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Lane-changes prediction based on adaptive fuzzy neural network

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ABSTRACT

Lane changing maneuver is one of the most important driving behaviors. Unreasonable lane changes can cause serious collisions and consequent traffic delays. High precision prediction of lane changing intent is helpful for improving driving safety. In this study, by fusing information from vehicle sensors, a lane changing predictor based on Adaptive Fuzzy Neural Network (AFFN) is proposed to predict steering angles. The prediction model includes two parts: fuzzy neural network based on Takagi–Sugeno fuzzy inference, in which an improved Least Squares Estimator (LSE) is adopt to optimize parameters; adaptive learning algorithm to update membership functions and rule base. Experiments are conducted in the driving simulator under scenarios with different speed levels of lead vehicle: 60 km/h, 80 km/h and 100 km/h. Prediction results show that the proposed method is able to accurately follow steering angle patterns. Furthermore, comparison of prediction performance with several machine learning methods further verifies the learning ability of the AFNN. Finally, a sensibility analysis indicates heading angles and acceleration of vehicle are also important factors for predicting lane changing behavior.

1. Introduction

Automatic vehicles, relying on the collaboration of artificial intelligence, visual computing, radar monitoring device, and global positioning system, can automatically and safely operate motor vehicles in the absence of any human activities. As a key part of Advanced Driver Assistance System (ADAS), this technology can largely improve the driving safety and avoid traffic accidents. Furthermore, it can also help to rationalize driving behavior, improve travel efficiency and further relive traffic pressures. The whole driving process generally contains several maneuvers, such as, lane changing, overtaking, car following and so on. In fact, due to the impact of many external factors, the behavior of a driver is complicated and mainly depends on human's physiological status and psychological activity. In addition, modeling driving behavior is a complex problem which involves control theory, robotics, and psychology. As one of most common and challenging behavior, drivers should not only consider the safety distance from the front vehicle on the current lane but also the safety space between the front and latter vehicles on target lane during lane changing process. Traffic accidents caused by unreasonable lane-changing behavior will result in personal injury and deterioration of traffic condition. Therefore, exploring the intent recognition and analyzing the route patterns are definitely conducive to improving the safety of lane changing behavior (Hou, Edara, & Sun, 2015; You et al., 2015).

1.1. Related works

Currently, one practical solution is sole turn signal. It is an apparent indicator to reflect lane-changing intention of drivers. However, this signal can be also used for other behavior, such as specific direction turning. Furthermore, many researchers (Deutscher, 2007; Lee, Olsen, & Wierwille, 2004; Ponziani, 2012; Schmidt, Beggiato, Hoffmann, & Krems, 2014) have conducted experiments to estimate the sensitivity of the turn signal as indicator for lane change. They found that this method lacked sensitivity and specificity to predict lane changing behavior. Another method is considered as using data from multi-sensor installed on the vehicle to predict the behavior of lane changing. Morris, Doshi, and Trivedi (2011) introduced several data source to be implemented for route or path prediction, which include driver behavior observation (e.g., eye-tracking, electrocardiogram), sensor information about the environment (e.g., safe distance detection, GPS data) and vehicle parameters (e.g., vehicle speed, acceleration, steering wheel angle). By integrating these data source, various methods are pro-

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posed to predict lane changing behaviors. They can be classified into following five categories: (1) Hidden Markov Model (HMM) (Kuge, Yamamura, & Shimoyama, 2000; Liu & Pentland, 1997; Pentland & Liu, 1999; Sathyanarayana, Boyraz, & Hansen, 2008); (2) Neural Networks (NN) (Cheng, Xiao, & LeQuoc, 1992; Ding, Wang, Wang, & Baumann, 2013; Macadam & Johnson, 1996; Tomar, Verma, & Tomar, 2010); (3) Regression Model (RM) (Henning, Georgeon, & Krems, 2007; Olsen, 2003); (4) Cognitive Model (CM) (Baumann & Krems, 2007; Pickering, 2001; Salvucci, 2006; Salvucci, Mandalia, Kuge, & Yamamura, 2007); (5) Fuzzy Logic System (FLS) (Errampalli, Okushima, & Akiyama, 2008; Hessburg & Tomizuka, 1995; Kim, 2002; Okushima & Akiyama, 2005; Shi & Zhang, 2013);

