Using the Reaction Delay as the Driver Effects in the Development of Car-Following Models

A. Khodayari[1] and A. Ghaffari[2]

[1] Ph.D Student, [2] Prof. K. N. Toosi University of Technology, Tehran, Iran.

* arkhodayari@dena.kntu.ac.ir

Abstract

Car-following models, as the most popular microscopic traffic flow modeling, is increasingly being used by transportation experts to evaluate new Intelligent Transportation System (ITS) applications. A number of factors including individual differences of age, gender, and risk-taking behavior, have been found to influence car-following behavior. This paper presents a novel idea to calculate the Driver-Vehicle Unit (DVU) instantaneous reaction delay of DVU as the human effects. Unlike previous works, where the reaction delay is considered to be fixed, considering the proposed idea, three input-output models are developed to estimate FV acceleration based on soft computing approaches. The models are developed based on the reaction delay as an input. In these modeling, the inputs and outputs are chosen with respect to this feature to design the soft computing models. The performance of models is evaluated based on field data and compared to a number of existing car-following models. The results show that new soft computing models based on instantaneous reaction delay outperformed the other car-following models. The proposed models can be recruited in driver assistant devices, safe distance keeping observers, collision prevention systems and other ITS applications.

Keywords: *Car-Following, Instantaneous Reaction Time, Intelligent Transportation System, Soft Computing.*

1. INTRODUCTION

Car-Following is quite common in many traffic fields such as railway, highway. This is a crucial tactical-level model for a microscopic simulation system and the most popular modeling approaches for Traffic Estimation and Prediction System (TrEPS). In TrEPS, these microscopic models are increasingly being used by transportation experts to evaluate the applications of new intelligent transportation systems (ITS) [1]. Car-following, as shown in figure 1, describe the longitudinal action of a driver when he follows another car and tries to maintain a safe distance from the leading car [2]. 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 [3].

Regarding literatures, car-following models can be classified into 14 groups as follows: Gazis-Herman-Rothery Model [4], Collision Avoidance/Safe Distance Model [5], Linear / Helly Model [6], Action Point Model [7], Fuzzy Logic-Based Model [8], Desired Spacing Model [9], Capacity Drop and Hysteresis Theory Model [10], Neural Network Model [11], Optional Velocity Model [12], Adaptive Neural Fuzzy Inference System Model [13], Emotional Learning Fuzzy Inference System Model [14], Local-Linear Neural Fuzzy Model [15], Local Quadratic Neural Fuzzy Model [14] and Genetic Algorithm Based Optimized Least Squares Support Vector Machine Model [14]. All models presented for car-following

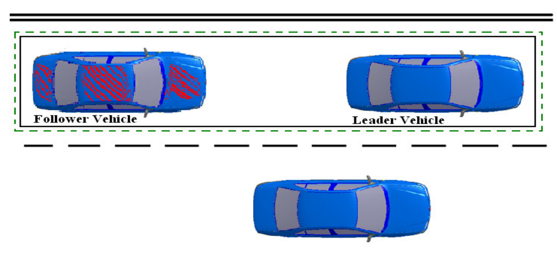


Fig. 1. Car-following behavior (LV and FV) [2].

behavior are evaluated based on their ability to predict or estimate the increase or decrease of FV acceleration.

In a general classification, car-following behavior microscopic models can be divided into two groups: equation-based and input-output-based. In the equation-based model, the car-following behavior is presented by a set of mathematical equations. These equations are explained based on choosing variables and adjustments of parameters in linear or nonlinear forms, such as GHR, CA, and Helly models. The important point in equation-based models is the calculation and obtaining model parameters. Therefore, these parameters are always chosen by the average of experiment values and considering them as a constant value of the DVU. As these parameters are functions of time, results of these models are only matched to the test cases and are not reliable. In the input-output-based model, the car-following behavior is presented based on the real measured values and using signal-based modeling approaches. In these models, the inputs and outputs are modeled to design and train based on the experimental or real data. Therefore, in these models, physical assumptions, environmental conditions, and human effects cannot be directly considered. In the input-output models, by considering the constant DVU reaction time, the output values are applied to train the model. As the DVU reaction time is not actually constant, the other parameters vary with time. Because of the difference between the real data and those used for the model, there could be errors in the modeling results [16].

