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Improved adaptive neuro fuzzy inference system car-following behaviour model based on the driver–vehicle delay

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Abstract: In the past decades, different forms of car-following behaviour model have been intensively studied, proposed and implemented. These models are increasingly used by transportation experts to utilise for appropriate intelligent transportation systems. Unlike previous works, where the reaction delay is considered to be fixed, an improved adaptive neuro fuzzy inference system (ANFIS) model is proposed to simulate and predict the car-following behaviour based on the reaction delay of the driver–vehicle unit. An idea is proposed to calculate the reaction delay. In this model, the reaction delay is used as an input and other inputs–outputs of the model are chosen with respect to this parameter. Using the real-world data, the performance of the model is evaluated and compared with the responses of other existing ANFIS car-following models. The simulation results show that the proposed model has a very close compatibility with the real-world data and reflects the situation of the traffic flow in a more realistic way. Also, the comparison shows that the error of the proposed model is smaller than that in the other models.

1 Introduction

The success of the intelligent transportation systems (ITS) deployment depends on the availability, new technology, price and government policy of the advanced traffic analysis tools and is used to predict network conditions and analyse network performance in the planning and operational stages. Therefore, there is a strong need for a traffic estimation and prediction system (TrEPS) to meet the information requirements and to aid in the evaluation of ITS traffic management and information strategies [1]. In TrEPS, microscopic models are increasingly being used by transportation experts to evaluate the applications of new ITS [2]. A variety of applications, including car navigation systems, lane keeping assistance systems and collision prevention systems, directly use the microscopic traffic flow models [1]. The scientific study of traffic flow began in the 1930s, with the application of probability theory to describe the road traffic. The pioneering studies were conducted by Bruce D. Greenshields at the Highway Research Board [3].

Based on Rasmussen's human–machine model [4], as shown in Fig. 1 [5], the driver behaviour can be classified into a hierarchy with three levels: strategic, tactical and operational. At the highest or strategic level, the goals of each driver are determined, and a route is planned based on these goals. The lowest operational level reflects the real actions of the drivers, for example, steering, pressing pedal and gearing. At the middle level, certain manoeuvres are selected to achieve short-term objectives, for example, interactions with other road users and road infrastructures. The behaviour at this level is dominated by the most recent situations, but is also influenced by drivers' goals at the higher level.

To develop a microscopic traffic simulation of high fidelity, researchers are often interested in imitating human's real driving behaviour at a tactical level. In other words, without describing the detailed driver's actions, driver–vehicle units (DVUs) in the simulation are modelled to replicate their states in reality, that is, the profiles of vehicle position, velocity, acceleration and steering angle. Fig. 2 indicates the model structure of a DVU, in which the detailed driver's actions become internal [1]. A number of factors have been found to influence car-following behaviour, and these include individual differences of age, gender and risk-taking behaviour [2, 6]

Among the important microscopic traffic flow modelling approaches, car-following models are aimed to describe the process of following a leader vehicle (LV) by a follower one. Car-following behaviour describes the longitudinal action of a driver when he follows another car and tries to maintain a safe distance with the leading car. The majority of the available car-following models assume that the driver of the follower vehicle (FV) responds to a set of variables, such as relative velocity and relative distance between the LV and the FV, velocity of the FV, and/or desired distance and/or velocity of the target driver. The response is

Fig. 1 *Rasmussen's human–machine model [5]*

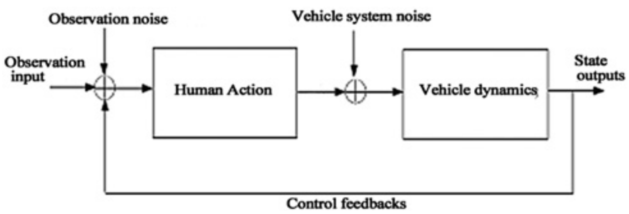

Fig. 2 *Structure of a DVU model [1]*

typically considered to be variations of acceleration or velocity of the following vehicle [7]. The highly non-linear nature of the car-following behaviour 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 (ANNs) and fuzzy inference system (FISs), 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 [8].

In this paper, we have focused on an ANFIS model design to predict the car-following behaviour in the real traffic flow, considering the effects of driver's behaviours. The reaction delay of a DVU is used as a human effect and applied as an input of the car-following model. This paper is organised as follows: A brief review of the car-following models is presented in Section 2. In Section 3, a new idea in calculating the reaction delay of DVU is presented. In Section 4, the ANFIS model design based on the reaction delay input is proposed to model and predict the DVU behaviour in car-following scenarios. Some numerical simulation results for the proposed ANFIS model and five other ANFIS prediction models are given in Section 5. Lastly, conclusion and future works are presented in Section 6.