(1) For the Hidden Markov Model (HMM), HMM can infer unobservable (hidden) states from observable actions, and studies in this part mainly focus on constructing probabilistic model to predict driving routes. Kuge et al. (2000) introduced a driver behavior recognition model based on HMM considering driver characteristics by using driving simulation data. Sathyanarayana et al. (2008) proposed a hierarchical framework to modeled driver behavior signals, in which the first layer considered isolated maneuver recognition and second layer models the entire route based on HMM. (2) For the Neural Networks (NN), due to its strong generalization and learning ability as well as adaptability, NN is also a popular approach selected by scholars to finish lane-changing prediction. To overcome the disadvantage that existing lane change models do not consider the uncertainties and perceptions in the human behavior, Tomar et al. (2010) constructed a neural network with multilayer perceptron to predict the lane changing trajectory in future steps based on field data from the Next Generation Simulation (NGSIM). Ding et al. (2013) developed a Back-Propagation (BP) neural network to predict lane-changing trajectory, and they also compared prediction results between BP neural network and Elman Network using the data collected from driving simulator data and NGSIM. (3) For the Regression Model (RM), because of its simple structure and fast calculation speed, researches used this approach to fit the relationship between input variables (vehicle speed, acceleration, safe distance and so on) and output variables (steering wheel angle or lane changing routes). In order to model lane changing process with slow lead vehicle, Olsen (2003) applied a logistic regression model considering the distance to the front and rear adjacent vehicle, forward time-to-collision (TTC), and turn signal activation. Henning et al. (2007) used regression model to predict the intention of lane changes considering some environmental and behavioral indicators: glance to the left outside mirror, turn signal, and lane crossing. (4) For the Cognitive Model (CM), it can be used to approximate human cognitive processes for the purposes of comprehension and prediction. Salvucci (2006) introduced an Adaptive Control of Thought-Rational cognitive architecture and proposed an integrated driver model to accomplish processes of control, monitoring and decision making in a multilane highway environment. Baumann and Krems (2007) introduced some major preconditions of safe driving in drivers' cognitive process. (5) For the Fuzzy Logic System (FLS), it is built on a probabilistic reasoning process that uses fuzzy input parameters. Through optimizing parameters in fuzzy membership functions, FLS can be used to accurately predict driving trajectories in lane changing process. Errampalli et al. (2008) introduced fuzzy reasoning in lane changing model to realistically indicate uncertainties and perceptions in driving behavior, and they compared simulation results with traditional multinomial logit model to validate its effectiveness. Shi and Zhang (2013) adopted fuzzy logic to analyze multi lane change behavior, in which several indicators are considered as input variables and steering wheel angle is set as output variable to evaluate the efficiency of lane change process.

1.2. Aims of study

Abundant works focused on lane changing behavior prediction have been obtained in previous researches, however, there still exists some issues need to be solved in emulating the complex and multi-ruled behavior of the driver and incorporating the uncertainties of driver's perception and decisions. Fuzzy logic is a kind of method that can deal with the transformation between qualitative and quantitative information. By implementing fuzzy comprehensive judgment, it deals with some problems with fuzzy information that are difficult to be solved by traditional methods. Fuzzy logic is good at expressing the qualitative knowledge and experience with uncertainty. In the process of lane changing, the decision-making behavior of the driver obviously contains fuzzy or uncertain process. So, it is effective and feasible to use fuzzy logic theory to analyze the behavior of the lane changing. However, according to current studies, there are several disadvantages: (1) the rules used in fuzzy inference are not comprehensive; (2) lacking adaptive learning mechanism will result in unsatisfactory prediction performance; (3) indicators or factors considered in fuzzy input variables are limited.

