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Modify Car Following Model by Human Effects Based on Locally Linear Neuro Fuzzy

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***Abstract*—Nowadays, simulation has become a cost-effective option for the evaluation of infrastructure improvements, on-road traffic management systems, and in vehicle driver support systems due to the fast evolution of computational modeling techniques. This paper presents a Locally Linear Neuro-Fuzzy (LLNF) model to simulate and predict the future behavior of a Driver-Vehicle-Unit (DVU). Local Linear Model Tree (LOLIMOT) learning algorithm is applied to train the model using real traffic data. This model was developed based on a new idea for estimating the instantaneous reaction of DVU, as an input of LLNF model. The model's performance was evaluated based on real observed traffic data and also through comparisons with the results of LLNF models based on constant reaction delay. The results showed that LLNF model based on instantaneous reaction delay input outperformed the other car following models.**

I. Introduction

INTELLIGENT transportation systems (ITS) are a multidisciplinary area with its focus on incorporating up-to-date information technologies of all kinds in the field of transportation. Recent advances in intelligent and automated vehicles, and continuous improvements of information-based road infrastructures, have propelled research to understand their interactions and to evaluate them on a large scale.

Simulation has become a cost-effective option for the evaluation of infrastructure improvements, on-road traffic management systems, and in vehicle driver support systems due to the fast evolution of computational modeling techniques. Moreover, a rapid development of sophisticated microscopic simulation models over the past decade has led to a tide of applications of microscopic simulation in transportation engineering [1].

Car following models, as the most popular microscopic traffic flow modeling, are increasingly being used by transportation experts to evaluate new ITS applications [2, 3]. 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 [4].

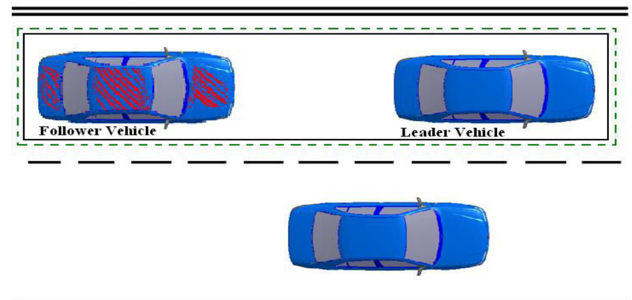

Fig. 1, Car following behavior (LV and FV) [4].

Humans play an essential role in the operation and control of human-machine systems such as driving a car. 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 [5]. Based on Rasmussen's human-machine model, driver behavior can also be separated into a hierarchical structure with three levels: the strategic, tactical, and operational level [6]. 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.

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 [5].

Regarding literatures [7, 8], car following models can be classified into 14 groups as follows: Gazis-Herman-Rothery [9], collision avoidance/safe distance [10], linear model/Helly [11], action point [12], fuzzy logic-based model [13], desired spacing [14], capacity drop and hysteresis theory [15], neural network [16], optional velocity [17], adaptive neural fuzzy inference system [18], emotional

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learning fuzzy inference system [19], local-linear neural fuzzy [20], local quadratic neural fuzzy [19] and genetic algorithm based optimized least squares support vector machine [19]. 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 were always chosen by average of experiment values and regarding them as a constant value of DVU. Because these parameters are the functions of time, results of these models are match test cases only and are not reliable. In input-output models, by considering the constant DVU reaction time, output values are applied to input. Since the DVU reaction time is not actually constant, other parameters vary with time. So the error in modeling results because of the difference between real data and data used for modeling [18].

The highly nonlinear nature of car following behavior necessitates the development of intelligent algorithms to describe, model and predict this phenomenon. Neuro fuzzy models 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 [18]. LLNF models like other neuro fuzzy systems are adaptive networks and provide robust learning capabilities and are widely utilized in various applications such as system identification and prediction. LOLIMOT is a type of Takagi-Sugeno-Kang neuro fuzzy algorithm which has proven its efficiency compared with other neuro fuzzy networks in learning the nonlinear systems and pattern recognition [21].

In this paper, we are going to focus on LLNF system design based on LOLIMOT learning algorithm for modeling and prediction of car following behavior in real traffic flow, considering the effects of driver's behaviors. The presented model can be utilized in several applications of intelligent transportation systems.

