following models can be classified into 14 groups as follows: Gazis-Herman-Rothery [5], collision avoidance/safe distance [6], linear model/ Helly [7], action point [8], fuzzy logic-based model [9], desired spacing [10], capacity drop and hysteresis theory [11], neural network [12], optional velocity [13], adaptive neural fuzzy inference system [14], emotional learning fuzzy inference system [15], local-linear neural fuzzy [16], local quadratic neural fuzzy [17] and genetic algorithm based optimized least squares support vector machine [18]. All models presented for car following behavior are evaluated based on their ability to predict or estimate of increase or decrease of FV acceleration.

In a general classification, car following behavior microscopic models can be divided into 2 groups: mathematical equation-based and input-output based. The most important point in mathematical models is calculation and obtaining model parameters. Therefore, these parameters can be always obtained by average of values or regarding them as a fix value of DVU. Because these parameters are as a function of time, results of these models are proper for test cases and are not reliable. In input-output models, by considering the fixed DVU reaction time, output values are applied to input. Since the DVU reaction time is not actually fixed, other parameters vary with time. So an error in modeling is appeared because of the difference between real data and data used for modeling.

III. NEW ANFIS CAR FOLLOWING MODEL DESIGN

In this section, considering a proposed idea, an input-output model is presented to estimate FV acceleration. Using this method, DVU instantaneous reaction time as input for system is calculated and then other inputs and outputs are chosen according to DVU reaction delay. DVU reaction delay in subsequent moments is not the same, so input and output must be chosen as a function of the proper and correct reaction times. In fact, the stimulus and reaction should be considered as an input and output with respect to accurate instantaneous reaction time. So the previous models in which DVU reaction time was considered as a constant value can be modified by introducing this proposed idea.

Reaction delay is a common characteristic of humans in operation and control, such as driving a car. The operational coefficients and delay characteristic of humans can vary rapidly due to changes of factors such as task demands, motivation, workload and fatigue. However, estimation of these variations is almost impossible in the classical paradigms. Therefore, an assumption of a fixed reaction delay in a certain regime still cannot be completely circumvented. Driver reaction time was defined as the summation of perception time and foot movement time by earlier car-following research. In psychological studies, the driver reaction process is further represented in four states: perception, recognition, decision and physical response. Although research on car following models has been historically focused on exploration of different modeling frameworks and variables that affect this behavior, it has been recognized that the reaction delay of each driver is an indispensable factor for the identification of car following models [18].

Many studies have estimated the reaction time based on indoor experiments and driving simulators. To estimate driver reaction delays from real data, several approaches have been proposed. Fig. 4 indicates how the DVU instantaneous reaction delay can be calculated by using the proposed idea. This idea is based on the fact that the delay time is the time between the variation of relative velocity and acceleration of FV which is the concept of the stimulus and reaction. Variations in relative velocity and FV acceleration are the maximums or minimums of velocity trajectory or FV acceleration, respectively. DVU instantaneous reaction is the time difference between two subsequent variations: relative velocity as stimulus and FV acceleration as reaction.

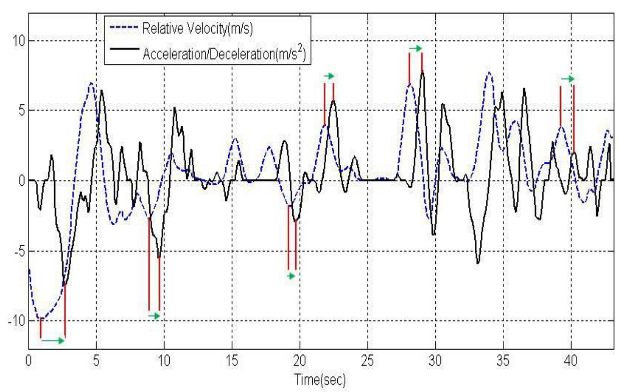

Figure 4. calculation DVU instantaneous reaction delay

Now introduces the basics of the ANFIS network architecture applied for the car-following prediction system. A detailed coverage of ANFIS can be found in [19, 20]. ANFIS enhances fuzzy controllers with self-learning capability for achieving optimal control objectives. An adaptive network is a multilayer feed-forward network where each node performs a particular node function on incoming signals. It is characterized with a set of parameters pertaining that node. To reflect different adaptive capabilities, both square and circle node symbols are used. A square node (adaptive node) has parameters, while a circle node (fixed node) has none. The parameter set of an adaptive network is the union of the parameter sets associated to each adaptive node. To achieve a desired input–output mapping, these parameters are updated according to given training data and a recursive least square (RLS) based learning procedure.