2 Brief review of car-following models

All the models being presented for the car-following behaviour are evaluated based on their ability to predict or estimate the motion feature such as the acceleration/deceleration of FV. Based on the literature, the car-following models can be classified into the following 13 groups:

2.1 Gazis–Herman–Rothery models

The first formulation of this model was developed at the General Motors Research Laboratory in Detroit. The Gazis–Herman–Rothery (GHR) model considers acceleration as a function of the following three variables: the velocity of the LV, the relative velocity and the relative distance between LV and FV, and the driver's reaction delay. Subsequently, many works have been done to develop and improve these models [9, 10].

2.2 Collision avoidance/safe distance models

This model was first presented by Kometani and Sasaki. A number of variants of the model have also been reported in the literatures [9, 11]. This model describes the safe following distance (required to avoid collision with the vehicle ahead) as a function of the velocities of LV and FV, and the driver's reaction delay. The Gipps model [12], which is widely used in microscopic traffic simulation, is based on the collision avoidance (CA) model. One of the factors for the popularity of the model is the realistic behaviour reported for situations involving either a pair of vehicles or platoons.

2.3 Linear/Helly models

The basic form of this model relates the acceleration of the FV to the desired following distance, velocity of the FV, relative distance and velocity between LV and FV, and driver's reaction delay [13]. The origin of this model is the GHR model, but has been further improved by Helly [14]. The model presents a good fit to the observed data. The main difficulty is with the calibration of constant parameters for a particular study.

2.4 Psychophysical/action point models

This model is based on the assumption that a driver will perform an action when a threshold, expressed as a function of velocity difference and distance, is reached. Three different types of thresholds are implemented. Clearly, the ability to perceive velocity differences and estimate distances vary widely among the drivers, and hence, the difficulty in estimating and calibrating the individual thresholds is associated with this model [9, 15].

2.5 Desired spacing models

These models are based on a desired spacing criterion, which is assumed as a linear function of the velocity [16, 17]. The models are based on the premise that the desired spacing is an individual driver characteristic and drivers have different desired spacing criteria in acceleration and deceleration. These models eliminate the problems associated with the reaction delays used in other models because they describe car-following behaviour based on the desired spacing between the vehicles, without attempting to explain the behavioural aspects of the car-following. A more detailed discussion of these models can be found in [16].

2.6 Capacity drop and traffic hysteresis theory models

The capacity drop and traffic hysteresis for multiphase vehicular flow, proposed by Zhang and Kim [18], is based on the Pipes car-following theory (which is a linear model that describes traffic behaviour of drivers observing the driving rules suggested in the California Motor Vehicle Code).

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2.7 Optimal velocity models

Based on the optimal velocity, a congested flow is generated spontaneously from a homogeneous flow for a certain range of traffic density. A well-established congested flow obtained in a numerical simulation shows a remarkable repetitive property, such that the velocity of a vehicle evolves exactly in the same way as that of its preceding one, except with a time delay. This leads to a global pattern formation in time development of the vehicle's motion, and gives rise to a closed trajectory on a headway-velocity plane connecting congested and free-flow points [19].

2.8 Fuzzy logic-based models

This model is based on fuzzy set theory, which describes how adequately a variable fits the description of a term [20, 21]. The application of fuzzy logic principles to the GHR model has been reported in [22]. This model divides the selected inputs into a number of fuzzy sets. Logical operators are then used to produce fuzzy output sets or rule-based car-following behaviour. The main difficulty in the application of this model is the determination of membership functions, which are crucial to the operation of the model.

2.9 Neural network (NN) models

Few studies on NN-based car-following behaviour are discussed in [23]. Hongfei *et al.* [24] applied a back-propagation NN to develop a car-following model using the data collected by a novel technique known as the 'five-wheel system'. They predicted only the acceleration of the FV as opposed to its velocity or headway to the LV. Panwai and Dia [2, 25] developed a NN-based car-following model, using the real-world data and compared it with the existing models. Another study tested the back propagation and radial-basis function NNs to model the car-following behaviour, and found that the latter has higher precision [26]. Shankar *et al.* [27] developed a NN-based car-following model using substantial proportion of LV and FV data.

2.10 ANFISs-based models

Mar and Feng-Jie presented a controller based on ANFIS for the car-following collision prevention system to non-linearly control the speed of the vehicle [28]. The inputs are relative distance and velocity, and the output of the controller is acceleration or deceleration rate of FV. Ma proposed a multi-regime framework based on the statistical property in each regime and mathematical models adopted in those regimes [29]. This framework is an extension of Takagi–Sugeno–Kang (TSK) FIS and can be expressed by a neural–fuzzy system. Genetic algorithm (GA) is designed as the main learning method for this system. A fuzzy logic model for representation and simulation of pedestrian behaviour in such a manoeuvre is proposed in [30]. The calibration of fuzzy model membership functions is executed through an adaptive NN, which considers a sample of gap acceptance decisions collected on field.