II. LLNF Car Following Model Design Based on the Human Effects

A more accurate representation of car following behavior should take into account the nonlinearity of human response and limitations of human perception system. An LLNF model can map between variables the driver can perceive and variables the driver can directly control with arbitrary accuracy based on fuzzy reasoning and neural learning. This makes the system natural and suitable to model a human in the loop system. In this section, a modified LLNF car following estimator is presented, using instantaneous reaction delay of DVU as an input of car following model and also choosing suitable other inputs and outputs with respect to instantaneous reaction delay in order to train an LLNF model.

A. LLNF System and LOLIMOT Learning Algorithm

The main idea in developing LLNF has been originated from radial functions theory. Radial functions, integrated into neural networks in 1988, have been widely used in estimation and mathematical theories. Capability of such functions as general approximators has been demonstrated in several researches. LLNF models are reformulations of Takagi-Sugeno fuzzy systems using basis functions [22]. Transparency and comprehensibility of LLNF models is a key feature making it possible to use several learning and optimization algorithms in these models. LLNF model is based on partitioning the input space into small linear sub-spaces with proper fuzzy validity functions. Each linear part of the model with its associate fuzzy validity function can be described as a nonlinear neuron. Therefore, the general model is a neuro fuzzy network with one middle layer and a linear neuron in output layer that can simply calculate the sum of weighted outputs of all locally linear neurons. This architecture has been illustrated in Fig. 2. Fuzzy validity functions are considered as normal Gaussian functions [23].

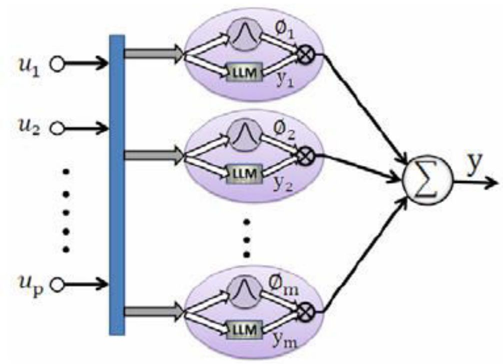


Fig. 2, Network structure of a static local linear neuro-fuzzy with M neurons for p inputs [23].

Learning or optimization methods are used to adjust two sets of parameters which are associated to locally linear models and to validity (membership) functions.

LOLIMOT learning algorithm will be used here to determine the nonlinear premise parameters of the rules. Rapid convergence is the main benefit of this method. LOLIMOT learning algorithm is based on gradual improvement of the model [22]. Starting form an initial condition, the input space is incrementally partitioned into subspaces that specify the effective region of their corresponding locally linear models (LLM). In other words, instead of a costly nonlinear optimization, LOLIMOT uses a simple constructive search for adjusting the premise parameters of the rules.

In a simple but efficient manner and using vertical and horizontal axes, LOLIMOT partitions the input space into hyper-rectangles and a Gaussian function is placed in the center of each hyper-rectangle having a standard deviation equal to 1/3 of the rectangle's length. Therefore, nonlinear parameters of membership functions are computed using a simple method. To partition the input space in each stage, the LLM causing the largest weighted error in output is selected by LOLIMOT. The validity region of the selected LLM is partitioned into two new hyper-rectangles in direction of each axis and one neuron is placed in each new region. The direction which results in a smaller modeling error is selected and the whole process is repeated iteratively until a certain stop criterion is reached. The partitioning process of a two dimensional input space using LOLIMOT is illustrated in Fig. 3. The initial model is constructed using an optimized linear least square estimation and neurons are added only if prediction error is decreased [23, 24].

