

Prediction of Car Following Behavior Based on the Instantaneous Reaction Time using an ANFIS-CART Based Model

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Abstract:

Car-following models are among the most important components of micro traffic flow simulation which is studied by transportation experts to evaluate new applications of intelligent transportation systems. Until now, several car-following models have been proposed. An obvious disadvantage of the former models is the great number of parameters which are difficult to calibrate. In this paper, a car-following model was modeled and developed by combining an Adaptive Neuro-Fuzzy Inference System (ANFIS) and a Classification And Regression Tree (CART) to simulate and predict future behavior of each driver-vehicle-unit (DVU). In this model, the reaction time was instantaneously calculated based on the time interval between acceleration and relative velocity by the proposed model and was considered as a new input. The results were compared with the fixed reaction time and the reaction time proposed by Ozaki. To evaluate the performance of the model, we compared the proposed model's output data with real conditions and it was found that the precision of the proposed model was significantly high with regard to the instantaneous reaction time. According to the implemented simulation, the proposed model reached a good validity on the basis of proximity to a real situation of car-following.

Keywords: Traffic engineering, Car following modeling, reaction time, microscopic simulation, intelligent transportation system (its)

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1. Introduction

Recently, traffic problems have made researchers to propose many models for studying different complex traffic phenomena [Chowdhury, Santen et al. 2000, Helbing 2001, Bellomo, Delitala et al. 2002, Klar and Wegener 2004]. Based on understanding complex traffic behaviors, existing traffic flow models can be divided into two categories, including (a) macroscopic in the former, i.e., traffic acts as a compressed fluid composed of cars, and (b) microscopic models in the latter, i.e., each car is displayed as a component and the traffic is considered as a system of interactive components which is driven away from equilibrium [Zhao and Gao, 2005]. The car-following model is the basis of modeling of the driving behavior in micro traffic simulation. In the car-following models, the most well-known effective parameters are the speed of the front car, distance, and relative speed to determine the acceleration change of the behind car [Bando, Hasebe et al. 1995, Bando, Hasebe et al. 1998, Helbing and Tilch 1998, Treiber, Hennecke et al. 2000, Jiang, Wu et al. 2001, Ge, Cheng et al. 2005, Tang, Wu et al. 2011].

In our study, the objective variable is the acceleration changes of the behind car and the predictor variables are stimulants of the car-following flow, including the parameters of distance difference, velocity difference, and the speed of the front car. In addition, reaction time was entered into the model as new inputs to show the effect of these parameters on the accuracy of the car-following model.

The paper is organized as follows: Section 2 provides an overview of the most important car-following models. Datasets used in this study are briefly introduced in Section 3. Section 4 provides a comprehensive introduction to ANFIS and CART, describes the reason for combining these two methods, implements the model with real data of the traffic, and finally, evaluates the model performance given the instantaneous reaction time as a new input parameter. In Section 5, the proposed methodology is thoroughly validated. Finally, Section 6 summarizes the results.

2. Literature Review

In this section, a brief literature review of former car-following models would be presented.

2.1 Former Car Following Models

Car-following models have been studied and investigated for more than half a century. Pipes and Reuschel began working on the theory [Reuschel 1950, Pipes 1953]. Each car individually makes acceleration changes such as responses to peripheral stimuli. Thus, the motion equation for the follower vehicle can be summarized as Response \propto Stimulus [Yan-lin and Tie-jun 2002]. This section presents four famous and general car-following models:

2.1.1 Gazis-Herman-Rothery (GHR) Model

The GHR model is one of the earliest and best-known models in a way many studies have been done based on it. Its original formula is shown below [Brackstone and McDonald, 1999]:

$$a_n(t) = C V_n^m(t) \frac{\Delta V(t-T)}{\Delta X^l(t-T)} \quad (1)$$

where a_n is the acceleration of following vehicle implemented at time t , V_n is the speed of the following vehicle, ΔX and ΔV are the distance headway and relative speeds between the following and leading vehicle, respectively, T is the driver reaction time, and m , l , and C are the constants that must be determined.

2.1.2 Collision Avoidance (CA) Model

A mathematical model for the collision avoidance state was introduced by Kometani and Sasaki as follows [Kometani and Sasaki 1959]:

$$\Delta X(t-T) = \alpha V_{(n-1)}^2(t-T) + \beta_1 V_n^2(t) + \beta_2 V_n(t) + \delta, \quad (2)$$

where $V_{(n-1)}$ is the leading vehicle velocity, and α , β_1 , β_2 , δ are the constant coefficients to be determined. The calculations in this model are based on optimal distance to avoid collision with the front car.

2.1.3 Linear Model

The linear or Helly model is the extension of GHR model. The equation of this model is as follows [Brackstone and McDonald 1999]:

$$a_n(t) = \rho_1 \Delta V(t-T) + \rho_2 (\Delta X(t-T) - D_n(t)), \quad (3)$$

$$D_n(t) = \alpha + \beta V_n(t-T) + \gamma a_n(t-T), \quad (4)$$

where $D_n(t)$ is the desired following distance at time t and ρ_1 , ρ_2 , α , β , γ are the constant coefficients to be determined.

2.1.4 Gipps Model

One of the most important developments done on the CA model was in 1981 by Gipps [Brackstone and McDonald 1999]. He considered several drivers' behavior factors overlooked in the previous model. High computational cost for calibration of parameters is the main disadvantage for this model. Eq. (5) demonstrates the Gipps model used in this paper:

$$V_n(t+T) = \min\left\{V_n + 2.5 \left(\frac{V_n}{\max V_n}\right) \left(0.025 + \frac{V_n^2}{\max V_n}\right)^{\frac{1}{2}}\right\}, \{-B_f T + B_f\{2(\Delta X - S) - TV_n + \frac{V_{n-1}^2}{B_l}\}\}, \quad (5)$$

where $A_f = 1.7$, $B_f = 3$, $B_l = 3.5$ and $S = 6.5$. And ΔX is the space length between the follower and the leader vehicles. Also, S is the safety distance that is based on the maximum velocity of vehicles. So, $\Delta X < S$ corresponds to an incident, which may involve the vehicle crashing. This parameters are selected according to [Wilson 2001].

3. Dataset

The real data for the car-following flow from US Federal Highway Administration's Next Generation Simulation (NGSIM) dataset [Cambridge Systematics Inc., 2005] was used to determine and evaluate the performance of the proposed model. Some properties of NGSIM data are as follows:

- To support the expansion of microscopic driver behavior algorithms, the Next Generation Simulation (NGSIM) program is collecting detailed, high-quality traffic datasets which this enrichment in dataset does not exist in any other dataset. Until now, many of dissertation and papers were used this dataset [Chen, Laval et al. 2012, Khodayari, Ghaffari et al. 2012, Khodayari, Ghaffari et al. 2012, Laval, Toth et al. 2014, Monteil, Billot et al. 2014, da Rocha, Leclercq et al. 2015, Liu, Zhu et al. 2016]. NGSIM stakeholder groups identified that the collection of real-world vehicle trajectory data is an important dataset for researching on microscopic driver behavior. The NGSIM datasets represent the most detailed and accurate field data collected to deal for traffic microsimulation research and development.
- It is very detailed datasets collected in 2005.