Highly nonlinear nature of car-following behavior necessitates the development of intelligent algorithms to describe, model and predict this phenomenon [2]. In this paper, we have focused on some soft computing models design to predict the car-following behavior in the real traffic flow, considering the effects of driver's behaviors. The instantaneous reaction delay of DVU is used as a human effect and applied as an input of the car-following model. Artificial Neural Networks (ANN), Fuzzy Logic and Adaptive Neuro Fuzzy Inference System (ANFIS) are some of the soft computing approaches which are used in this paper.

2. CALCULATING THE INSTANTANEOUS REACTION DELAY

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's reaction time has been defined as the summation of perception time and foot movement time by earlier car-following research. In psychological studies, the driver's reaction process has been further represented in four states: perception, recognition, decision, and physical response. Although researches on car-following models have 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 [17].

Many studies have estimated the reaction time based on indoor experiments and driving simulators. As a very common and well-known idea proposed by Ozaki in [18] in calculating the reaction time, it has been shown that there is a high correlation between the reaction time and acceleration/deceleration of the LV and the relative distance between LV and FV. In [18], the reaction time is expressed by relative distance and acceleration rate of LV. The description of reaction time is chosen as a simple model, considering the result of the regression analysis. The major specification of the model is described in Equation (1) as follows:

$$T = \begin{cases} 1.5+0.01\mathrm{s}(t)-0.6\mathrm{a}_{\mathrm{LV}}(t) & (\textit{acceleration}) \\ 1.3+0.02\mathrm{s}(t)+0.7\mathrm{a}_{\mathrm{LV}}(t) & (\textit{deceleration}) \end{cases} \tag{1}$$

Where $s(t)$ represents the relative distance between two cars and a_{LV} is the acceleration of the leader vehicle. In this work, we have termed the idea proposed by Ozaki to estimate the instantaneous reaction delay of DVU as Ozaki idea.

To estimate driver's reaction delays from real data, several approaches have been proposed. According to the result of the reaction-time analysis of a single driver in the experiment on a test track, it is suggested that the reaction time can be very much dependent on the condition. Moreover, the reaction time appears to change during a single maneuver of acceleration or deceleration.

The reaction delays appear to change during a single maneuver acceleration or deceleration in the car-following behavior. These single maneuvers can be divided into four actions that are observed in the actual traffic flow: start of deceleration, maximum deceleration, start of acceleration, and maximum acceleration. Delay time to start the deceleration is the time lag from zero value of the relative velocity to null acceleration rate at the start of deceleration. Delay time for maximum deceleration is the time lag between the negative maximum values of the relative velocity and the acceleration rate. Delay time to start the acceleration is the time lag from zero value of the relative velocity to the null acceleration rate at the start of acceleration. Delay time for maximum acceleration is the time lag between the positive maximum values of the relative velocity and acceleration rate. In the analysis, the four actions are combined into two groups considering the DVU operation. In the DVU, drivers change the accelerator pedal and brake pedal in the driving operation. Considering the timing of changing the pedals, action at the start and succeeding maximum operation are combined. Start of deceleration action and maximum deceleration are grouped to the deceleration condition, and start of acceleration and maximum acceleration are grouped to the acceleration condition [16]. There is a high correlation between the delay time and acceleration of FV. The greater the acceleration rate is, the faster the change is expected in the relative velocity, which results in easier perception by the FV [19, 20].

To estimate the reaction delay time, we have proposed an idea based on analyzing the observed data of many LV-FV in the real traffic flow. This idea is based on the fact that the delay time is the time

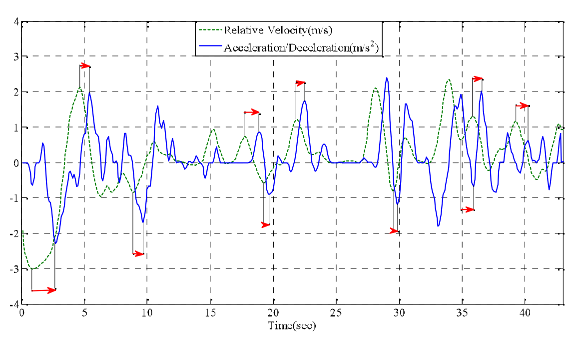


Fig. 2. Calculation of DVU's instantaneous reaction delay based on Stimulus-Reaction idea [16].

between stimulus and reaction. In car-following behavior, the variation of relative velocity and acceleration of FV 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's instantaneous reaction is the time difference between two subsequent variations: relative velocity as stimulus and FV acceleration as reaction. This idea is called Stimulus-Reaction to estimate the instantaneous reaction delay of DVU in the subsequent sections. Instantaneous delay value can be estimated by using this idea and analyzing the real data. Figure 2 is indicates the difference between the relative velocity and acceleration/deceleration of the real data.