In order to design an ANFIS prediction system, a dataset of car following behavior is needed. So, real car following data from US Federal Highway Administration's NGSIM dataset is used to train the ANFIS prediction model [21]. In June 2005, a dataset of trajectory data of vehicles travelling during the morning peak period on a segment of Interstate 101 highway in Emeryville (San Francisco), California has been made using eight cameras on top of the 154m tall 10 Universal City Plaza next to the Hollywood Freeway US-101. On a road section of 640m, as shown in Fig. 5, 6101 vehicle trajectories have been recorded in three consecutive 15-minute intervals. This dataset has been published as the "US-101 Dataset". The dataset consists of detailed vehicle trajectory data on a merge section of eastbound US-101. The data is collected in 0.1 second intervals. Any measured sample in this dataset has 18 features of each driver-vehicle unit in any sample time, such as longitudinal and lateral position, velocity, acceleration, time, number of road, vehicle class, front vehicle and etc.

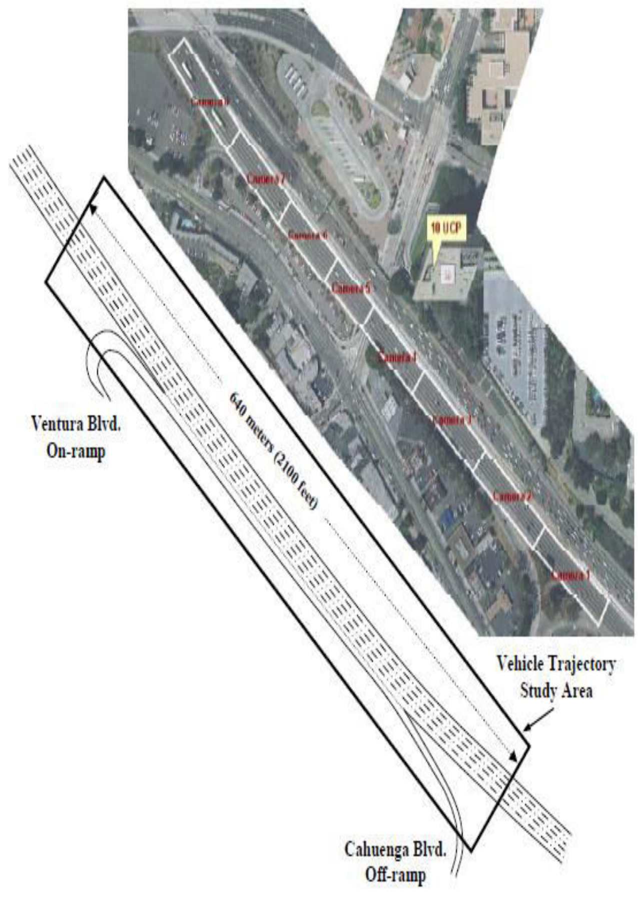

Figure 5. A segment of Interstate 101 highway in Emeryville, San Francisco, California.

The trajectory data seems to be unfiltered and exhibits some noise artefacts, so we have applied a moving average filter to all trajectories before any further data analysis. Comparison of unfiltered and filtered data is shown in Fig. 6.