- Freeway I-80 in Emeryville, California (3 quarter hours)
- Freeway US-101 in Los Angeles, California (3 quarter hours)
- The arterial of Lanker Shim Boulevard in Los Angeles, California (2 quarter hours)
- The arterial of Peachtree Street in Atlanta, Georgia (2 quarter hours)
- Recording the position of cars in every 0.1 seconds using high-accuracy cameras

In this paper, the car-following modeling was performed using micro data on the Freeway US-101 traffic flow in Los Angeles, California. This traffic data is related to a quarter of an hour from 8:20 to 8:35 A.M. on January 15, 2005, i.e., the primarily congested conditions, including the trajectory of 1870 automobile and about more than 1.5 million records. Each record contains 18 information fields representing the motion status of each car in 0.1 seconds shown in Table 3. Table 1 shows the number of vehicles according to their types, and Table 2 demonstrates the mean speed vehicle and the traffic flow for each lane. Figure 1 shows the plan of studied cross section in this highway.

3.1 Conditions of Data for Using in Car Following Modeling

Among the total data, a suitable sample was selected to determine the car following positions based on the following conditions [Kim 2005, Kim et al. 2003]:

- Both front and behind vehicles are cars.
- No vehicle should change the lane in the car-following duration, and a third vehicle should not be placed between them.
- The car-following duration must be at least 30 seconds.

Under these conditions, the micro-information of the car following flow was extracted in this paper.

3.2 Alleviate the Noise in Data with the Wavelet Method

After the initial observation of noise in the collected data [Punzo, Borzacchiello et al. 2011], a wavelet denoising technique was used for alleviating the noise in the data. Figure 2 illustrates the procedure of denoising by wavelet technique [Tsai 2002].

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Table 1. Number of vehicles according to their types

Vehicle Type	Number of vehicles	Percentage
Motorcycle	5	0.3%
Automobile	1870	97.6%
Truck and Buses	40	2.1%
Sum	1915	100%

Table 2. Mean speed of vehicles and traffic flow for each lane

Lane Identification	Mean Speed (m/s)	Flow (Vehicle per hour)
1	8.95	1394
2	9.31	1460
3	9.27	1390
4	9.48	1374
5	9.68	1490
Average	9.34	7108

Table 3. Vehicle Trajectory File Data Dictionary

Col	Name	Description
1	Vehicle ID	Vehicle identification number
2	Frame ID	Frame Identification number
3	Total Frames	Total number of frames in which the vehicle appears in this data set.
4	Global Time (Epoch Time)	Elapsed time since Jan 1, 1970.
5	Local X	Lateral (X) coordinate of the front center of the vehicle
6	Local Y	Longitudinal (Y) coordinate of the front center of the vehicle
7	Global X	X Coordinate of the front center of the vehicle based on CA State Plane III in NAD83.
8	Global Y	Y Coordinate of the front center of the vehicle based on CA State Plane III in NAD83.
9	Vehicle Length	Length of vehicle
10	Vehicle Width	Width of vehicle
11	Vehicle Class	Vehicle type: 1 - motorcycle, 2 - auto, 3 - truck
12	Vehicle Velocity	Instantaneous velocity of vehicle
13	Vehicle Acceleration	Instantaneous acceleration of vehicle
14	Lane Identification	Current lane position of vehicle.
15	Preceding Vehicle	Vehicle Id of the lead vehicle in the same lane.
16	Following Vehicle	Vehicle Id of the vehicle following the subject vehicle in the same lane.
17	Spacing (Space Headway)	Spacing provides the distance between the front-center of a vehicle to the front-center of the preceding vehicle.
18	Headway (Time Headway)	Headway provides the time to travel from the front-center of a vehicle to the front-center of the preceding vehicle.

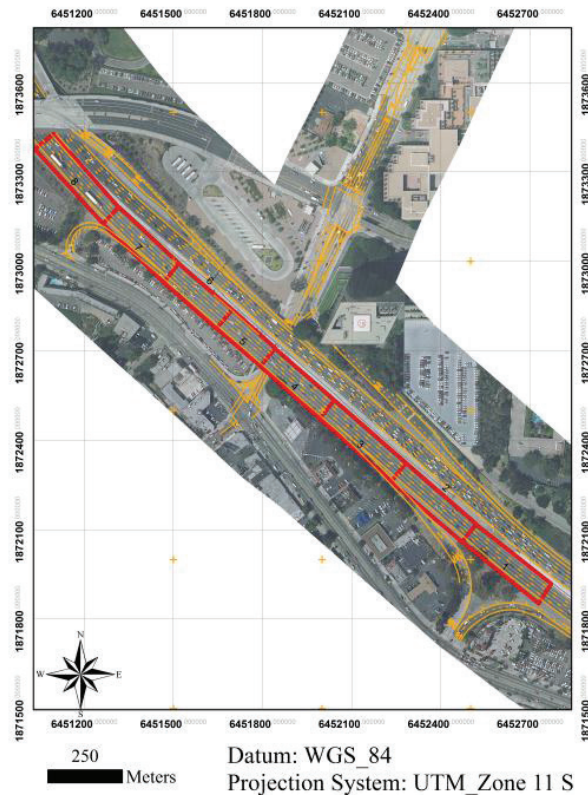


Figure 1. U.S Highway 101 (Hollywood Freeway) in Los Angeles, California

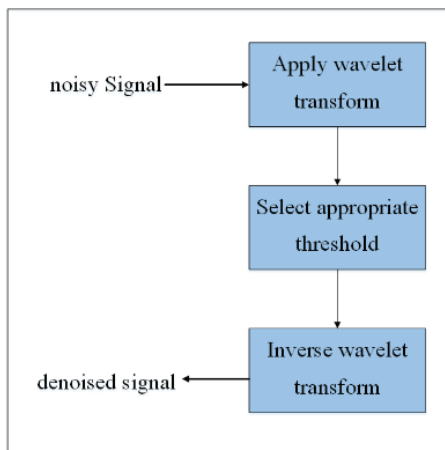


Figure 2. The general procedure of denoising by the wavelet
 In this research, the Symlets wavelet at the fourth order was used [Misiti, Misiti et al. 1996]. The following figure compares the real data and the data filtered by the Symlets wavelet.

4. Proposed Methodologies

In this section, the steps of car following modeling based on combining the Adaptive Neuro Fuzzy Inference System (ANFIS) and the Classification and Re-

gression Tree (CART) methods would be described. Figure 4 presents the flow chart of the main steps in this study.