Based on the real data which are shown in figure 2 and analyzing them, there is a tendency that as the absolute level of acceleration rate of the FV becomes greater; the reaction delay will become shorter. It should be noted that the estimated delay time here is the most appropriate value during the period of acceleration or deceleration [17, 20]. From a careful observation of the real observed data (see figure 2), it has been found that some FV deceleration action starts before the relative velocity changes from positive to negative values.

The reaction time of each action is collected from the observed data in the range from 3.5 to ?1.5 sec. Moreover, all the negative time lags have been observed at the start of deceleration. A close investigation of the early start of deceleration actions with negative time lags revealed that most of them are observed when the relative distance to the LV immediately in front is small, and the relative velocity to the two vehicles ahead is large enough so that the FV can anticipate that its LV should soon decelerate, which may be owing to the fact that the FVs act with the anticipation of their LVs' next action. However, even though negative delay time is achieved at the start of deceleration, the time lag at the maximum deceleration falls down within the range of time lags by the normal reaction to the vehicle in front as well as to the condition further ahead, while during the deceleration, they pay more attention to the vehicles immediately in front. If the calculated reaction time is negative, then it is assumed to be null in the simulation. To calculate the instantaneous reaction delay and design new car-following models based on instantaneous reaction delay, we have employed the following methods.

3. SOFT COMPUTING CAR-FOLLOWING MODELS DESIGN BASED ON HUMAN EFFECT

The highly nonlinear nature of the car-following behavior necessitates the development of intelligent algorithms to describe, model, and predict this phenomenon. Neuro fuzzy models, such as adaptive neuro fuzzy inference system (ANFIS), are combinations of artificial neural networks (NNs) and fuzzy inference systems (FIS), 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.

In this section, considering the proposed idea, three input-output models are presented to estimate FV acceleration based on soft computing approaches. Using this method, DVU instantaneous reaction time as input for systems 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. ANN, FIS and ANFIS approaches are used to design the car-following models.

3. 1. ANN Car-following Model Design

ANN is a proper method to solve the complex and ill-defined problems. They are particularly useful in system modeling, such as in implementing complex mapping and system identification. They operate like a black box model, and require no detailed information about the system [21]. To design ANN model, shown in figure 3, it is assumed that the ANN 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 is one hidden layer with 10 nods and back-propagation algorithm is used to train this model. To estimate driver reaction delays from real data, the DVU instantaneous reaction delay was calculated by using the proposed idea and then other inputs and outputs are chosen according to DVU reaction delay.

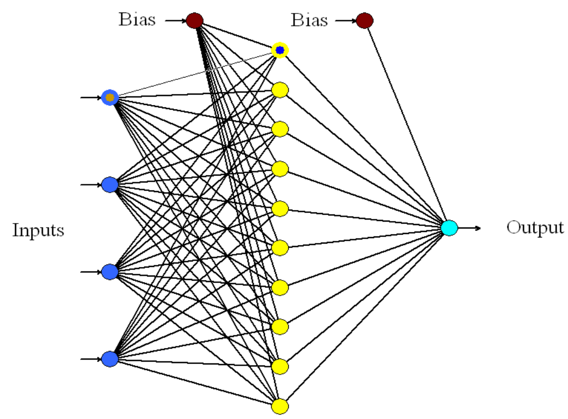
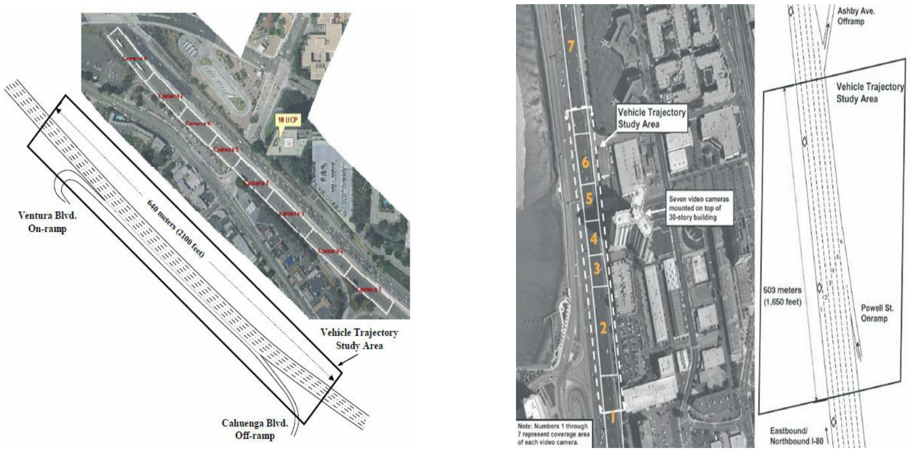