Aim to aforementioned three deficiencies, this study proposes a fuzzy neural network with adaptive learning ability to predict lane changing behavior. The main work includes following three parts. (1) Establish FNN model, determine the input and output variables, and construct the rule base and inference mechanism. (2) Introduce an adaptive learning process, in which the prediction errors are used to adjust structure of fuzzy membership function, and then improve fuzzy reasoning process by enriching the rule base. (3) Consider the effects of various information in input variables for driving behavior, which includes vehicle parameters: vehicle speed, acceleration, heading angles, and distance from the front vehicle in the horizontal axis and vertical axis, the output variables is determined as driving steering angle. Finally, using the data collected from driving simulator, the effectiveness of this study is validated based on statistical analysis of prediction results.

The remainder of the paper is organized as follows. Section 2 briefly introduces the models used in study. The car-steer modeling based on FNN is provided in Section 3. Section 4 discusses the experiment results and compares prediction accuracy between different models. Section 5 provides the conclusion of the paper.

2. Lane-changing driving behavior

For the vehicle model, we consider a simplified movement model of a four wheeled vehicle as following:

$$\left.\begin{array}{l} x(k+1) = x(k) + v(k)\cdot\Delta s\cdot\cos[\theta(k)] \\ y(k+1) = y(k) + v(k)\cdot\Delta s\cdot\sin[\theta(k)] \\ \theta(k+1) = \theta(k) + v(k)\cdot\Delta s\cdot\tan\alpha(k)/l \end{array}\right\} \tag{1}$$

where θ is the heading of the vehicle, x and y represent the position of vehicle, x_0 and y_0 represent the centroids of vehicle, which are determined on the basis of vehicle rear wheel, α is the steering angle, v indicates the instantaneous velocity, l means the wheelbase, Δs is the computation sampling time, and k is the simulation step, see Fig. 1a. Define t_0 as the starting time, T as the ending time when subject vehicle finishes the lane changing maneuver, the $k\in[t_0, T]$. Therefore, according to the values of x, y and θ, we can determine vehicle attitude. Fig. 1b shows lane changing maneuver. Lag vehicle 2 is the subject vehicle, lead vehicle 2 is the lead vehicle in the current lane, and the lag vehicle 1 and lead vehicle 1 represent the following vehicle and lead vehicle in the target lane, respectively. The acceleration (acc) can be calculated as:

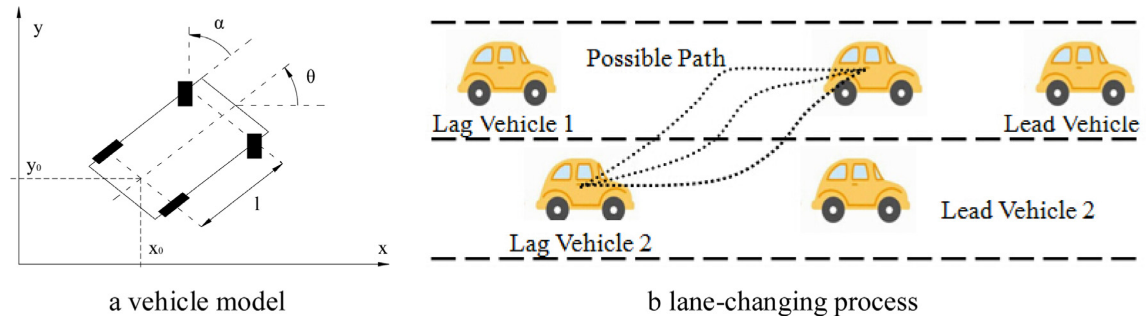


Fig. 1. Vehicular lane-changing model.