4.1 Classification and Regression Tree (CART)

The CART model is a non-parametric one, without any default for the relationship between the independent variables and the objective variable. It is an important data mining method and is widely used in business, industry, engineering, and other applied sciences. The CART model is a powerful tool in determining the most important independent variables and solving prediction and categorization problems [Loh 2008]. In general, methods based on linear models divide quantitative variables space into separate areas and allocate data to corresponding groups. These methods divide data recursively to determine the interactions between variables for further detections. Depending on the type of the main objective problem in a study, the classification and regression tree models can establish a precise classification or detect a predictor structure for the desired problem. If the goal is to determine a predictor struc-

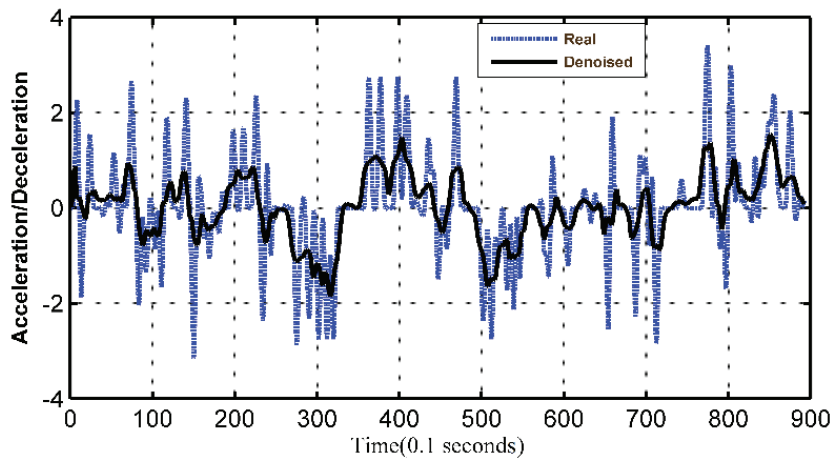


Figure 3. Comparison of the unfiltered and the filtered data

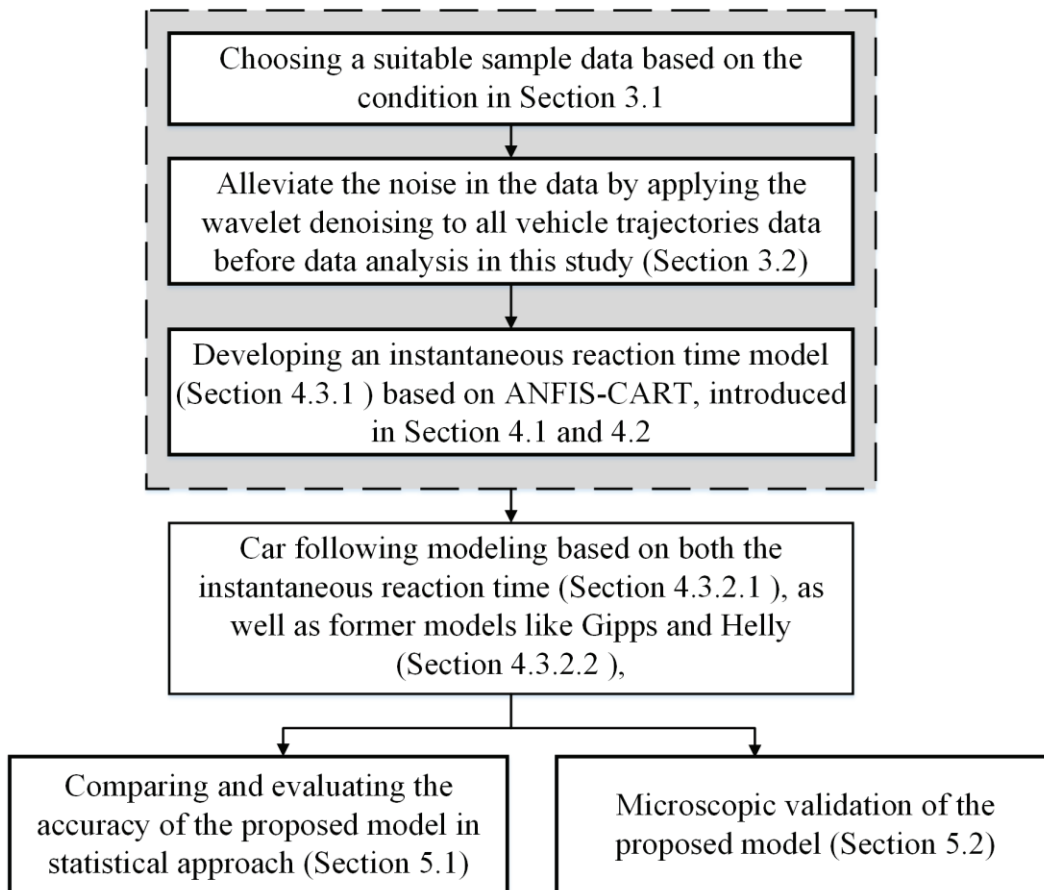


Figure 4. The proposed methodology flow chart

ture, understanding the variables and their interactions will become essential. In different problems, these two objectives are examined in parallel [Morgan and Sonquist 1963]. If the decision tree performs the modeling using an objective variable with nominal values, it is called classification tree, and if it performs the modeling using an objective variable with continuous values,

it is called a regression tree. The use of regression trees refers to the automatic interaction detection program introduced by Morgan and Sonquist [Morgan and Sonquist 1963]. This method was modified and extended by Breiman [Breiman, Friedman et al. 1984]. The classification and regression tree algorithm contains three important tasks. The first task is 'how to segment data

at each step?’ The second task is ‘when to stop segmentation?’ The last one is ‘how to predict the value Y for each X in a segment?’ [Loh, 2008]. This method is attractive and unique for models for three main reasons. First, it shows the model results in a way that is easy to understand and simulate by human. Second, the decision tree is a non-parametric model. It does not require user intervention and is very suitable for the pursuit of exploratory knowledge. Third, the algorithm is ratable; in other words, the satisfactory performance of ratings is associated with the increasing size of the training sample. This is the case for the decision tree of built models and the accuracy of decision tree is equivalent or superior to other models [Timofeev 2004]. The regression tree cannot be classified. Instead, the solution vector Y represents the solution values for each observation in the matrix of variable X. Separation is made in the regression tree in accordance with the least squares of residuals method, given the total variance expected for two conclusions of nodes. Regression trees do not have classes. Instead, there is response vector Y, which represents the response values for each observation in variable matrix X. It should be mentioned that the splitting rules of classification, e.g., Twoing or Gini, can not be performed because of lacking pre-assigned classes for regression trees [Timofeev 2004]. The squared residuals minimization algorithm is used for splitting the regression trees. In this regard, for two resulting nodes, Eq. (6) is minimized [Timofeev 2004]:

$$arg \min [P_l Var(Y_l) + P_r Var(Y_r)] \quad (6)$$

where $Var(Y_l)$ and $Var(Y_r)$ are the response vectors for the corresponding left and right child nodes. P_l and P_r are the probabilities of left and right nodes of parents, respectively. $x_j \leq x_j^R$, $j=1,2,\dots,M$, are the optimum separation questions, each of which is the satisfaction condition of the above formula [Dobra 2002], where x_j is the variable j and x_j^R is the best splitting value of variable x_j . See [Breiman, Friedman et al. 1984] for more information.