Fig. 3. Designed ANN model for car-following behavior.

In order to design an ANN 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 [22]. In June 2005, a data set of trajectory data of vehicles travelling during the morning peak period on a segment of Interstate 101 highway in Emeryville (San Francisco), California, was made using eight cameras on top of the 154-m-tall 10 Universal City Plaza, next to the Hollywood Freeway US-101. On a road section of 640 m, as shown in figure 4(a), 6101 vehicle trajectories were recorded in three consecutive 15-min intervals. This data set has been published as the "US-101 Dataset." The data set consists of detailed vehicle trajectory data on a merge section of eastbound US-101. The data were collected in 0.1-sec intervals. Any measured sample in this data set has 18 features of each DVU in any sample time, such as longitudinal and lateral position, velocity, acceleration, time, number of road, vehicle class, front vehicle, etc. The other dataset was published as the I-80 Dataset. Researchers for the NGSIM program collected detailed vehicle trajectory data on eastbound I-80 in the San Francisco Bay area in Emeryville, CA, as shown in figure 4(b), on April 13, 2005. The study area was approximately 500



(a) (b)

Fig. 4. (a) A segment of Interstate 101 highway in Emeryville, San Francisco, California [22], (b) A segment of eastbound I-80 in the San Francisco Bay area in Emeryville, California [23].

meters in length and consisted of six freeway lanes, including a high-occupancy vehicle lane. An onramp also was located within the study area. Seven synchronized digital video cameras, mounted from the top of a 30-story building adjacent to the freeway, recorded vehicles passing through the study area. This vehicle trajectory data provided the precise location of each vehicle within the study area every one-tenth of a second, resulting in detailed lane positions and locations relative to other vehicles. A total of 45 minutes of data are available in the full dataset, segmented into three 15-minute periods. These periods represent the buildup of congestion, or the transition between uncongested and congested conditions, and full congestion during the peak period [23].

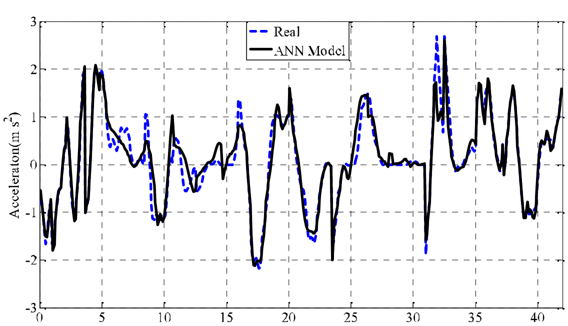


Fig. 5. Results for ANN estimator based on instantaneous reaction delay input.

However, the trajectory data appeared unfiltered and exhibited some noise artifacts; hence, they were filtered as done earlier in [20, 24, 25]. We designed and applied a moving average filter for a duration of about 1 sec to all trajectories before any further data analysis.

In the development of ANN 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, 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 5 shows the performance results for ANN estimator for DVU car-following behavior based on instantaneous reaction delay input to estimate the FV acceleration. As seen in this figure, the trajectories of real driver and ANN model are quite same.

