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Using the Human Effect in the Development of Soft Computing Car Following Models

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***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 DVU instantaneous reaction delay of Driver-Vehicle Unit (DVU). Considering the proposed idea, three input-output models are developed to estimate FV acceleration based on soft computing approaches. This idea is used to select the proper inputs and outputs to design the 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.**

***Index Terms*—Car Following, Instantaneous Reaction Time, Intelligent Transportation System, Soft Computing.**

I. Introduction

CAR following is quite common in many traffic fields such as railway, highway and so on. 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 Fig. 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].

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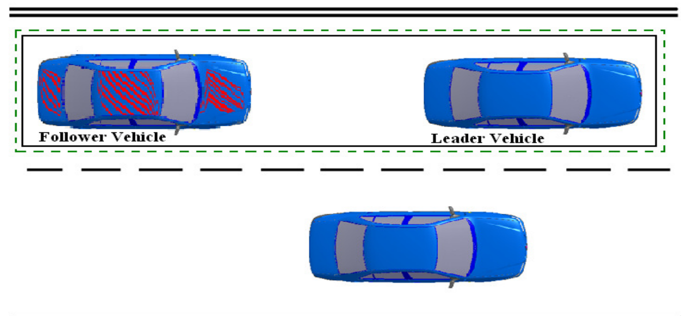


Fig. 1, Car following behavior (LV and FV) [2].

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 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 2 groups, mathematical equation-based and input-output based. The most important point in mathematical models is calculating 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 [13].

A number of factors have been found to influence car following behavior, and these include individual differences of age, gender, and risk-taking behavior. Highly nonlinear nature of car following behavior necessitates the development of intelligent algorithms to describe, model and predict this phenomenon [2].

In this paper an innovative idea to calculate the instantaneous reaction delay of DVU is proposed. This idea is used to model and predict the DVU behavior in car following scenarios by soft computing approaches. 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.

II. Calculating the Instantaneous Reaction Delay

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. 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. Many studies have estimated the reaction time based on indoor experiments and driving simulators. To estimate driver reaction delays via real data, several approaches have been proposed [16]. 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 dependent on the condition. Moreover, the reaction time appears to change during a single maneuver of acceleration or deceleration.

Now, as a new idea, the reaction time of the two actions, acceleration and deceleration, are analyzed using the observed data of many LV-FV in the actual traffic flow. Fig. 2 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 stimulus and reaction. In car following behavior, the variation of relative velocity and acceleration of FV are the concepts 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. The reaction time of each action is collected from the observed data in the range from 3.5sec to -1.5sec. 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 [13].

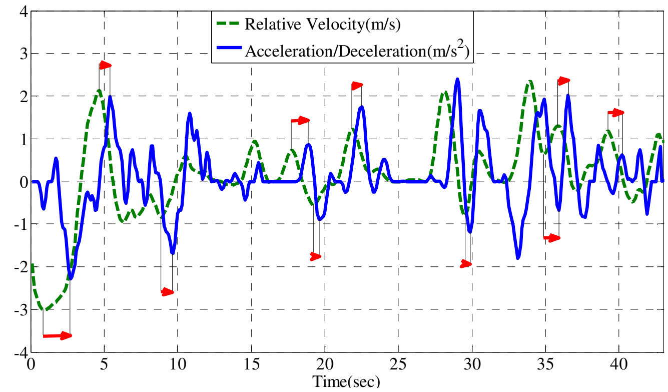


Fig. 2, Calculation DVU instantaneous reaction delay based stimulus-reaction idea [12].

This idea is called Stimulus-Reaction to estimate the instantaneous reaction delay of DVU in the subsequent sections. In order to calculate instantaneous reaction delay and design new car following models based on this delay, we will use this method as follow.

III. Soft Computing Car Following Models Design Based on Human Effect

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 [13]. ANN, FIS and ANFIS approaches are used to design the car following models.

A. *ANN Car Following Model Design*

Artificial neural networks offer an alternative way to tackle complex and ill-defined problems. They can learn from examples and are particularly useful in system modeling, such as in implementing complex mapping and system identification. ANN models may be used as alternative methods in engineering analyses and predictions. They learn the relationship between the input parameters and the controlled and uncontrolled variables by studying previously recorded data, in a way similar to how a non-linear regression might be performed [17].

To design ANN model, shown in Fig. 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 [18]. 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.