In this paper, due to the existence of a continuous objective variable, we used the regression tree and considered data for relative velocity, relative distance, speed of the front car, and the driver's reaction time as input stimuli and considered the acceleration changes proportional to these stimuli as the desired output.

4.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The adaptive network of fuzzy inference system is based on fuzzy logic. This section addresses the main structure of ANFIS. You can see [Cruz and Mestrado 2009] for more details. Here, we describe a simple example of ANFIS structure algorithm and its operational steps. The ANFIS system is based on the functional equivalence subject to certain constraints between the neural network and the fuzzy systems of Takagi, Sugeno and Kang (TSK) type [Lezanski 2001]. The output is calculated by inputs weighted based on fuzzy rules. These rules are based on human knowledge and determined by computational algorithms based on neural networks. In order to assume an ANFIS model that can function properly, special attention should be paid to the number of basic parameters, the system rules, and the number of inputs. Generally, ANFIS is a fuzzy inference system which is defined in the work structure of an adaptive neural network using a combinational training procedure. The ANFIS system is capable of mapping inputs and outputs based on human knowledge and the input and output pair data [Geronimo, Cruz et al. 2013]. The ANFIS method is superior to other methods such as autoregressive models and linear prediction methods [Geronimo, Cruz et al. 2013].

Suppose a first-degree TSK fuzzy inference system [Takagi and Sugeno 1985] that contains the two following rules:

Rule1: if x is A_1 and y is B_1 , then $f_1 = p_1x + q_1y + r_1$,

Rule 2: if x is A_2 and y is B_2 , then $f_2 = p_2x + q_2y + r_2$,

In this regard, Figure 5 shows the mechanism of fuzzy reasoning and these rules in our case could be as follows:

Rule1: if Velocity is high and Headway is short, then Acceleration= p_1 Velocity+ q_1 Headway+ r_1

Rule2: if Velocity is slow and Headway is large, then Acceleration= p_2 Velocity+ q_2 Headway+ r_2

Figure 6 shows the architecture of ANFIS and its layers where each layer is described below:

Layer 1: Each node in this layer creates the degree of membership of the Linguistic variable according to the functions of the desired degree of membership. For example, by regarding the degree of ‘‘Gaussian’’ shaped membership function, for the i th node, we have the following formula (see reference [Zhao and Bose 2002])

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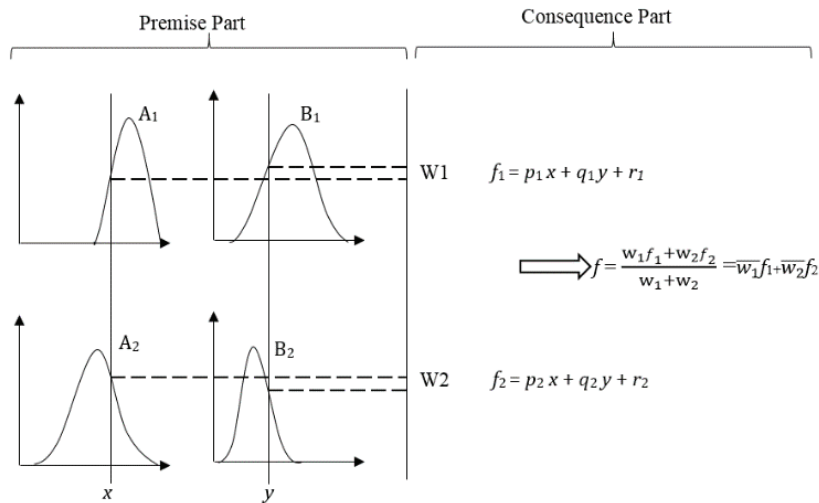


Figure 5. The first-order TSK fuzzy model [Jang, Sun et al. 1997]

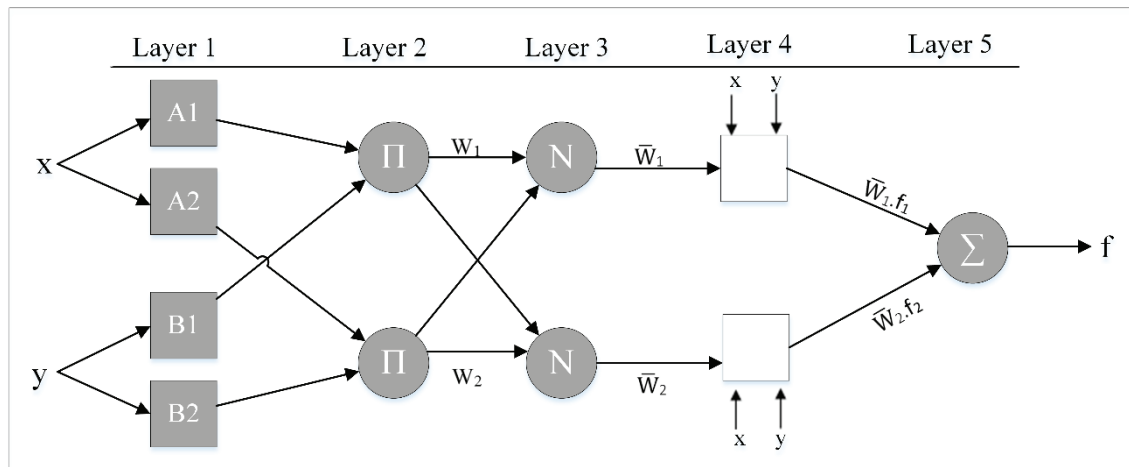


Figure 6. The architecture of an ANFIS with two inputs and one output [Jang, Sun et al. 1997]

to learn about other degree of membership functions):

$$N_i^1 = \mu A_i(x) = \frac{1}{1 + \exp(-a_i(x - c_i))}. \quad (7)$$

where N_i^j represents the output of the i th node, x is the input of the i th node, A_i is the linguistic variable corresponding to that node, and (a_i, c_i) are parameters that change the membership function.

Layer 2: In this firing strength layer, each rule is calculated according to the following formula:

$$N_i^2 = w_i = \mu A_i(x) * \mu B_i(x). \quad i = 1, 2. \quad (8)$$

Layer 3: This layer calculates the ratio of rules' strength firing for the i th node to the sum of all the rules' firing strength as follows:

$$N_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}. \quad i = 1, 2. \quad (9)$$

Layer 4: Node i in this layer has the following node function:

$$N_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i). \quad (10)$$

where \bar{w}_i is the output of the third layer and p_i, q_i, r_i is its parameter set.