3. 2. Fuzzy Car-following Model Design

Fuzzy inference systems use IF-THEN-ELSE rules to relate linguistic terms defined in output space and input space. Every linguistic term corresponds to a fuzzy set. A FIS could then be used to represent the open loop mapping in car-following processes, which is able to approximate any nonlinear function with arbitrary accuracy and therefore is able to identify car-

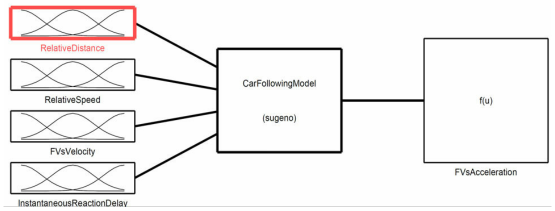
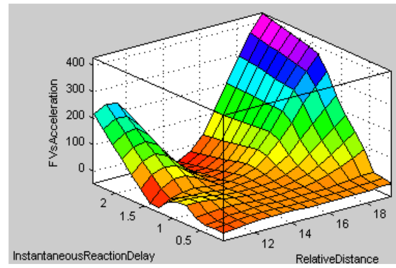


Fig. 6. Designed Fuzzy model for car-following behavior.

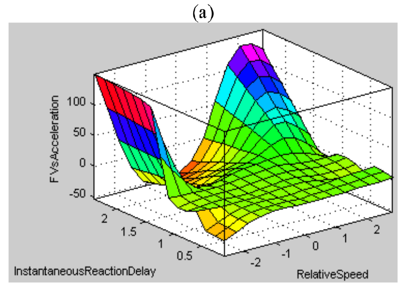
following behavior more accurately [26]. To design the fuzzy model, as shown in figure 6, it is assumed that the fuzzy inference system applied to the prediction model has four inputs and one output, whose inputs are instantaneous reaction delay, relative speed, relative distance and velocity of FV, and output is acceleration of FV.

We use Gaussian membership function for every fuzzy set. There are three membership functions for each input, as shown in figure 7 which inputs are relative distance (a), relative speed (b), velocity of FV (c) and instantaneous reaction delay (d).

At first, the rule base contains 81 fuzzy if-then rules of Takagi-Sugeno's type in the fuzzy car-following model. A total of 53 Fuzzy rules are used here, which have some corresponding relationship with the common sense when driving a car. For example, rule 1 means "if relative distance is much too close and relative speed is closing fast and FV speed is high and



(a)



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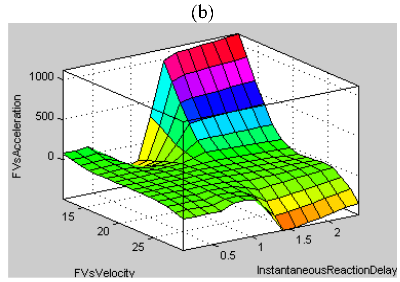
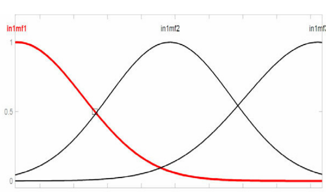
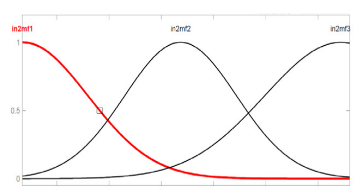


(c)

Fig. 8. The fuzzy surface of model for FV acceleration output [Takagi-Sugeno's parameter], (a) relative distance and instantaneous reaction delay, (b) relative speed and instantaneous reaction delay, (c) velocity of FV and instantaneous reaction delay.



(a)



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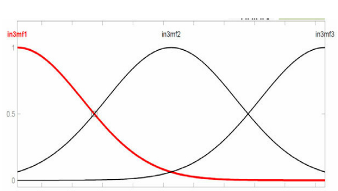

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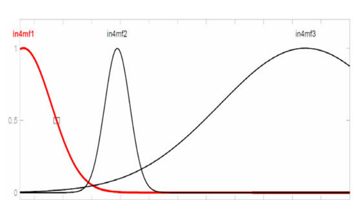

(d)

Fig. 7. Inputs of fuzzy model, (a) relative distance, (b) relative speed, (c) velocity of FV and (d) instantaneous reaction delay.

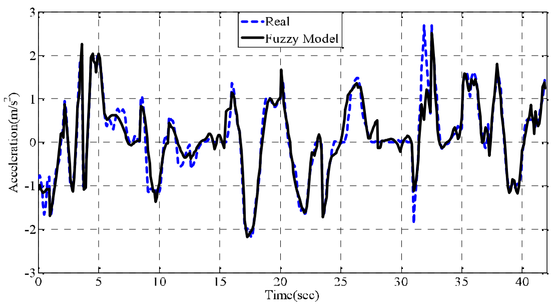

Fig. 9. Results for fuzzy estimator based on instantaneous reaction delay input.

instantaneous reaction delay is large, then the negative acceleration is strong". The fuzzy surface is illustrated in figure 8.