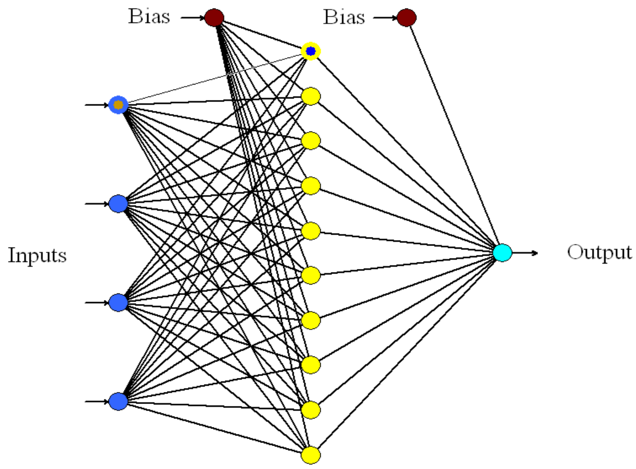


Fig. 3, Designed ANN model for car following behavior.

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 [19]. This dataset has been published as the "US-101 Dataset" and consists of detailed vehicle trajectory data on a merge section of eastbound US-101, as shown in Fig. 4. 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 roads, vehicle class, front vehicle and etc. The trajectory data seems to be unfiltered and exhibits some noise artefacts, so we have applied a moving average filter for duration about 1 sec to all trajectories before any further data analysis [2].

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.

Fig. 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.

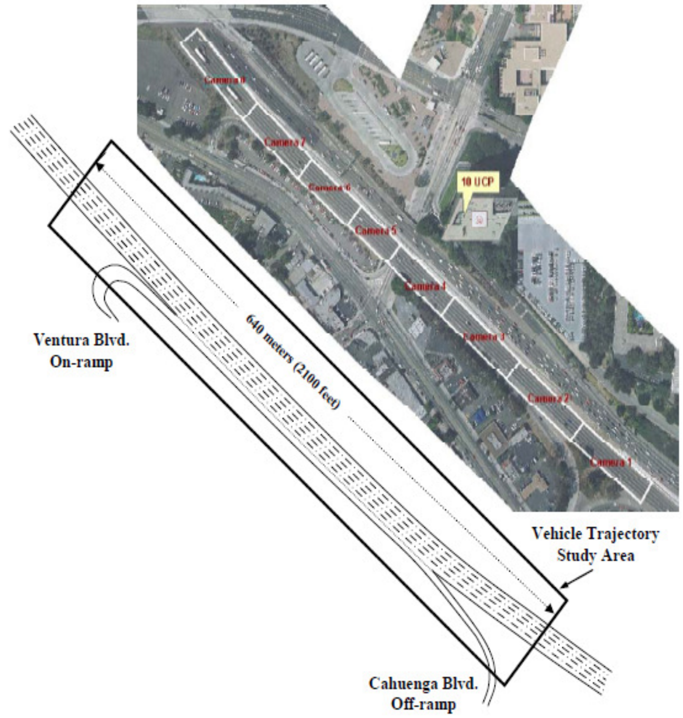


Fig. 4, A segment of Interstate 101 highway in Emeryville, San Francisco, California [19].

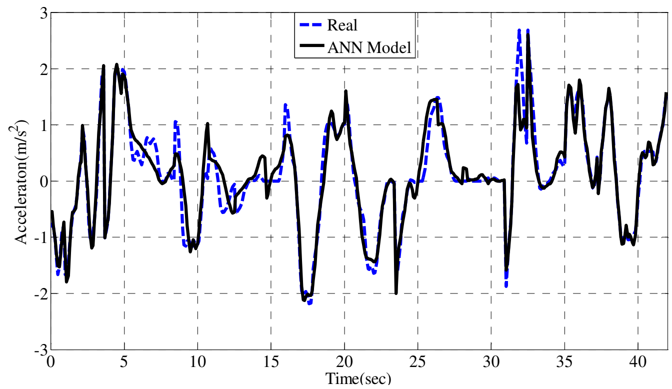


Fig. 5, Results for ANN estimator based on instantaneous reaction delay input.

B. *Fuzzy Car Following Model Design*

Fuzzy systems are established on fuzzy logic which is based on the idea that sets are not crisp but some are fuzzy, and these can be described in linguistic terms such as fast, slow and medium. 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 following behavior more accurately [20].

To design the fuzzy model, as shown in Fig. 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.

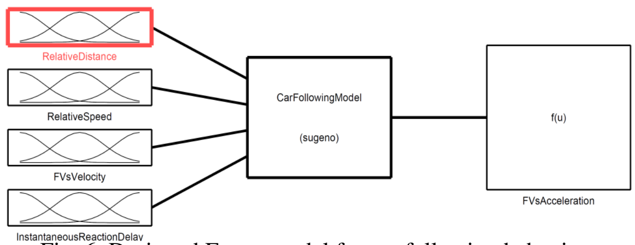


Fig. 6, Designed Fuzzy model for car following behavior.