Layer 5: This layer calculates all the output such as the sum of all input signals as follows:

$$N_i^5 = \text{final output} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}. \quad (11)$$

In the same way, an adaptive network is created which functions similar to a fuzzy inference system which is called Adaptive-Neuro Fuzzy Inference System (ANFIS).

4.3 ANFIS-CART

This section provides the main factor affecting the combination of the CART theory with ANFIS. For example,

consider the decision tree in Figure 7 which is equivalent to the crisp rule set:

$$\text{if } x > a \text{ and } y > b, \text{ then } z = f_1 \quad (12)$$

$$\text{if } x > a \text{ and } y < b, \text{ then } z = f_2 \quad (13)$$

$$\text{if } x < a \text{ and } y > c, \text{ then } z = f_3 \quad (14)$$

$$\text{if } x < a \text{ and } y < c, \text{ then } z = f_4 \quad (15)$$

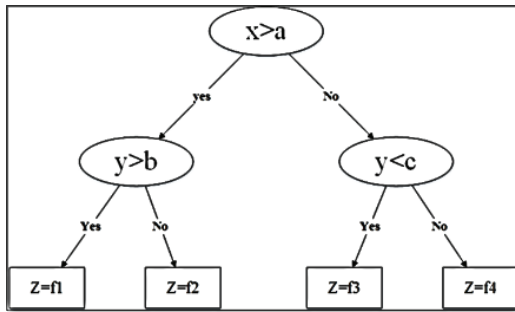


Figure 7. Binary decision tree

Accordingly, each input fires one of these rules and other rules are not enabled. This crispness reduces the computational load in the tree structure using the CART but it undesirably creates discrete boundaries. Hence, the fuzzy logic is used to solve this problem. In the proposed method of this paper, when $x > c$, it can be presented by the following sigmoidal function with fuzzy logic features.

$$\mu_{x>a}(x; a, \gamma) = s(x; a, c, \gamma) = \begin{cases} 0 & \text{if } x \leq c - a \\ 0.5 \left[\frac{x - (c - a)}{a} \right]^{2\gamma} & \text{if } c - a < x \leq c \\ 1 - 0.5 \left[\frac{x - (c - a)}{a} \right]^{2\gamma} & \text{if } c < x \leq c + a \end{cases} \quad (16)$$

where x is the input to node; and $\{a, c, \gamma\}$ is the parameter set that changes the shape of the membership function. c locates distance from the origin and a determines steepness of the function. If a is positive, the MF will be open to the right, whereas if it is negative, it will be open to the left. The former represents the concept of “very large positive”, whereas the later represents “very large negative” in linguistic terms [Zhao and Bose 2002].

Based on the fuzzy version of rules in the above crisp functions, we can obtain another class of an adaptive network, i.e., ANFIS, to identify prior and posterior pa-

rameters of the fuzzy inference systems. In this case, the first layer calculates the degree of membership of input variables by the selected membership functions. In the second layer, the obtained degree of membership is multiplied by the firing strength detected for each rule. The share of each rule is calculated based on the firing strength given in the third layer, and finally, all outputs of this fuzzy inference system are obtained in the fourth layer [Jang, 1994].

4.3.1 Defining Driver’s Reaction Time

In this study, different methods were investigated for determining the reaction time. Initially, the observed instantaneous reaction time was calculated according to the GHR model, defined in Eq. (1). In this model, according to [Brackstone and McDonald 1999] the values of parameters l, m, C were determined. Based on theory proposed by Khodayari [Khodayari, Ghaffari et al. 2012], the driver reaction time is defined by the time interval between relative speed as stimulus and acceleration as response. Figures 8 demonstrate this time interval in the dataset used in this paper.

4.3.1.1 Calculating Instantaneous Reaction Time Based on ANFIS-CART

For calculating the instantaneous reaction time with the proposed model, the inputs including the velocity of leading vehicle, the relative velocity between leading and following vehicle, the spacing between these vehicle, and the acceleration of following vehicle, as well as the observed reaction time with GHR model were considered. 70 percent of this data per lane was allocated as training data and the remained data was considered as the test data for demonstrating the accuracy and calibrating the proposed model in determination of instantaneous reaction time. The following figure shows the instantaneous reaction time outperformed by the proposed ANFIS-CART model. In addition, Ozaki proposed a model to determine the reaction time according to both increasing and decreasing accelerations using a piecewise linear function [Ozaki 1993]. This model was re-calibrated by the sample data in this study and the following equations were obtained for both increasing and decreasing ac-

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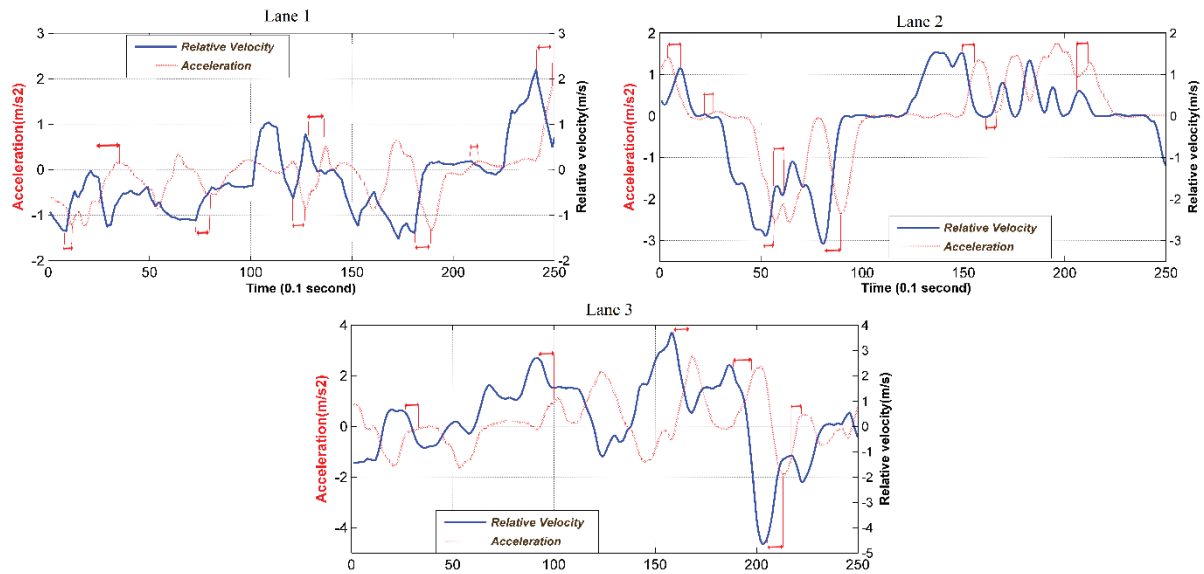