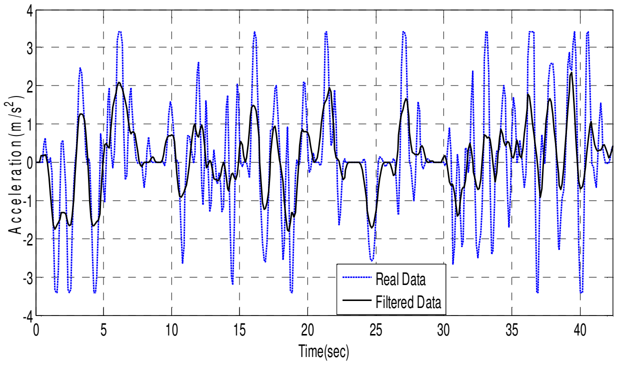

Figure 6. Comparison of unfiltered and filtered data.

To design ANFIS model shown in Fig. 6, it is assumed that the fuzzy inference system applied for prediction model has four inputs and one output, which inputs are instantaneous reaction delay, relative speed, relative distance and velocity of FV, and output is acceleration of FV. There are three dsigmf membership functions for each input. The rule base contains 81 fuzzy if-then rules of Takagi-Sugeno's type [22] and hybrid algorithm is used to train this model.

In the development of ANFIS prediction model, the available data are usually divided into two randomly selected subsets. The first subset is known as the training and testing data set. This data set is used to develop and calibrate the model. The second data subset (known as the validation data set), which was not used in the development of the model, is utilized to validate the performance of the trained model. For this paper, 70% of the master data set was used for training and testing purposes. The remaining 30% was set aside for model validation.

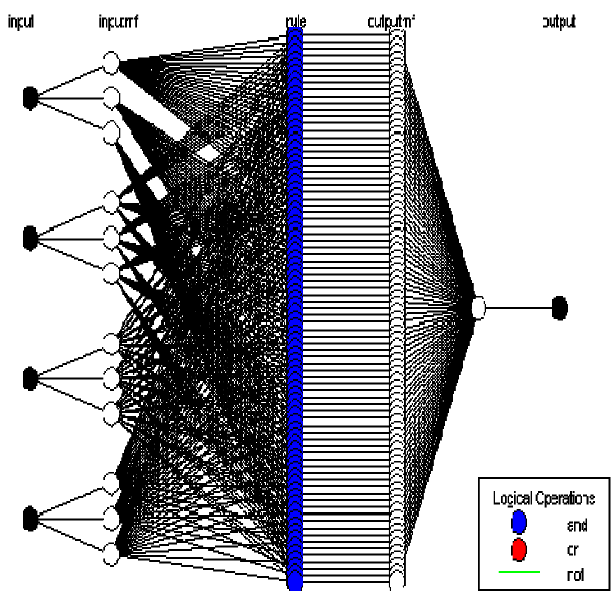

Figure 7. Designed ANFIS model for car following behavior.

IV. Discussion and Results

To evaluate the competence of ANFIS estimator system based on the instantaneous reaction delay idea; two ANFIS estimator systems with constant delay and three inputs are designed and simulated. 0.1s and 0.3s are assumed for constant delay. Also to train and test the performance of these systems, same real traffic data are used as input and output.

Fig. 8 shows the performance results for ANFIS estimator for DVU car following behavior based on instantaneous reaction delay as input to estimate the FV acceleration. As seen in this figure, the trajectories of real driver and ANFIS model are quite same.

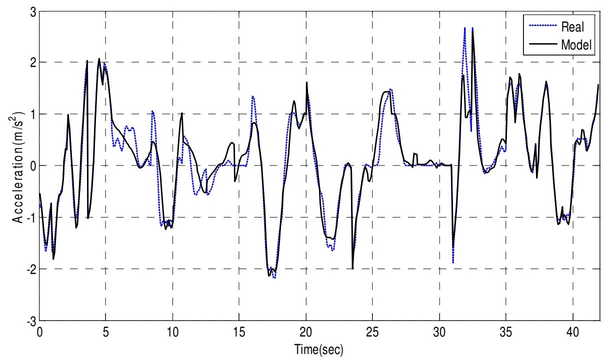

Figure 8. Results for ANFIS estimator based on instantaneous reaction delay

Fig. 9 shows the performance of ANFIS estimator for DVU in car following behavior based on the constant delay of 0.1s. Fig. 10 shows the performance of ANFIS estimator for DVU in car following behavior based on the constant delay of 0.5s.