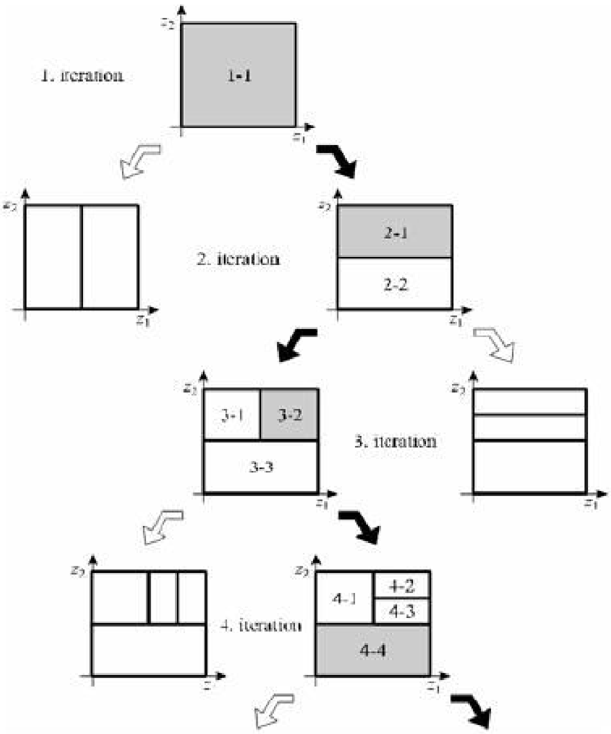


Fig. 3, Operation of the LOLIMOT algorithm in the first five iterations for a two dimensional input space [24]

LOLIMOT learning algorithm satisfies the parsimony principle using minimum adjustable parameters and can be generalized easily. To prevent overfitting and to achieve maximum generalization, error indices are computed for validation data sets and the algorithm is stopped when the error indices for these data sets starts to rise. Transparency and comprehensibility are remarkable features of LLNF models which allow the usage of fast least square method to optimize consequent parameters of the rules and the usage of incremental tree learning methods for tuning the premise parameters.

B. DVU Reaction Time

Reaction delay is a common characteristic of humans in operation and control, such as driving a car. 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. 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 [25].

Many studies have estimated the reaction time based on indoor experiments and driving simulators. 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. 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 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 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 3.5 to -1.5sec. If the calculated reaction time might be negative, reaction time is assumed to be null in the simulation. Since this idea is called Stimulus-Reaction to estimate the instantaneous reaction delay of DVU in the next sections.

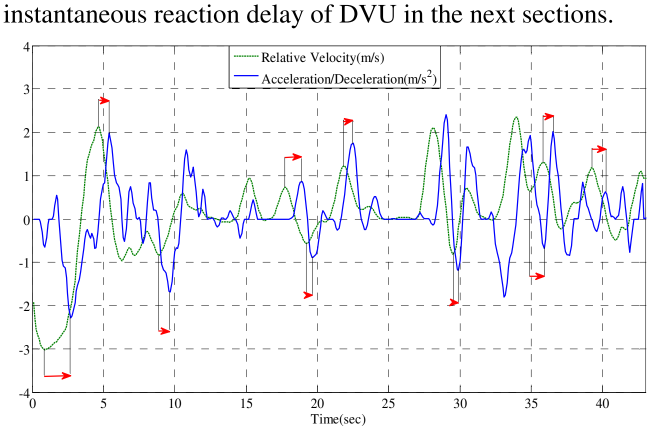


Fig. 4, Calculation DVU instantaneous reaction delay based on Stimulus-Reaction idea [18].

In order to calculate instantaneous reaction delay and design a new car following model based on instantaneous reaction delay, we will use this method as follow.

C. LLNF Car Following Model

In this section, considering the LLNF modeling based on LOLIMOT learning algorithm and proposed Stimulus-Reaction 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.

In order to design an LLNF prediction model, 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 LLNF prediction model [26]. 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 0.1sec intervals. Any measured sample in this dataset 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 and etc.