Figure 8. Calculation DVU (Driver-Vehicle-Unit) instantaneous reaction delay for each lane

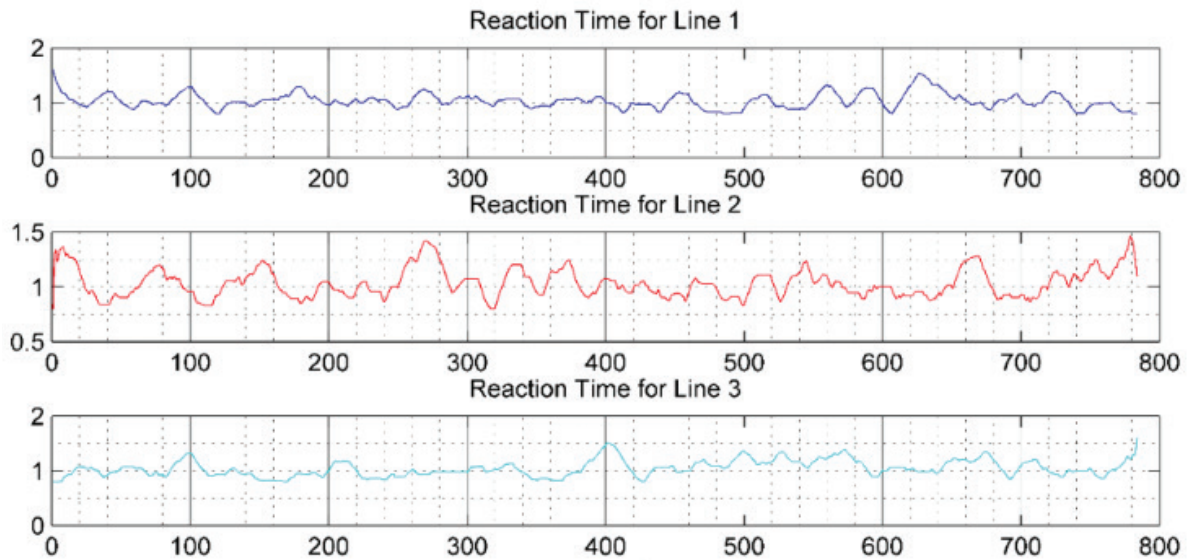


Figure 9. Instantaneous reaction time outperformed by the proposed ANFIS-CART

celerations.

When acceleration occur, reaction time = $0.91 + 0.01\text{Spacing} + 0.04 a_n$, (17)

When deceleration occur, reaction time = $0.76 + 0.017\text{Spacing} + 0.04 a_n$, (18)

where a_n is the acceleration of following vehicle implemented at time t and Spacing is the distance headway between the following and leading vehicles.

As well as these two methods, three fixed reaction times were considered which include fixed reaction times of 0.5, 1, and 1.5 seconds.

4.3.2 The Car Following Modeling

To show the effect of instantaneous reaction time on simulating real vehicle movements, a car-following model is needed. The car-following model considered in this study is also based on combining ANFIS and CART methods. The output of the car-following model in this study is the acceleration/deceleration of the following vehicle in the next time step. The inputs are the current speed of leading vehicle, relative speed, the spacing of the following vehicle, and the reaction time.

4.3.2.1 Car Following Modeling by Considering Instantaneous Reaction Time

For modeling the car-following based on the ANFIS-CART using micro data on traffic flow and taking into account different methods of determining the reaction time, we implemented 3 car-following states which are related to different lanes of the US101 Highway. The results of this modeling in different states of reaction time can be seen in Figure 10.

4.3.2.2 Car Following Modeling with Most Dominant Models

Finally, the parameters of the Helly model [Eq (3)] are selected according to [Brackstone and McDonald 1999]. The Gipps model was also implemented using [Eq (5)]. The Gipps parameters also were selected according to [Brackstone and McDonald 1999]. Figure 11 demonstrates the difference among Helly model, Gipps model, and the real data.

5. Validation of Methodology

Two measures are employed to validate the proposed methodology. The first measure is the mean square error [Eq. (19)]. The second measure is the Index of agreement [Eq. (20)]. Moreover, micro simulation validation was carried out, too.

5.1 Statistical Validation

To demonstrate the accuracy of the proposed model, the following criteria were used:

- The Mean Square Error (MSE) was used to determine the accuracy of the model. The following equation shows the calculations of the measure of accuracy [Levinson, 1947]:

$$MSE = \frac{\sum_{i=1}^n (y(t_i) - y'(t_i))^2}{n} \tag{19}$$

- Index of agreement (d) indicates the extent to which the predicted values are error-free. The closer the value of this parameter becomes to 1, the better our model of prediction will be. The following equation shows this index formula [Robinson 1957]:

$$d = 1 - \frac{\sum_{i=1}^n (y(t_i) - y'(t_i))^2}{\sum_{i=1}^n (|y'(t_i) - \bar{y}| + |y(t_i) - \bar{y}|)^2} \tag{20}$$

where $y'(t)$ is the value predicted by the model with instantaneous reaction time, $y(t)$ is the real value or the test data value, and \bar{y} is the mean values of real data. Table 4 summarizes the statistical results of the model for various states.

Based on the above tables, by considering the instantaneous reaction time, the proposed model yields the best statistical parameters for all lanes of the route.