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

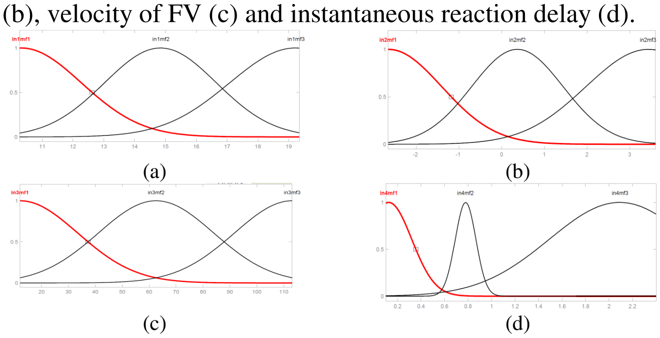


Fig. 7, Inputs of fuzzy model, (a) relative distance, (b) relative speed, (c) velocity of FV and (d) instantaneous reaction delay.

At first, the rule base contains 81 fuzzy if-then rules of Takagi-Sugeno's type in the fuzzy car following model [18]. We totally got 53 fuzzy rules, which have some corresponding relationship with the common sense when driving a car. For example, rule 1 means "if relative distance is too much close and relative speed is closing fast and FV speed is high and instantaneous reaction delay is large, then the negative acceleration is strong".

Fig. 8 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.

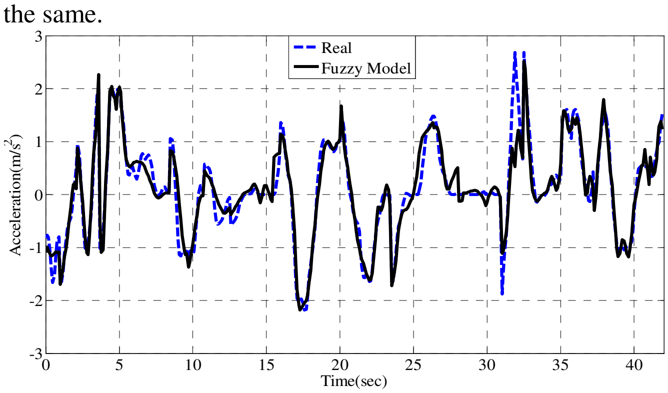


Fig. 8, Results for fuzzy estimator based on instantaneous reaction delay input.

C. 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 [21].

To design ANFIS model shown in Fig. 9, 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 [22].

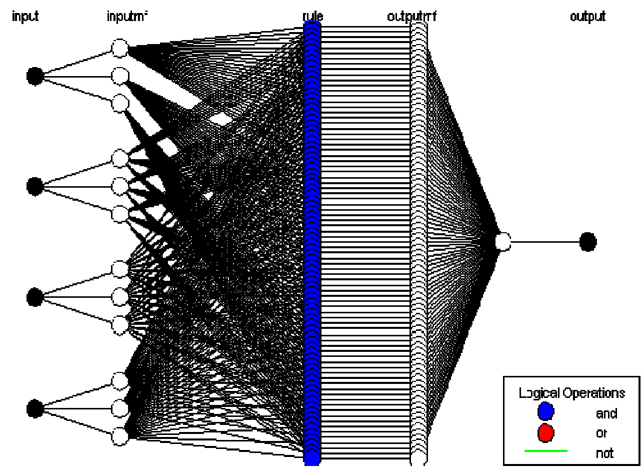


Fig. 9, Designed ANFIS model for car following behavior.

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.

Fig. 10 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.

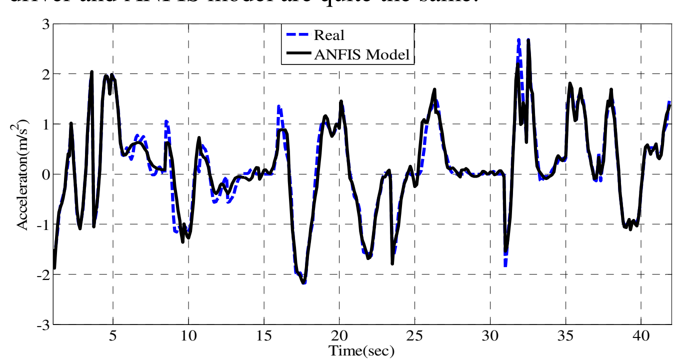
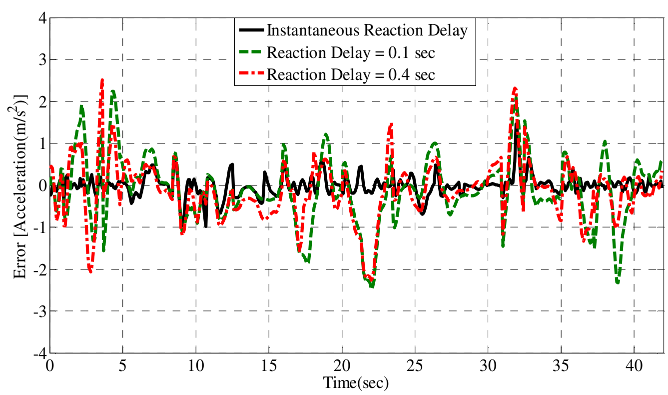