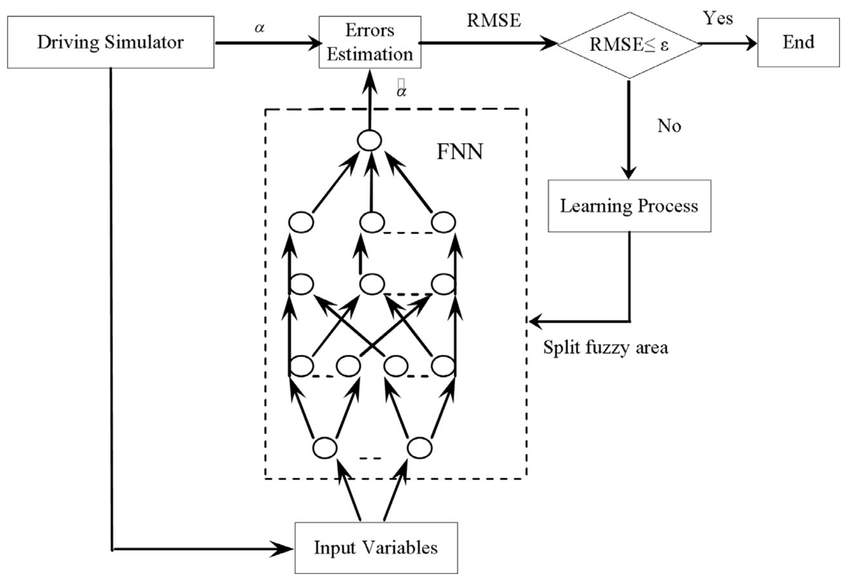


Fig. 2. Structure of prediction system.

$$acc(k+1) = \frac{v(k+1) - v(k)}{\Delta s} \tag{2}$$

Once driver decides to change lane, his/her goal will be to make a smooth transition from the current lane to the desired lane without colliding with the other vehicles around it. He/she should consider several factors, the safe space on target lane, and the distance from the lead vehicle on current lane. In an ideal situation, the lateral location of subject vehicle, y_t, is the middle of the target lane, the heading, θ_t, equals to 0, and horizontal location, x_t, can vary with a certain range. This range is limited by some constraints, which are the safety of the lag vehicle and the lead vehicle. In other words, there should be enough space to move into the lag vehicle's front area without colliding with the lead vehicle. Due to the diversity of drivers, including different driving habits and experiences, their lane changing trajectories express different patterns shown in Fig. 1b.

3. Lane-changing behavior prediction

3.1. System structure

The prediction system proposed in this study mainly includes following three parts, see Fig. 2.

(1) Data collection from driving simulator. In this part, we collected vehicle parameters, the locations of subject vehicle and lead vehicle in horizontal and vertical coordinates, instantaneous velocity, acceleration, heading and steering wheel angles. The detailed description about experiment and data collection is provided in Section 4.1.
(2) Fuzzy Neural Network (FNN). In this part, we design its structure including four sub layers: input variables (distance between subject vehicle and lead vehicle, relative velocity, heading and acceleration in the current lane), membership functions, fuzzy reasoning mechanism and output variable (steering wheel angles, α). We will introduce this part in Section 3.2.
(3) Adaptive learning algorithm. According to the prediction errors (Root Mean Square Error: RMSE) between estimated $\hat{\alpha}$ and observed values α, the fuzzy membership functions will be automatically split and then fuzzy rules will be updated. Based on new FNN, $\hat{\alpha}$ is updated and the new RMSE is then calculated. If the value of RMSE is lower than a preset threshold ε, then the prediction process is stopped and final prediction results can be obtained. Otherwise, the learning process will be implemented until achieving satisfactory prediction results.

3.2. FNN based prediction model

The structure of an FNN contains five layers as shown in Fig. 2. The first layer is the input layer, in which the input variables are stored and each node represents a variable. During the lane changing process, the driver needs to consider the relative traveling state from the lead vehicle and subject vehicle's operating conditions. Therefore, we identified three relative indicators: the distance between the subject vehicle and lead vehicle in the horizontal and vertical coordinates in the current lane (Δx and Δy), the relative

a simulation vehicle b simulation scenario

Fig. 3. Driving simulator.