2.11 Emotional learning-based FISs models

Zarringhalam [31] presented an innovative model based on emotional learning-based fuzzy inference systems (ELFISs) for the analysis of DVU's behaviour. Emotional factors, such as excitement, stress and fear were believed to disturb operators in decision making, but are nowadays declared as constructive components of this process. The proposed models have been designed for modelling and prediction of the DVU's behaviour in the car-following scenarios.

2.12 Locally linear neuro fuzzy (LLNF) models

LLNF models are combinations of the ANNs and FISs, which simultaneously use the advantages of both methods. They can decompose a complicated modelling problem into some easier-to-solve sub-problems. Khodayari *et al.* [32] proposed a LLNF model to predict the future behaviour of a DVU in a car-following scenario.

2.13 Locally quadratic neuro fuzzy models (LQNFMs)

Zaringhalam *et al.* presented a LQNFM for the prediction of the future states of a vehicle in a car-following scenario [31]. An efficient heuristic learning algorithm based on correlation analysis has been proposed to train the LQNFM using real traffic data. Future behaviour of velocity and following the distance time series of the target vehicle are predicted using the LQNFM. To enhance the prediction performance, causal variables are integrated in the predictor model. Multi-step-ahead prediction is considered to simulate the effect of driver's reaction delay while developing the model [31].

In a general classification, the car-following behaviour microscopic models can be divided into two groups: equation-based and input–output-based models. In the equation-based models, the car-following behaviour is presented by a set of mathematical equations. These equations are explained based on choosing variables and adjustments of parameters in linear or non-linear forms, such as GHR, CA and Helly models. The important point in equation-based models is the calculation of model parameters. Therefore these parameters are always chosen by the average of experimental values and considering them as a constant value of the DVU. As these parameters are functions of time, the results of these models are only matched to the test cases and hence are not reliable. In the input–output-based models, the car-following behaviour is presented based on real measured values and signal-based modelling approaches. In these models, the inputs and outputs are designed 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 delay, the output values are applied to train the model. As the DVU reaction delay 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 modelling results [8].

3 New idea to calculate the 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, owing 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 delay 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 research on car-following models has been historically focused on exploration of different modelling frameworks and variables that affect this behaviour, it has been recognised that reaction delay of each driver is an indispensable factor for the identification of car-following models [33].

Many studies have estimated the reaction delay based on indoor experiments and driving simulators. As a very common and well-known idea in calculating the reaction delay, Ozaki [34] performed a study which showed that there is a high correlation between the reaction delay and acceleration/deceleration of the LV and the relative distance between LV and FV. The reaction delay is expressed by relative distance and acceleration/deceleration of LV. The description of reaction delay is chosen as a simple model, considering the result of the regression analysis. The major specification of Ozaki's idea is described in (1) as follows

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

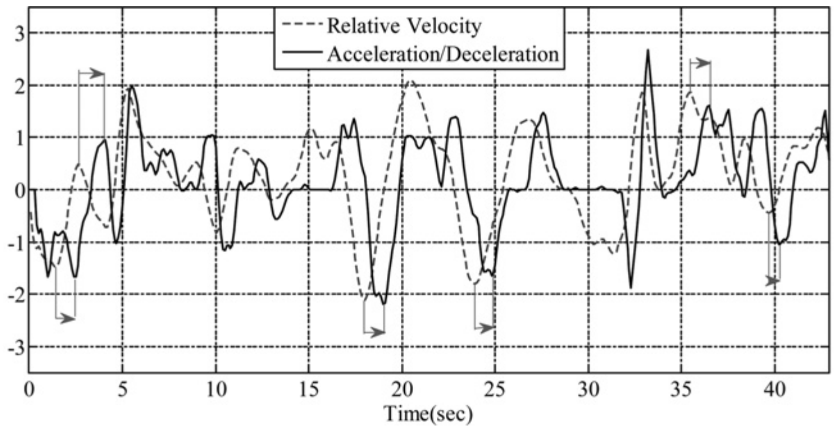
where $s(t)$ represents the relative distance between the two cars by meter dimension and a_{LV} is the acceleration of the LV by m/s^2 dimension.

Ozaki presented a mathematical equation to calculate the reaction delay of a driver–vehicle unit based on relative distance and acceleration/deceleration of LV. He utilised real experimental data to validate his idea, and he also considered both the situations of acceleration and deceleration of LV. In his idea, coefficients of the parameters are constant. But we believe that in reality these coefficients are not constant and differ based on the situations.