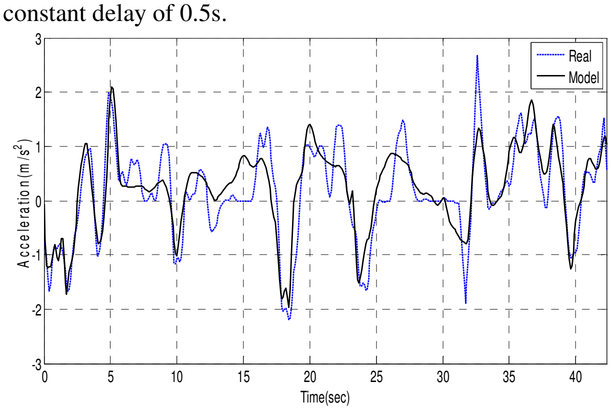

Figure 9. Results for ANFIS estimator based on constant reaction delay 0.1 sec

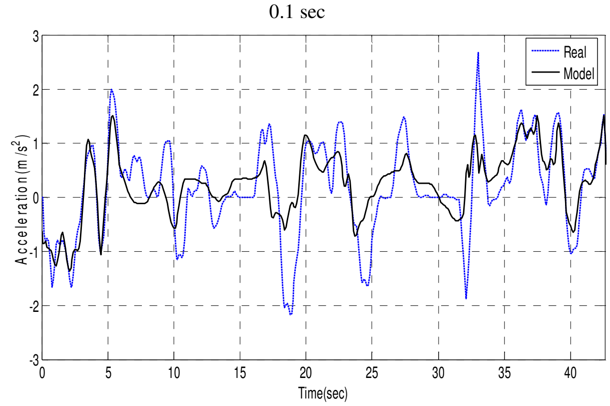

Figure 10. Results for ANFIS estimator based on constant reaction delay 0.5 sec

To examine the performance of developed models, various criteria are used to calculate errors. The criterion mean absolute percentage error (MAPE), according to equation (1), shows the mean absolute error can be considered as a criterion for model risk for using it in real world conditions. Root mean squares error (RMSE), according to equation (2), is a criterion for comparing error dimension in various models. Standard deviation error (SDE), according to equation (3), indicates the persistent error even after calibration of the model. In these equations, x_i shows the real value of the variable being modeled (observed data), $\hat{x}_i$ shows the real value of variable modeled by the model and $\bar{x}$ is the real mean value of the variable and N is the number of test observations.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|x_i - \hat{x}_i|}{x_i} \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2} \quad (2)$$

$$SDE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{|x_i - \hat{x}_i|}{x_i} - \frac{MAPE}{100}\right)^2} \quad (3)$$

Errors in modeling with considering MAPE, RMSE and SDE are summarized in Table I.

TABLE I
RESULT OF ERROR FOR ANFIS CAR FOLLOWING MODEL

ANFIS CAR FOLLOWING MODEL	Error Criteria		
	MAPE	RMSE	SDE
Based on instantaneous reaction delay	0.1462	0.2514	0.0253
Based on reaction delay = 0.1 sec	0.4331	0.3946	0.0364
Based on reaction delay = 0.5 sec	0.4459	0.4449	0.0452

ANFIS car following model based on instantaneous reaction delay has a lower error value comparing with models regarding fixed reaction delay in all 3 criteria. This result shows that this new model has a strong capability with respect to other models.

V. CONCLUSION

In this paper, a new ANFIS model for DVU in car following was studied. This model is based on instantaneous reaction delay idea for DVU as a input and also choosing suitable other inputs and outputs with respect to instantaneous reaction delay. In this model, the stimulus and reaction should be considered as an input and output with respect to accurate instantaneous reaction time. Satisfactory performance of the proposed model is demonstrated through comparisons with real traffic data and also the results of ANFIS models regarding fixed reaction delay. The simulation results show the efficiency of the proposed model in driver modeling and prediction of the driver's actions comparing with others ANFIS based model. The proposed method can be recruited in driver assistant devices, safe distance keeping observers, collision prevention systems and other ITS applications.

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