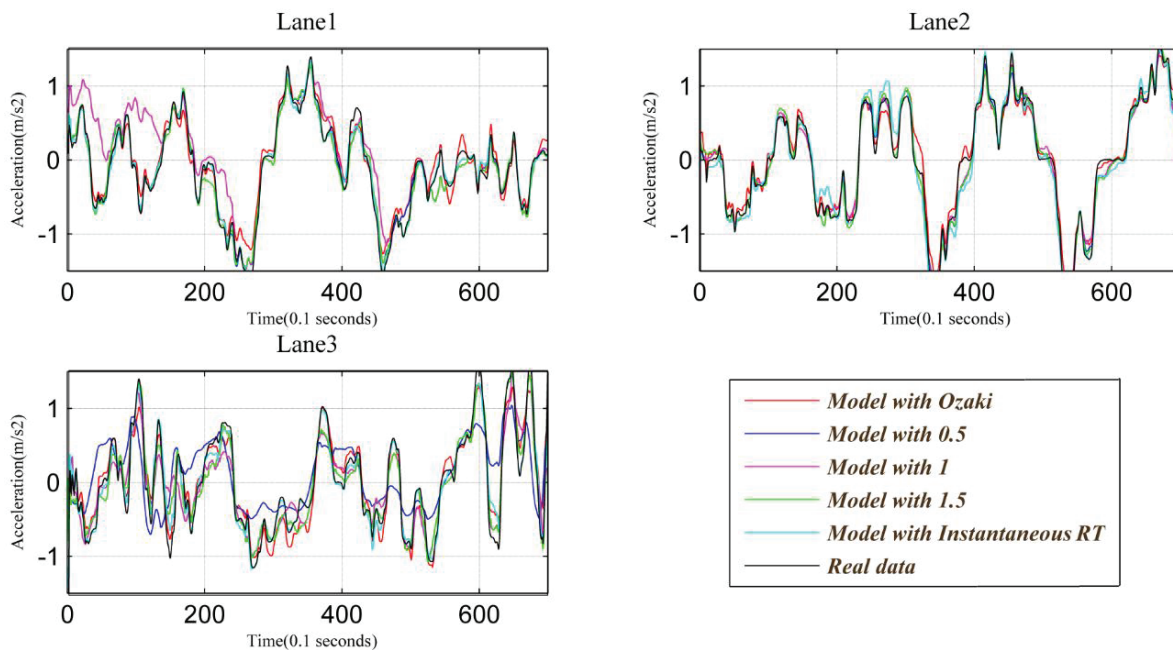


Figure 10. Predicting results of the different reaction times

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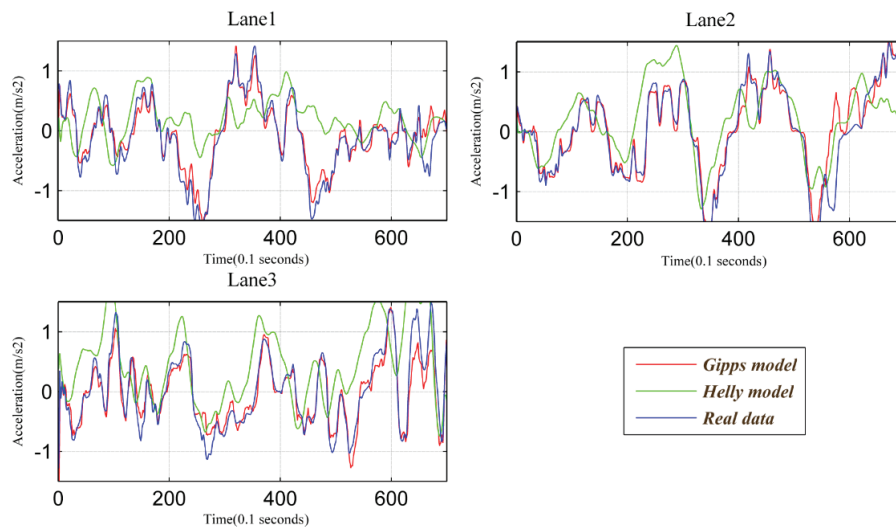


Figure 11. Predicting the results of the different conventional models (Helly and Gipps)

Table 4. Statistical summary for each observed and simulated vehicle (E and d are mean square error, and index of agreement, respectively)

Lanes ID		The proposed	Model	The	The	The
		method with	with	proposed	proposed	proposed
		Instantaneous	Ozaki	method	method	method
		Reaction	Reaction	with	with	with
		Time	Time	Constant	Constant	Constant
			[Ozaki,	Reaction	Reaction	Reaction
			1993]	Time 0.5	Time 1	Time 1.5
Lane 1	E	0.26	0.29	0.35	0.54	0.34
	d	78%	76%	76%	70%	76%
Lane 2	E	0.30	0.32	0.30	0.31	0.33
	d	78%	77%	75%	74%	75%
Lane 3	E	0.38	0.39	0.98	0.55	0.35
	d	77%	77%	48%	62%	70%
Mean value	E	0.31	0.33	0.54	0.47	0.34
	d	77.6%	76.6%	66.3%	68.6%	73.6%

Table 5. Statistical summary for former models based on the mean value of three lanes

	MSE	R ²
Helly model	1.453	0.12
Gipps model	0.89	0.18
GHR model	0.72	0.22
CA model	0.78	0.23

5.2 Microscopic Validation

In this section, we show the validity of the proposed model using the micro-simulation technique. After determining the model accuracy using the error test with the least squares error and showing the output dispersion of models with the real data and the use of index of agreement parameter as the determinant of prediction accuracy in the previous section, we considered Highway US101 and the three lanes on which data was collected.

During the simulation, two cars were assumed for each

lane: one as the front car and the other as the follower car. The front car started moving with the speed available at the collected data and the follower car instantaneously calculated the acceleration based on the proposed model of this paper by understanding the speed of the front car, their distance, and the relative speed. Based on this acceleration, displacement was calculated for the next moment. Simulation was performed dur-

ing 0.1-second steps and it was found that the proposed model has a good validity on the basis of proximity to a real situation of car-following in its simulation. Figure 13 depicts simulation results in three lanes considered for this purpose for 30 seconds.

The simulation results based on the following vehicle's displacement, velocity, and trajectory are plotted in Figures 13 to 15.