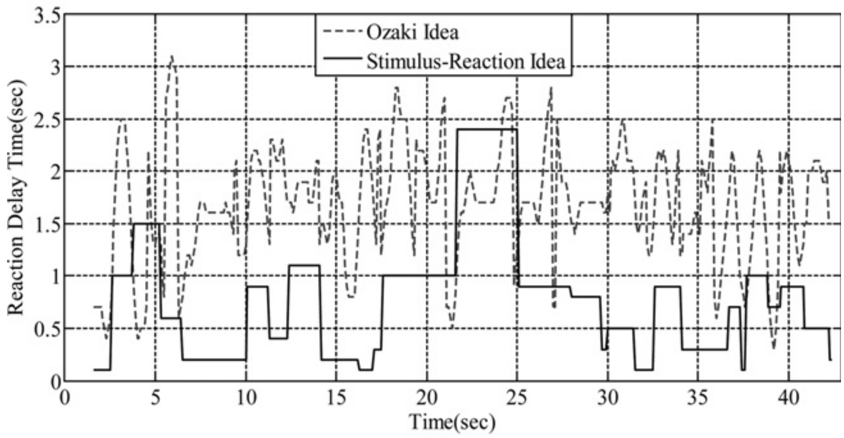
In our study, the reaction-time of many drivers was analysed. We noticed that for a single driver in the experiment on the test track, the reaction delay is highly dependent on different conditions like different driving behaviours, different lanes of the highway and also different range of velocities. Moreover, the reaction delay appears to change during a single manoeuvre of acceleration or deceleration.

Therefore, as a new idea, the reaction delay of the two actions, acceleration and deceleration, are analysed using the observed data of many LV–FVs in the actual traffic flow. This idea is based on the fact that the delay time is the time between the stimulus and the reaction.

The reaction delay appears to change during a single manoeuvre acceleration or deceleration in the car-following behaviour. These single manoeuvres can be divided into four actions that are observed in the actual traffic flow: start of the deceleration, the



a



b

Fig. 3 *Calculation of reaction delay*

a Calculation of DVU's reaction delay based on our new idea

b Estimation of the reaction delay obtained from the Stimulus–Reaction idea and the Ozaki idea

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maximum deceleration, start of the acceleration and the maximum acceleration.

The delay time to the start of the deceleration is the time lag from the zero value of the relative velocity to the null acceleration/deceleration at the start of deceleration. The delay time for maximum deceleration is the time lag between the negative maximum values of the relative velocity and the acceleration/deceleration. The delay time to the start of the acceleration is the time lag from the zero value of the relative velocity to the null acceleration/deceleration at the start of acceleration. The delay time for the maximum acceleration is the time lag between the positive maximum values of the relative velocity and acceleration/deceleration. In the analysis, the four actions are combined into two groups considering the DVU operation. Drivers change the accelerator pedal and brake pedal in the driving operation. Considering the time to change the pedals, the action of the start and the succeeding maximum operation are combined. The start of the deceleration action and the maximum deceleration are grouped to the deceleration condition, and the start of the acceleration and the maximum acceleration are grouped to the acceleration condition [8]. A high correlation was seen between the delay time and the acceleration of the FV. This correlation showed that as the acceleration/deceleration grows, a faster change is expected in the relative velocity. This result leads to easier perception by the FV.

In the car-following behaviour, the variations of relative velocity and acceleration/deceleration of FV is the concept of the stimulus and the reaction. Variations in the relative velocity and FV's acceleration/deceleration are the maximums or minimums of the velocity trajectory or FV's acceleration/deceleration, respectively. DVU's instantaneous reaction is the time difference between the two subsequent variations: relative velocity as the stimulus and the FV's acceleration/deceleration as the reaction. This idea is called Stimulus–Reaction to estimate the reaction delay of DVU in the subsequent sections. In our idea, reaction delay is the time difference between the stimulus (change of rate of relative velocity) and reaction (change of rate of acceleration of FV), that is, as Fig. 3 shows, reaction delay is the time distance between two subsequent maximum (or minimum) points of the two diagrams (shown by green arrow). Fig. 3*a* indicates how the DVU's reaction delay can be calculated using the proposed idea. Fig. 3*b* compares the estimation of the reaction delay obtained from Stimulus–Reaction idea with that of obtained from Ozaki idea. The data presented in this figure is based on the car-following behaviour shown in Fig. 3*a*. Note that in Fig. 3*b*, both diagrams are showing the reaction delay. Therefore it is obvious that we should put the title and units on y-axis. However in Fig. 3*a*, one diagram is showing the relative velocity and the other one is showing the acceleration/deceleration. Therefore since two different quantities are shown on one figure, this figure does not have a title on the y-axis. The legend inside the figure shows what each diagram present.