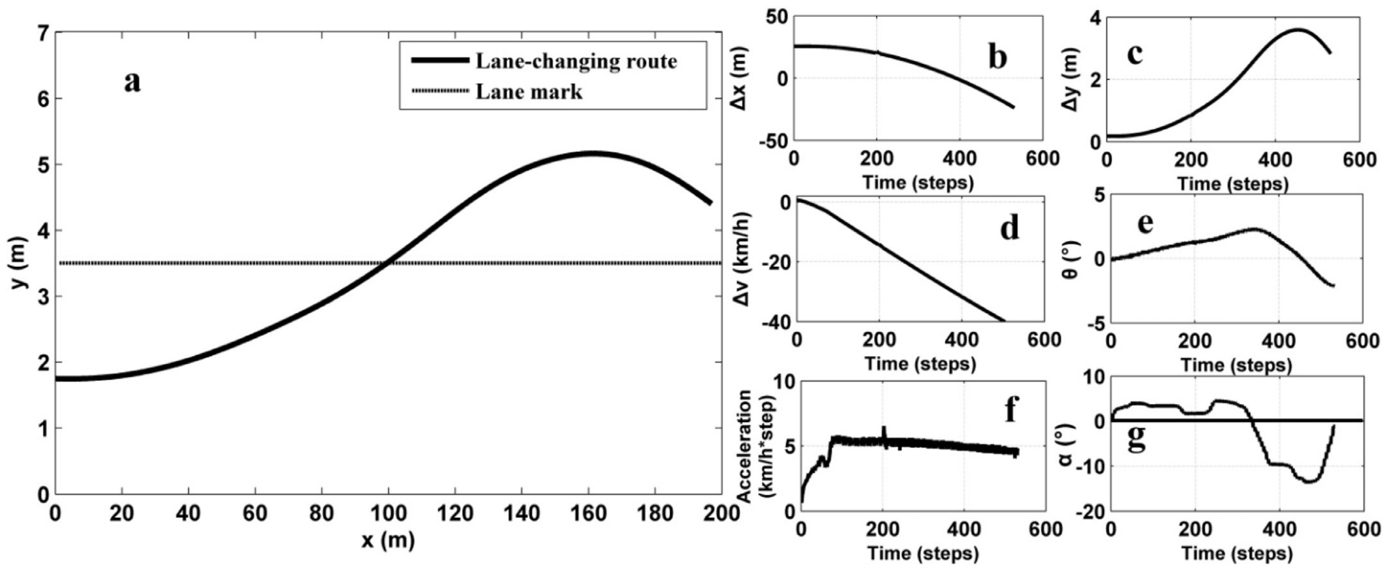


Fig. 4. Example of lane-changing route and data samples collected in the scenario with speed of 60 km/h.

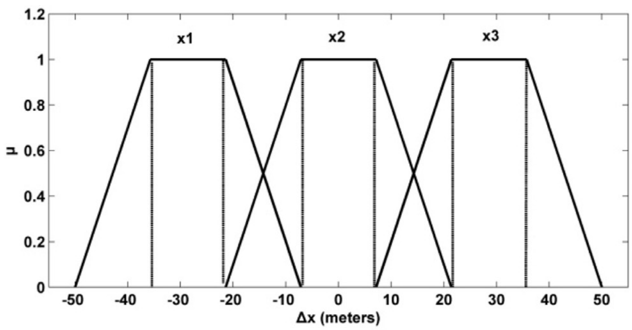
Table 1
Prediction results of models in scenario with different speed.