Figure 9 shows the performance results for FIS 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 fuzzy model are quite the same.

3. 3. ANFIS Car-following Model Design

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 [27]. To design ANFIS model shown in figure 10, 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 and hybrid algorithm is used to train this model [28].

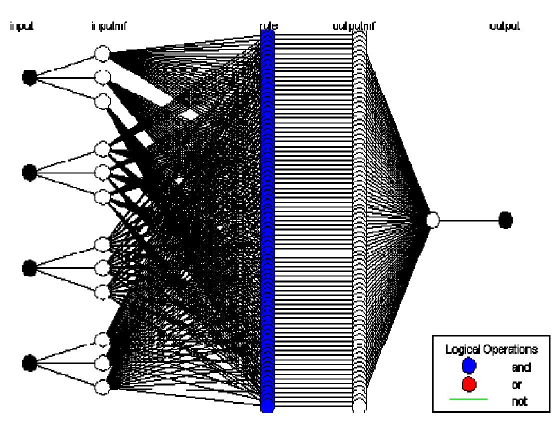

Fig. 10. Designed ANFIS model for car-following behavior.

In order to design an ANFIS prediction system, real car-following data from US Federal Highway Administration's NGSIM dataset is used to train the model. To estimate driver reaction delays via real data, the DVU instantaneous reaction delay is calculated by using the proposed idea and then other inputs and outputs are chosen according to DVU reaction delay. In the development of ANFIS prediction model, the available data are usually divided into two randomly selected subsets. 70% of the master data set is used for training and testing purposes. The remaining 30% is set aside for model validation.

Figure 11 shows the performance results for ANFIS estimator for DVU car-following behavior based on instantaneous reaction delay based our new idea as input to estimate the FV acceleration. As seen in this figure, the trajectories of real driver and ANFIS model are quite the same.

4. DISCUSSION AND RESULTS

To evaluate the competence of ANN prediction model based on the instantaneous reaction delay, two other ANN prediction model are designed and simulated. These ANN estimator systems include of constant delay and three inputs, which inputs are

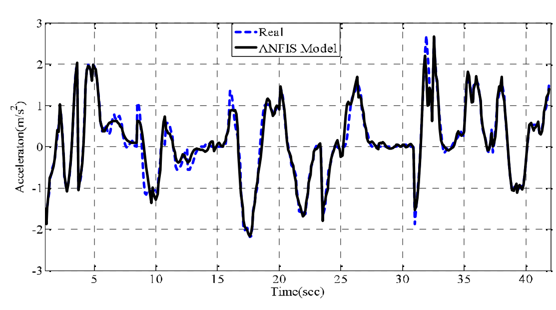

Fig. 11. Results for ANFIS estimator based on instantaneous reaction delay input.

relative speed, relative distance and velocity of FV, and output is the FV acceleration of 0.1 sec and 0.4 sec for constant delay. Also to train and test the performance of these systems, the same real traffic data are used as input and output. Figure 12(a) shows the errors of ANN estimators for DVU in car-following behavior. As depicted in this figure, the model considering instantaneous reaction delay has less error in estimation of FV acceleration comparing with other ANN models. In order to show the capability of fuzzy estimator system based on the instantaneous reaction delay, another fuzzy estimator system without instantaneous reaction delay input is designed. The car-following behavior model is simulated and verified using actual measured values as inputs. To estimate driver reaction delays from real data, the DVU instantaneous reaction delay is