Based on the real data which is shown in Fig. 3*a* and by analysing this figure, it can be seen that as the absolute level of the acceleration/deceleration of the FV becomes greater, the reaction delay becomes smaller. It should be noted that the estimated delay time is the most appropriate value during the period of acceleration or deceleration [19, 22]. Through a careful observation of the real observed data (see Fig. 3*a*), it was found that some FV deceleration actions started before the relative velocity changed from positive to negative values. Most of the car-following models treated so far neglected the correlations between vehicles; however, it is obvious that drivers often observe their two or more nearest vehicles ahead. This leads to multi-vehicle interactions with consequences on the phase separation and the fundamental diagram. Lenz *et al.* [35] extend the optimal velocity model by Bando to multi-vehicle interactions in the following way. They suppose that drivers do not only react on the dynamics of their leading vehicle but also take into consideration multi-anticipative driving behaviour up to multi-cars ahead [36]. Therefore the reaction delay of each action is collected from the observed data in a range from 3.5 to –1.5 s.

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 FV's act with the anticipation of their LVs' next action. However, even though negative reaction delay 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

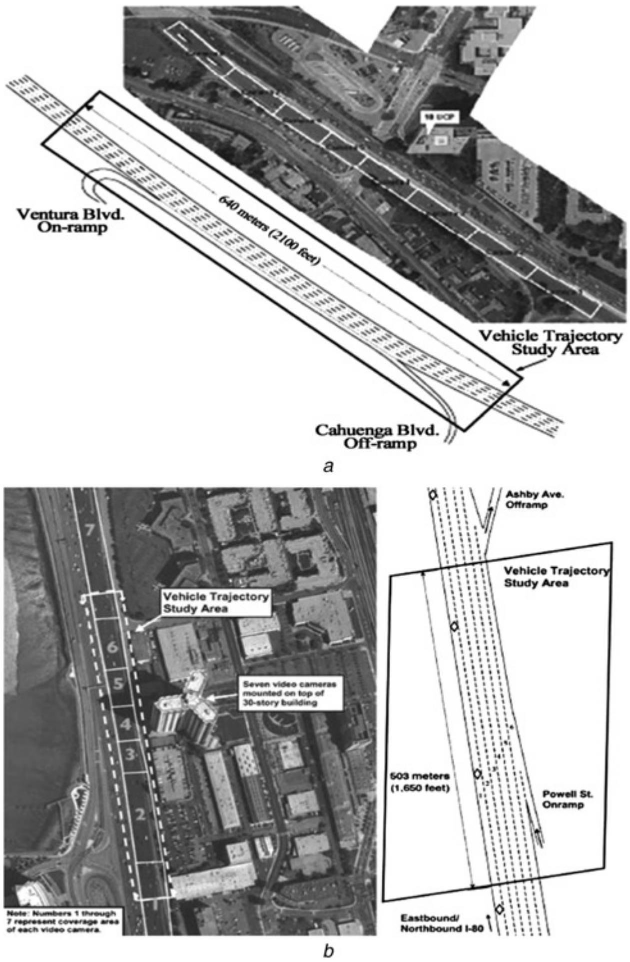

Fig. 4 *Segments of highways used for data collection*

a 101 highway
b I-80 [37] highway

attention to the vehicles immediately in front. If the calculated reaction delay is negative, then it is assumed to be null in the simulation.

4 New ANFIS car-following model design

In this section, considering the proposed idea, the car-following behaviour model design based on ANFIS is presented. In the previous works, reaction delay was considered to be fixed, whereas the proposed ANFIS car-following model is based on the reaction delay of the DVU. In this model, the reaction delay of the DVU is used as an input of the car-following model, and other inputs and outputs are chosen with respect to the reaction delay to train the ANFIS model.

Now, a novel input–output model, based on ANFIS, is presented to estimate the FV's acceleration. The most important point in this approach is to choose proper inputs and outputs, and to train the NN. The DVU's instantaneous reaction delay is used as an input. This variable is calculated considering the proposed idea. Proper outputs are chosen according to the DVU's reaction delay value based on Stimulus–Reaction idea. This means that the accurate and target output, for each step of inputs, must be chosen from the further step in the real data set. The difference in the time between inputs and output in the real data is equal to the DVU's reaction delay. This delay in subsequent moments is not the same, and hence, the input and output must be chosen as a function of the proper and correct reaction delays. In fact, the stimulus and reaction should be considered as an input and output with respect to the accurate instantaneous reaction delay. For clarity, we will denote the input values as having been taken at time 't'. The target value is stated to be the predicted FV acceleration at a time we will denote here as '$t+n$'. The value of n is equal to the value of the reaction delay, that is, for a given set of inputs if the reaction delay is calculated to be 0.3 s, then the model output is the predicted FV acceleration for 0.3 s later. Hence, the previous models in which the DVU's reaction delay was considered as a constant value can be modified by this newly proposed idea. It should be noticed that our model is only designed for cars, not for trucks and motorcycles.