Driving speed	Errors indicators	Prediction methods				
		AFNN	SVM	NN	HMM	MLR
60 km/h	RMSE	3.5452	4.2356	4.9739	6.5389	8.7299
	MAE	2.5989	3.1184	3.8044	4.7545	6.3193
	MPAE (%)	5.3405	13.0394	15.2897	17.7280	22.6091
80 km/h	RMSE	3.0328	3.9652	4.4112	5.2001	7.1378
	MAE	2.3931	3.3412	3.6687	3.9358	4.9817
	MPAE (%)	6.0714	9.33831	11.6137	12.1526	14.5196
100 km/h	RMSE	2.8993	3.8893	4.3430	5.0286	6.8353
	MAE	2.3148	3.3325	3.6392	4.0846	5.0810
	MPAE (%)	8.2763	10.3062	12.9601	13.1356	17.5457

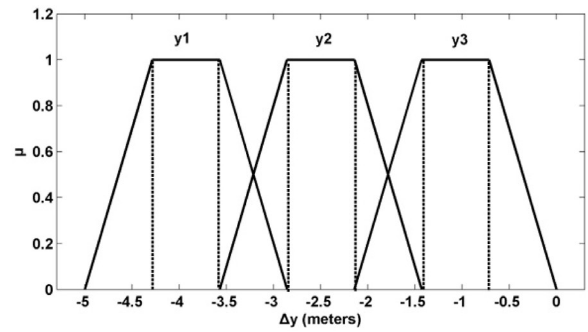
velocity between subject vehicle and lead vehicle (Δv) (Here, it should be noted that three relative indicators are calculated on the basis of lead vehicle in the coordinate system), and two indicator of subject vehicle: traveling heading (θ) and acceleration (*acc*). In the second layer, the input values can be transformed into fuzzy values or membership degrees to which they belong to the membership functions. Each node in the second layer represents a membership function. The third layer represents rule reasoning process, in which a Takagi–Sugeno type fuzzy inference is adopted. The fourth layer represents fuzzy quantification of the output variables. As the control and adjustment of the driver to subject vehicle in the lane changing process are accomplished by fusing information of the external environment and operating steering wheel, the steering wheel angle is the direct indicator reflecting driver's behavior. So, the output variable in this layer is determined as the steering wheel angle. This layer integrates contributions of different rules. Finally, the fifth layer represents the real values of the output variable.

In the FNN, we used a Takagi–Sugeno type fuzzy inference system to construct fuzzy rules. For each input sample, $X=[\Delta x,\ \Delta y,\ \Delta v,\ \theta,\ acc]$, has n memberships describing the degree, the number of rules is equal to n^5. The ith rule is shown as follows:

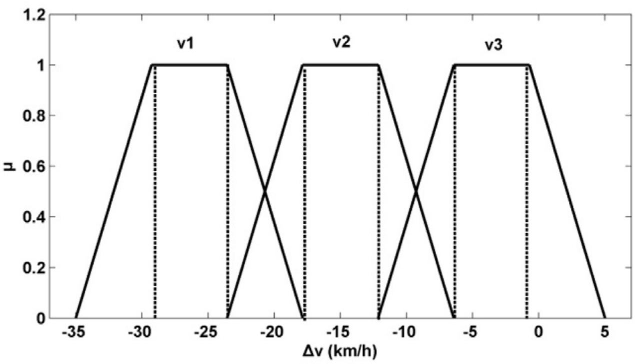
$$R_i : \text{IF}(\Delta x \text{ and is } A_i) \text{ and } (\Delta y \text{ is } B_i) \text{ and } (\Delta v \text{ and is } C_i) \text{ and } (\theta \text{ is } D_i) \text{ and } (acc \text{ is } E_i) \text{ THEN } y_i \text{ is } f_i(\Delta x,\ \Delta y,\ \Delta v,\ \theta,\ acc)$$



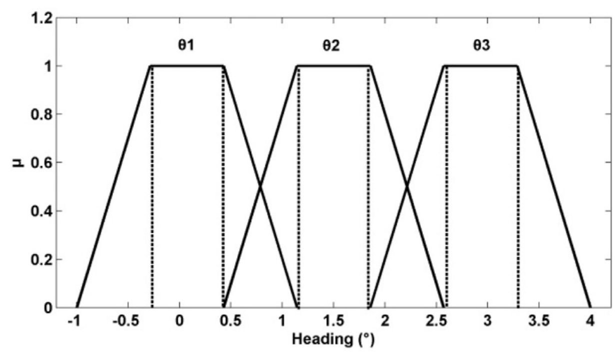
a Difference of distance in the horizontal coordinate