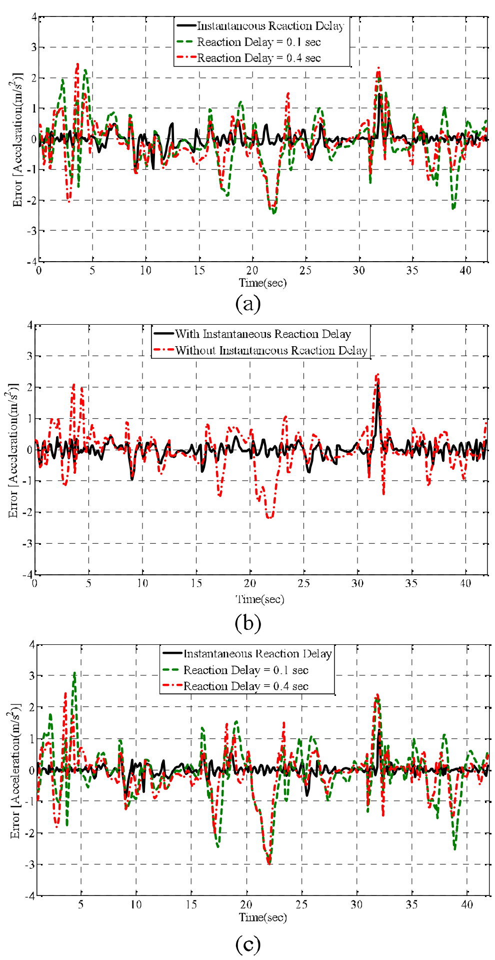

Fig. 12. estimation error for car-following models: (a) ANN, (b) FIS, (c) ANFIS.

calculated using the proposed idea. Figure 12(b) shows the errors of fuzzy estimators for DVU in car-following behavior. As noted in this figure, the model considering instantaneous reaction delay has less error in estimation of FV acceleration comparing with other fuzzy model. To clarify the ability of ANFIS prediction model based on the instantaneous reaction delay, two other ANFIS prediction model with constant delay and three inputs are designed and simulated, which inputs are relative speed, relative distance and velocity of FV, and output is the FV acceleration of 0.1 sec and 0.4 sec for constant delay. Also to train and test the performance of these systems, the same real traffic data are used as input and output. Figure 12(c) shows the errors of ANFIS estimators for DVU in car-following behavior. As shown in this figure, the model considering instantaneous reaction delay has much less error in estimation of FV acceleration comparing with other ANFIS models.

To examine the performance of developed models, various criteria are used to calculate errors. The criterion mean absolute percentage error (MAPE), according to equation (2), 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 (3), is a criterion for comparing error dimension in various models. Standard deviation error (SDE), according to equation (4), 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 [29].

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{|x_i - \hat{x}_i|}{x_i} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2} \tag{3}$$

$$SDE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{|x_i - \hat{x}_i|}{x_i} - \frac{MAPE}{100}\right)^2} \tag{4}$$

Errors in modeling of 3 designed ANN, 2 fuzzy and 3 ANFIS car-following models considering MAPE, RMSE and SDE are summarized in table I. the error

Table 1. Result of Error For Car-Following Models

Car-following Model	Error Criteria		
	MAPE	RMSE(m/s^2)	SDE
ANN			
Based on instantaneous reaction delay using Stimulus-Reaction idea	0.3626	0.3417	0.0327
Based on constant reaction delay = 0.1 sec	0.5916	0.5167	0.0441
Based on constant reaction delay = 0.4 sec	0.6734	0.6011	0.0507
FIS			
With instantaneous reaction delay input using Stimulus-Reaction idea	0.2739	0.3231	0.0312
Without instantaneous reaction delay input	0.5692	0.5237	0.0488
ANFIS			
Based on instantaneous reaction delay using Stimulus-Reaction idea	0.1442	0.1970	0.0269
Based on constant reaction delay = 0.1 sec	0.4912	0.4123	0.0385
Based on constant reaction delay = 0.4 sec	0.5398	0.4773	0.0409

calculation has been done with the same data as the inputs for all models.

As shown in table I, models based on instantaneous reaction delay have less error value comparing with models regarding fixed reaction delay in all 3 criteria. Results show that these new models based on soft computing approaches have a strong capability with respect to other models.

Among these proposed models in this paper, ANFIS has the least error value. The results confirm that ANFIS simultaneously using the advantages of both methods, integration of human expert knowledge expressed by linguistic variables, and learning based on the data, is a compatible model.

5. CONCLUSION

In this paper, a novel idea to calculate the DVU instantaneous reaction delay of DVU was presented. Considering a proposed idea, three input-output models were developed to estimate FV acceleration based on soft computing approaches. These models were based on instantaneous reaction delay idea for DVU as an input and also choosing suitable other inputs and outputs with respect to instantaneous reaction delay. In this model, considering the variable DVU's reaction time, output values were applied to input. The performance of models was evaluated based on field data and compared to a number of existing car-following models. The simulation results showed that new soft computing models based on instantaneous reaction delay was better in driver modeling and prediction of the driver's actions than the other car-following models. The proposed method could be recruited in driver assistant devices, safe distance keeping observers, collision prevention systems and other ITS applications.

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