Fig. 10, Results for ANFIS estimator based on instantaneous reaction delay input.

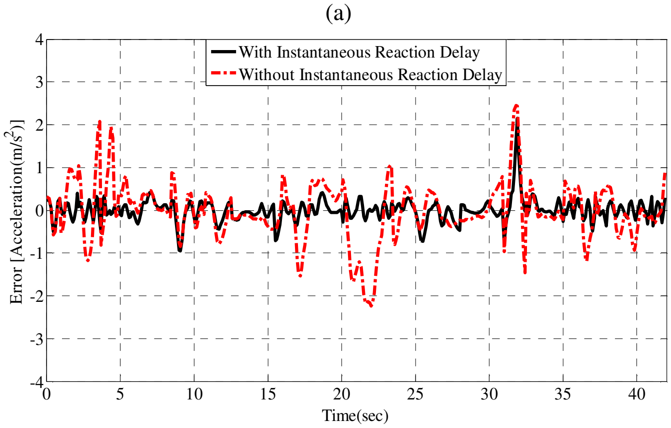
IV. Discussion and Results

In this section we are going to investigate the proposed soft computing models based on human effects. 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 relative speed, relative distance and velocity of FV, and output is acceleration of FV 0.1 sec and 0.4 sec are assumed for constant delay. Also to train and test the performance of these systems, the same real traffic data are used as input and output. Fig. 11(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.

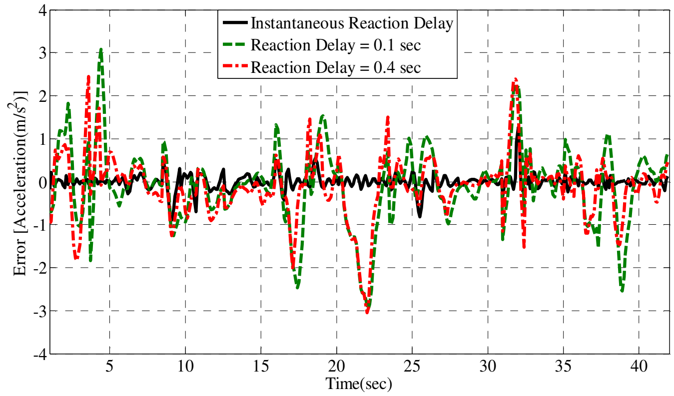
In order to show the capability of fuzzy estimator system based on the instantaneous reaction delay, another fuzzy estimator system without instantaneous reaction delay input is designed. The car following behavior model is simulated and verified using actual measured values as inputs. To estimate driver reaction delays from real data, the DVU instantaneous reaction delay is calculated using the proposed idea. Fig. 11(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.



(a)



(b)



(c)

Fig. 11, estimation error for car following models: (a) ANN, (b) FIS, (c) ANFIS.

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 acceleration of FV 0.1 sec and 0.4 sec are assumed for constant delay. Also to train and test the performance of these systems, the same real traffic data are used as input and output. Fig. 11(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 (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 [23].

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

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

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

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

TABLE I
RESULT OF ERROR FOR CAR FOLLOWING MODELS

CAR FOLLOWING MODEL	Error Criteria		
	MAPE	RMSE	SDE
ANN			
Based on instantaneous reaction delay	0.3626	0.3417	0.0327
Based on reaction delay = 0.1 sec	0.5916	0.5167	0.0441
Based on reaction delay = 0.4 sec	0.6734	0.6011	0.0507
FIS			
With instantaneous reaction delay input	0.2739	0.3231	0.0312
Without instantaneous reaction delay input	0.5692	0.5237	0.0488
ANFIS			
Based on instantaneous reaction delay	0.1442	0.1970	0.0269
Based on reaction delay = 0.1 sec	0.4912	0.4123	0.0385
Based on reaction delay = 0.4 sec	0.5398	0.4773	0.0409

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.

V. 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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