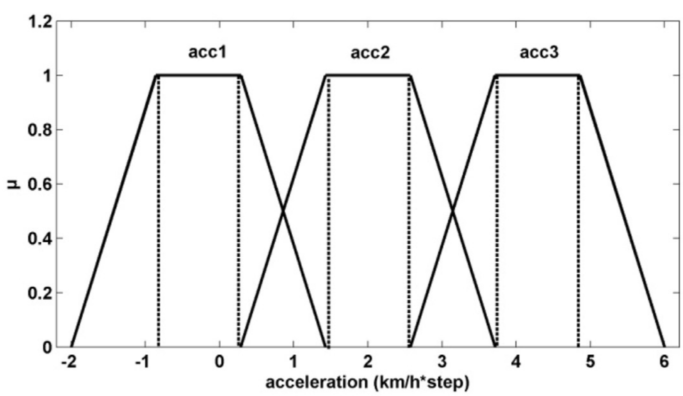
b Difference of distance in the vertical coordinate



c Relative velocity



d Heading angles



e Acceleration

Fig. 5. Initial membership functions of five input variables.

where A, B, C, D, E indicate a fuzzy set defined by its membership function, X_i is the antecedent variable, and f_i is the inference consequence of variable *y* when the *i*th rule is employed. In this study, the fuzzy membership functions are selected to be trapezoid type. The reason is that the drivers will not quickly change their driving behavior due to slight changes of external environment during lane changing process. Compared to the triangle function or Gaussian function, the values of membership degree in trapezoid function can remain constant when input variables distribute in a certain range. So, the trapezoid function with four parameters is defined as follows:

$$m(x) = \begin{cases} x - a/b - a & a \le x < b \\ 1 & b \le x < c \\ d - x/d - c & c \le x < d \\ 0 & x < a \, or \, d < x \end{cases} \tag{3}$$

where, *m* is defined as membership function of input variables, *a, b, c, d* are the parameters to determine the type of function. Overall, the total number of membership functions is *5n*. In the model, we use a first-order Takagi–Sugeno type (Takagi & Sugeno, 1985) to complete fuzzy inference system. The function $f_i(\Delta x, \Delta y, \Delta v, \theta, acc)$, $i = 1,2,\ldots K$, $K = n^5$, is a linear function. So, for an input data point $X^0 = [\Delta x^0, \Delta y^0, \Delta v^0, \theta^0, acc^0]$, the inferring results of the system, $\hat{\alpha}^0$, can be calculated as the weighted average of outputs from each rule:

$$\hat{\alpha}^0 = \frac{\sum_{i=1}^{K} w_i \cdot f_i(\Delta x^0, \Delta y^0, \Delta v^0, \theta^0, acc^0)}{\sum_{i=1}^{K} w_i} \tag{4}$$

where, w_i is the membership degree achieved for the *i*th rule, $w_i = \prod_{j=1}^{l} m(X_j)$, $j = 1,2,\ldots,l$, $l = 5$, and $m(X_j)$ represents the membership degree of input variable X_j activated in the *i*th rule. For the parameter estimation, we used a least squares estimator (LSE) in (Goodwin & Sin, 1984; Hsia, 1977) to train the linear functions.