In order to design an ANFIS prediction system, a data set of car-following behaviour is needed. Hence, real car-following data from the US Federal Highway Administration's NGSIM data sets have been used to train the model [37]. In 2005, a data set of trajectory data of vehicles on a segment of Interstate 101 highway in California (CA) has been published as the 'US-101 Data set'. As shown in Fig. 4*a*, 6101 vehicle trajectories were recorded. The other data set was published as the I-80 Data set. Researchers for the NGSIM program collected detailed vehicle trajectory data on I-80 in CA, as shown in Fig. 4*b*, in 2005 [37]. The data were collected at 0.1 s intervals. Any measured sample in this data set has 18 features of each DVU in any sample time, such as lateral and longitudinal position, velocity, acceleration, time and so on.

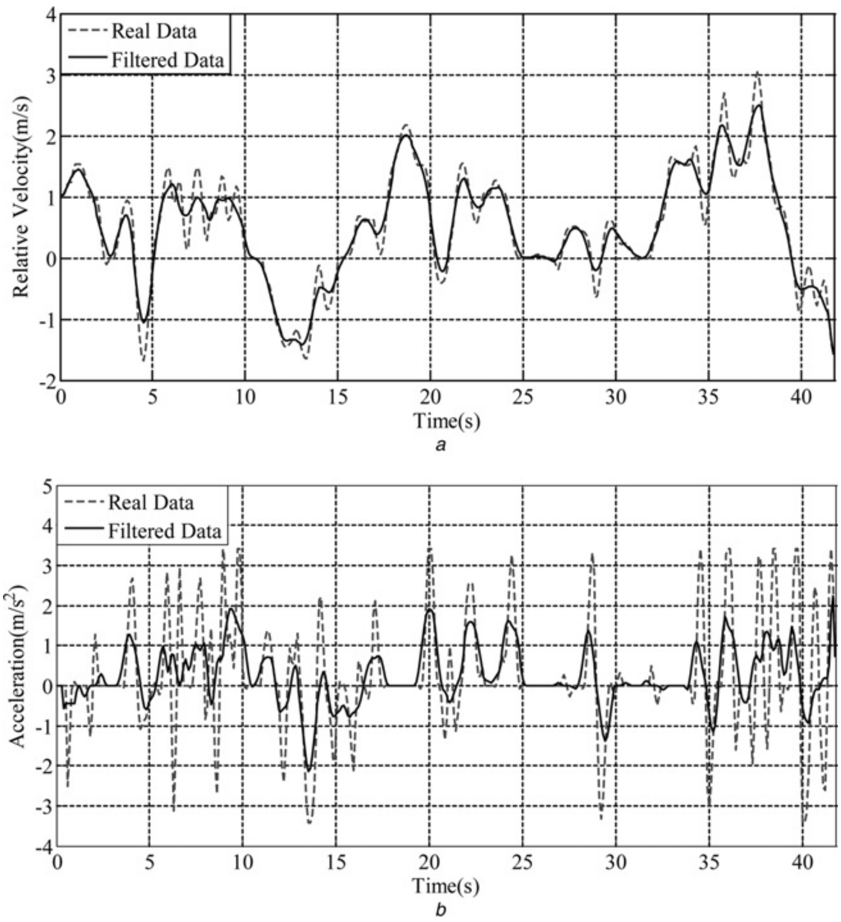

Fig. 5 *Comparison of unfiltered and filtered data*

a Relative velocity
b Acceleration

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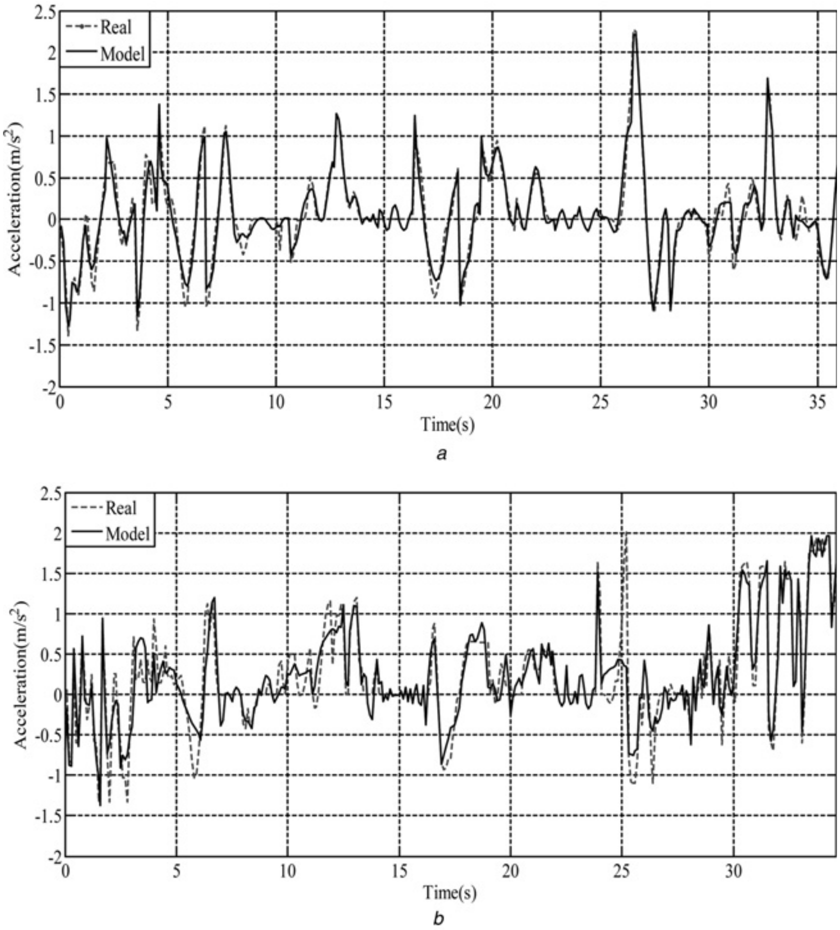