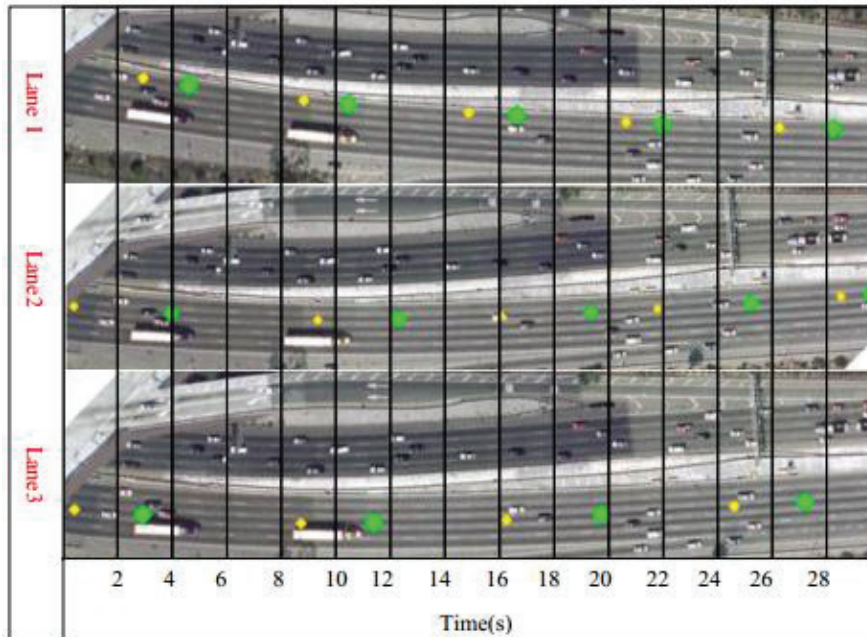


Figure 12. The simulation prototype

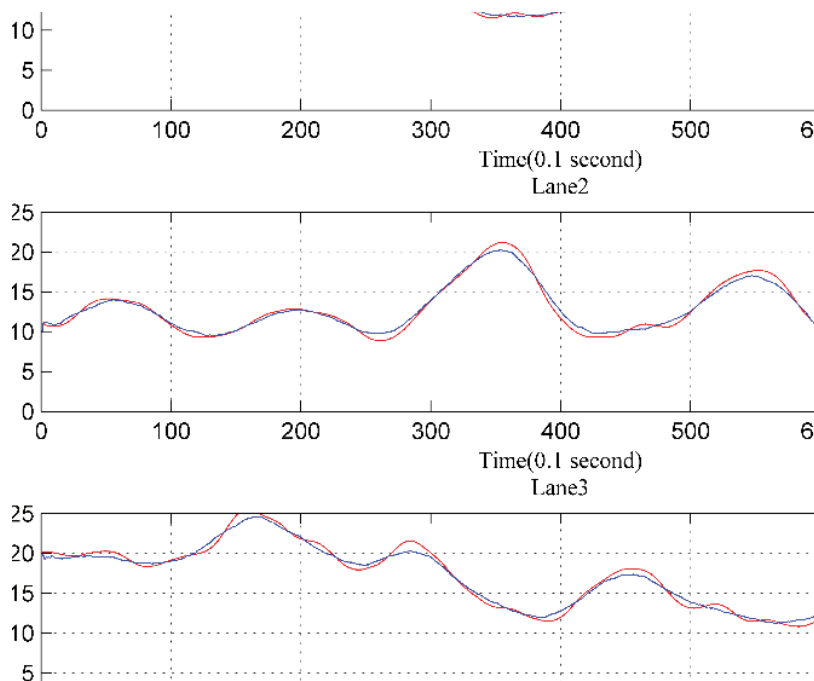


Figure 13. Simulation result of following vehicle's displacement

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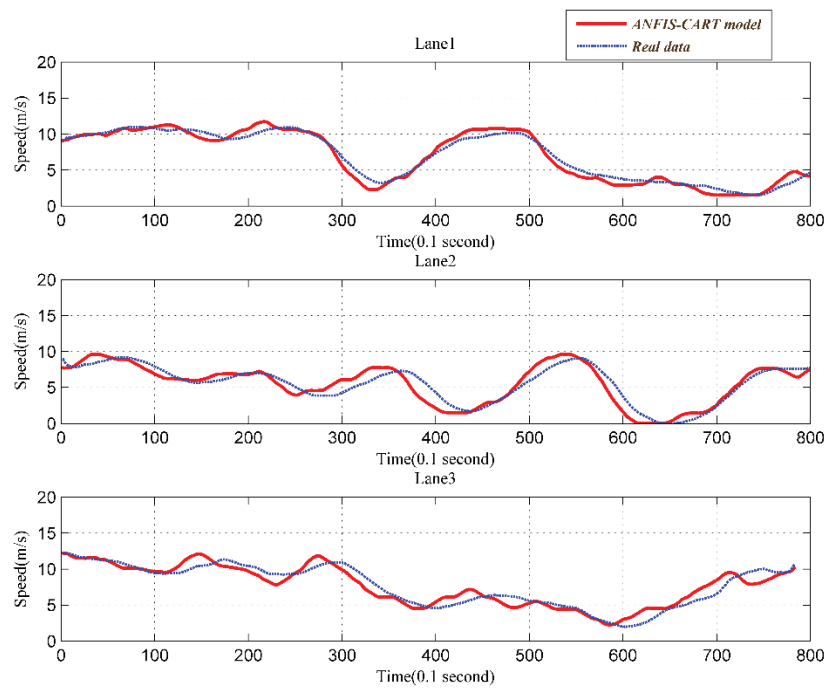


Figure 14. Simulation result of following vehicle's speed

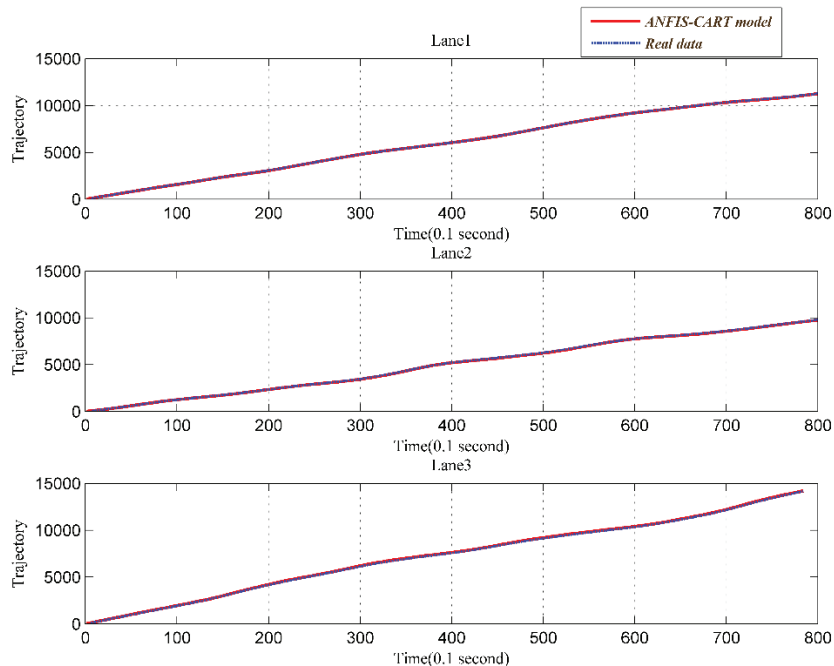


Figure 15. Simulation result of following vehicle's trajectory

According to Figure 13, the curves of ANFIS-CART based model outputs fit the field data well. The following speeds calculated by the proposed model seems to be as smooth as the field data. For the trajectory, the model fit to the field data well and the errors are within 10 meters.

6. Conclusion

Car-following models are among the most important topics in the field of traffic simulation at the micro level. All famous models that are used today include a set of parameters that require careful calibration. To solve this problem, this paper uses a combination of ANFIS

and CART to propose a car-following model for the first time. The model predicts the desired output, i.e. acceleration changes, by allocating four parameters including speed of the front car, relative distance to the front car, relative speed between the front car and the follower car, and the reaction time. To demonstrate the validity of this model, two techniques were used: theory of errors and micro simulation. In the theory of errors, the output data of the models were compared with reality and it was found that the proposed model has a good accuracy in the car-following modeling, considering the instantaneous reaction time as an input parameter. In the micro simulation, it was shown that the results from the moving vehicles in the actual route follow the actual conditions of the car-following flow based on the understanding of the follower car's driver about the performance of the front car, including the car speed and distance with it in every 0.1 seconds. This model can also be used in driver support tools, maintaining the safe distance, guiding unmanned vehicles and other applications of intelligent transportation systems.

7. References

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