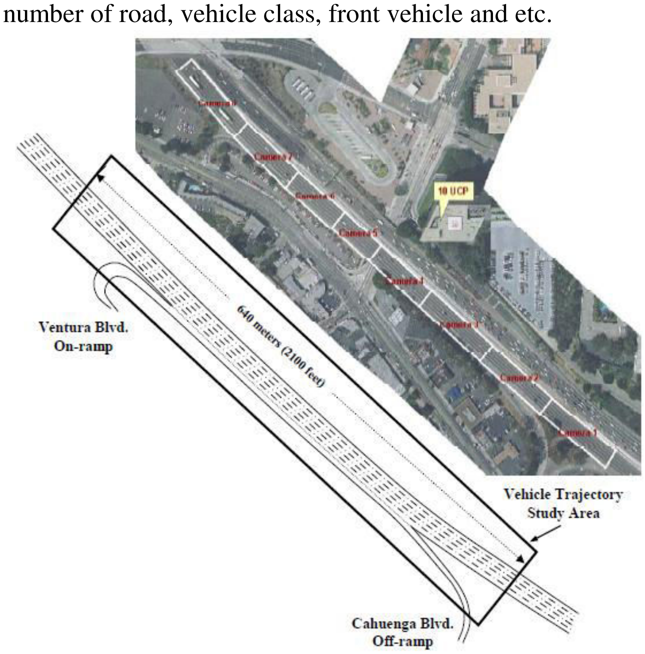


Fig. 5, A segment of Interstate 101 highway in Emeryville, San Francisco, California [26].

The trajectory data seem to be unfiltered and exhibit some noise artefacts, so we have designed and applied a moving average filter for duration about 1sec to all trajectories before any further data analysis. Comparison of unfiltered and filtered data is shown in Fig. 6.

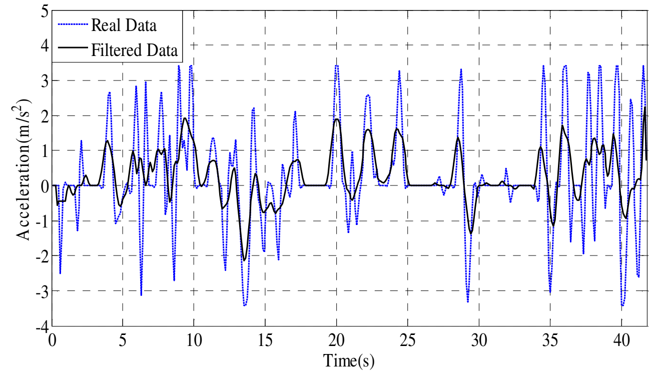


Fig. 6, Comparison of unfiltered and filtered data.

To design the LLNF model, it is assumed that the LLNF applied for prediction model has four inputs and one output, which inputs are instantaneous reaction delay estimated using Stimulus-Reaction idea, relative speed, relative distance and velocity of FV, and output is acceleration of FV. The training of the LLNF model is performed based on choosing suitable inputs and output with respect to instantaneous reaction delay. There is one hidden layer with 9 nods and back propagation algorithm is used to train this model [27].

In the development of LLNF 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.

III. Discussion and Results

In order to evaluate the competence of LLNF prediction model based on the instantaneous reaction delay input based on Stimulus-Reaction idea to predict and calculate instantaneous reaction time, three other LLNF prediction models with constant delay and three inputs were designed and simulated, which inputs are relative speed, relative distance and velocity of FV, and output is acceleration of FV. Constant delays of 0.1, 0.3 and 0.6sec are assumed for these models. To train and test the performance of these systems, same real traffic data are also used as inputs and output.