Fig. 6 *ANFIS estimator results based on the reaction delay input*
a Using Stimulus–Reaction idea
b Using Ozaki's idea

However, the trajectory data appeared unfiltered and exhibited some noise artefacts; hence, they were filtered as was done earlier in [38, 39]. We designed and applied a moving average filter for a duration of about 1 s to all trajectories before any further data analysis. Comparisons of the unfiltered and filtered data are shown in Fig. 5.

To design the ANFIS model, it is assumed that the applied ANFIS model for prediction has four inputs and one output. The four inputs are the estimated instantaneous reaction delay, the relative velocity, the relative distance and the velocity of FV. The output is the acceleration of FV. The training of the ANFIS model was performed based on choosing suitable inputs and output with respect to the instantaneous reaction delay. The fuzzy logic toolbox of MATLAB includes 11 built-in membership function types such as triangular membership function, trapezoidal membership function, Gauss distribution membership function and so on. One of these memberships is a Dsigmf membership, which is composed of the difference between two sigmoidal membership functions. In this study, three dsigmf membership functions are chosen 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.

In the development of the model, the available data are usually divided into two randomly selected subsets; the training and testing data sets. The first data set is used to develop and calibrate the model. The second data subset, not used in the development of the model, is utilised to validate the performance of the trained model. In this paper, 70% of the master data set was used for training purpose, and the remaining 30% was set aside for testing purpose.

5 Discussion and results

To evaluate the competence of the ANFIS prediction model based on the reaction delay input calculated by the stimulus–reaction idea to predict and calculate the reaction delay, three other ANFIS prediction models were designed and simulated. One of them was based on the reaction delay input obtained by Ozaki's idea, in which four of the inputs (relative velocity, relative distance, reaction delay and velocity of FV) were the same as those of the main model. Two ANFIS estimator systems with a constant delay and three inputs were also designed and simulated, where the inputs were the relative velocity, relative distance and velocity of FV, and the output was the acceleration of FV. Constant delays of 0.1 and 0.5 s were assumed for these models. These two last models predict the car-following behaviour for 0.1 and 0.5 s ahead.

We considered the delay time in the range from −1.5 to 3.5 s, but in the real traffic flow data set, most of the measured values are in the range from 0 to 0.6 s. To train and test the performance of these systems, real traffic data was used as inputs and output.

There is no explicit rule to measure reaction delay, when using 'change of rate of relative velocity' and 'change of rate of acceleration of the FV' only. The start and end points of these time periods are not certain. A driver necessarily does not show reaction exactly at the moment he saw the brake lights of the lead vehicle. Or, for example, the brake lights of the lead vehicle may not work instantly and may have a delay. What we intend to say is that in different situations, drivers have different reactions. Even a single driver may have different reactions when he/she is in different moods or is driving different vehicles or is in different environmental situations. Therefore, the reaction delay is not a definable parameter. This parameter can only be estimated and a distinct mathematical equation cannot estimate this parameter correctly as Ozaki did in his study. We proposed the Stimulus–Reaction idea to predict the reaction delay. The significant feature of our idea is that the models based on our idea showed much better performance than the models which were based on constant delay or other delay calculating ideas. Comparing the result of the model developed based on this idea with other models show the superiority of this model.

Fig. 6*a* shows the results of the ANFIS estimator for a DVU car-following behaviour based on reaction delay input calculated by the Stimulus–Reaction idea to predict the FV acceleration. As it can be seen from this figure, the acceleration/deceleration diagram of real driver and the one of the ANFIS model are quite similar. Fig. 6*b* indicates the results of the ANFIS estimator for DVU car-following behaviour based on instantaneous reaction delay input that was calculated by Ozaki's idea to estimate the FV acceleration.

Figs. 7*a* and *b* illustrate the performance of the ANFIS estimator for DVU car-following behaviour based on the various constant delays of 0.1 and 0.5 s.

To examine the performance of the four developed models, various criteria were used to calculate errors. The criterion mean absolute percentage error (MAPE), according to (2), shows the mean absolute error that can be considered as a criterion to model risk to use it in real-world conditions. Root mean squares error (RMSE), according to (3), is a criterion to compare error dimension in various models. Standard deviation error (SDE), according to (4), indicates the persistent error even after calibration of the model. In these equations, x_i shows the real value of the variable being modelled (observed data), $\hat{x}$ denotes the value outputted by the model, $\bar{x}$ is the real mean value of the variable and N is the number of test observations [40].

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

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

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

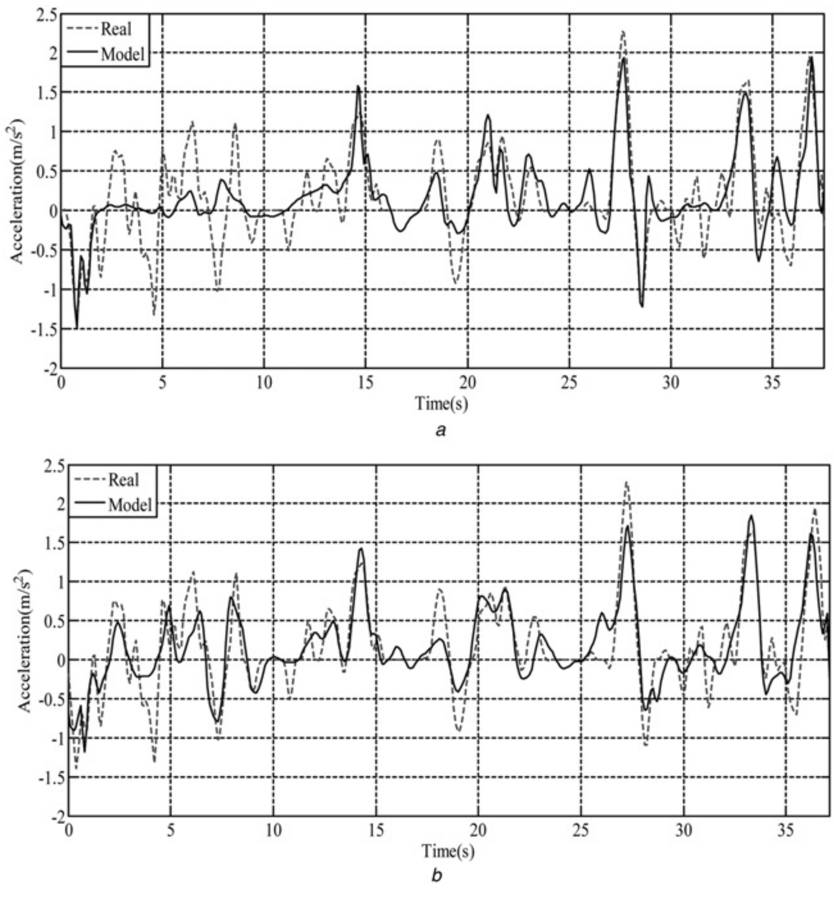

Fig. 7 *ANFIS estimator result based on the constant reaction delay*

a 0.1 s
b 0.5 s

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Table 1 Result of error for ANFIS car-following model

ANFIS car-following model	Error criteria		
	MAPE	RMSE	SDE
based on reaction delay input using Stimulus–Reaction idea	0.1142	0.1268	0.0244
based on reaction delay input Ozaki idea	0.1508	0.1985	0.0325
based on fix reaction delay = 0.1 s	0.2721	0.3673	0.0331
based on fix reaction delay = 0.5 s	0.2778	0.4173	0.0397

Errors in modelling the designed ANFIS car-following models by considering MAPE, RMSE and SDE are summarised in Table 1.

As shown in Table 1, ANFIS car-following model based on the reaction delay input calculated by the Stimulus–Reaction idea has a lower error value in comparison with the model based on the reaction delay input using Ozaki's idea and models based on the constant reaction delay through all error criteria. The results show that this proposed model has a strong capability with respect to the other models.

6 Conclusion

In this paper, an improved car-following model for the DVU was proposed. ANFIS was used as the modelling approach. Unlike the previous works, where the reaction delay is considered to be fixed, in this model, reaction delay for DVU was used as an input, and suitable inputs and outputs were chosen with respect to the reaction delay. The output values were applied to input, considering the DVU's variable reaction delay. Thus, the modelling error was decreased because of the match between the real data and those used for modelling. Satisfactory performance of the proposed model was demonstrated through comparisons with real traffic data as well as the results of other ANFIS models. The simulation results showed the efficiency of the proposed model in modelling and prediction of the DVU car-following behaviour in real traffic flow, when compared with other ANFIS-based models. The proposed method can be used in ITS applications such as collision prevention systems, driver assistant devices and safe distance keeping observers.

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