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

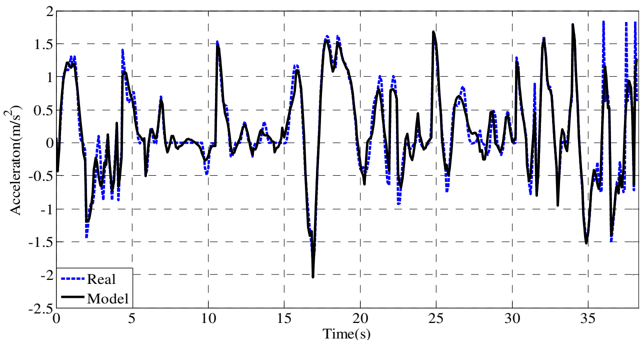
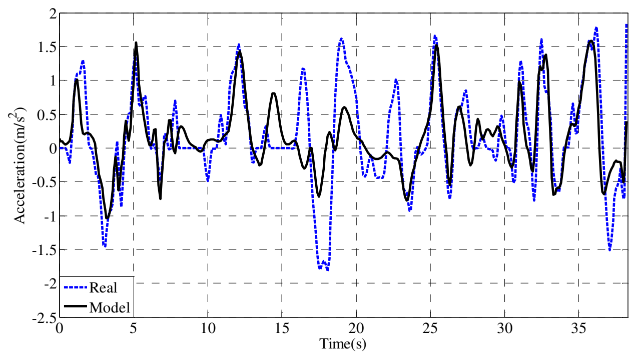
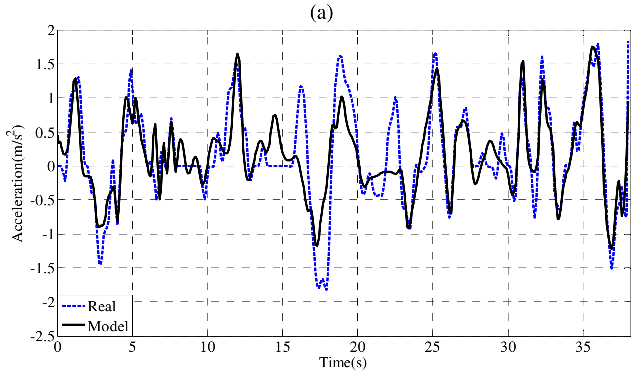


Fig. 8, LLNF estimator results based on instantaneous reaction delay input using Stimulus-Reaction idea.

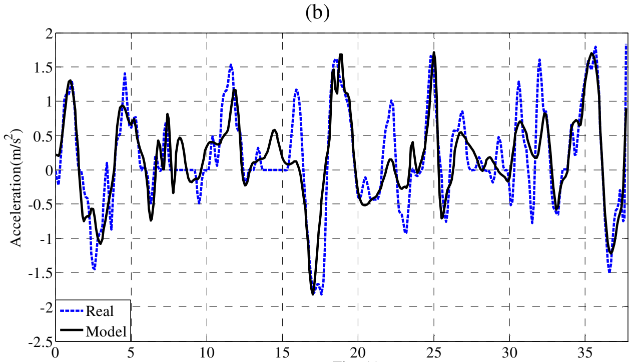
Fig. 10 shows the performance of LLNF estimator for DVU in car following behavior based on the various constant delays of 0.1, 0.3 and 0.6sec.



(a)



(b)



(c)

Fig. 10, LLNF estimator results based on constant reaction delay: (a) 0.1sec, (b) 0.3sec, (c) 0.6sec.

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 $\overline{x}$ is the real mean value of the variable and N is the number of test observations [28].

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

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

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

Errors in modeling of six designed LLNF car following models with considering MAPE, RMSE and SDE are summarized in Table I.

TABLE I
RESULT OF ERROR FOR LLNF CAR FOLLOWING MODEL

LLNF Car Following Model	Error Criteria		
	MAPE	RMSE	SDE
Based on instantaneous reaction delay using Stimulus-Reaction idea	0.0176	0.1876	1.0883
Based on constant reaction delay 0.1sec	1.4347	0.4903	3.1208
Based on constant reaction delay 0.3sec	1.7306	0.4048	2.5585
Based on constant reaction delay 0.6sec	0.6003	0.3811	2.3827

As shown in Table I, LLNF car following model based on instantaneous reaction delay input based on Stimulus-Reaction idea has a lower error value comparing with model regarding instantaneous reaction delay input by Ozaki idea and models regarding constant reaction delay in all 3 criteria. Results show that this new model has a strong capability with respect to other models.

IV. CONCLUSION

This paper proposes an intelligent method for predicting the future states of a vehicle in a car following scenario. Using real traffic data, a Locally Linear Neuro Fuzzy model for DVU in car following is developed and trained using LOLIMOT learning algorithm. This model uses instantaneous reaction delay for DVU as an input. 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 other fuzzy model. The simulation results show the efficiency of the proposed model in driver modeling and prediction of the driver's actions comparing with the other models. The comparisons verify the efficiency of the presented LLNF model by considering the human effects as well as its accuracy and low computational complexity. The proposed model can be used in driver assistant devices, safe distance keeping observers, collision prevention systems and other ITS applications. The proposed model can be used in several applications of ITS, such as driver assistant devices, safe distance keeping observers, collision prevention systems.

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