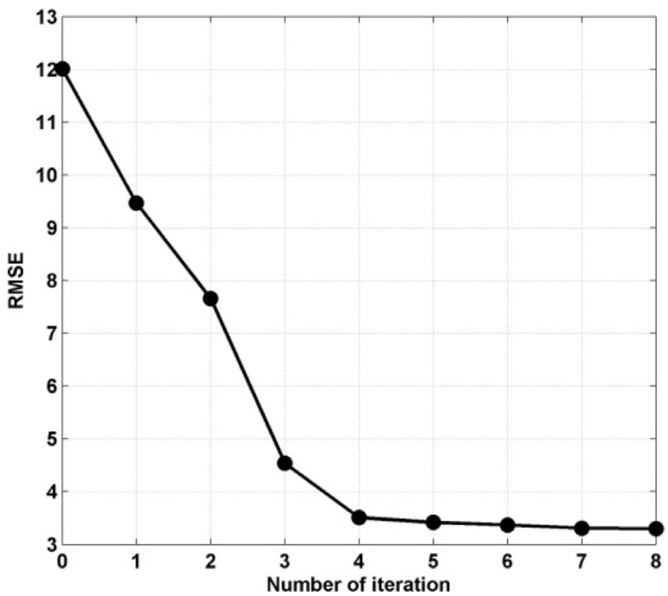


Fig. 6. Convergence of training errors.

Each of the linear function can be described as follows:

$$y = \beta_0 + \beta_1 X(1) + \beta_2 X(2) + \ldots + \beta_l X(l) \tag{5}$$

The training dataset included p data pairs, $\{([X(1,i), X(2,i),\ldots, X(l,i)], y_i), i=1,2,\ldots,p\}$, $X(l,i)$ means the ith data sample of the lth input variable. The dataset was used to calculate the coefficients $B=[\beta_0\ \beta_1\ \beta_2\ \ldots\beta_l]^T$ via the following equation based on LSE:

$$\begin{cases} B = \mathrm{P}\mathrm{A}^T y \\ \mathrm{P} = (\mathrm{A}^T\mathrm{A})^{-1} \end{cases} \tag{6}$$

where

$$\mathrm{A} = \begin{pmatrix} 1 & X(1,1) & X(2,1) & \cdots & X(l,1) \\ 1 & X(1,2) & X(2,2) & \cdots & X(l,2) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & X(1,p) & X(2,p) & \cdots & X(l,p) \end{pmatrix}$$

and

$$y = [y_1 y_2 y_3 \ldots y_p]^T$$

Define the kth row vector of matrix A in Eq. (6) to be $r^T{}_k = [1\ X(1,k)\ X(2,k)\ \ldots\ X(l,k)]$ and denote the kth element of y as y_k. Then the vector of coefficient B can be iteratively calculated by Eq. (7) shown in the following. The calculation process uses a recursive, improved LSE method [25,26] to complete the optimization.

$$\begin{cases} B_{k+1} = B_k + \mathrm{P}_{k+1} r_{k+1}(y_{k+1} - r_{k+1}^T B_k) \\ \mathrm{P}_{k+1} = \dfrac{1}{\lambda}\left(\mathrm{P}_k - \dfrac{\mathrm{P}_k r_{k+1} r_{k+1}^T \mathrm{P}_k}{\lambda + r_{k+1}^T \mathrm{P}_k r_{k+1}}\right) \end{cases} \quad k = t, t+1, \ldots, p-1 \tag{7}$$

where λ is the forgetting factor and its value is generally between 0.8 and 1.0, B_t and P_t are the initial values of B and P, which can be calculated in Eq. (6) by using the first t data pairs from the training dataset. Here, we define the g as the split ratio, if p represents the total number of training samples, then g^*p is the number of samples used in first step and $(1-g)^*p$ indicates the number of samples used in second step. In this study, we set g as 0.5 and λ as 0.85.

3.3. The learning algorithm

In the FNN, the rule base and rule inference are the most important parts to determine the effect of prediction. Generally, we firstly preset rules and set up inference mechanism, then optimize the system parameters, and finally obtain prediction result. However, due to the rules are preset, the rules may be inaccurate or inadequate, which will seriously affect prediction performance. In this section, we design an adaptive learning algorithm. According to the prediction errors, it can adaptively adjust membership function and improve the rule inference mechanism, and prediction accuracy can be enhanced eventually.

The prediction errors of FNN can be defined as the difference between estimated and the actual steering angles:

$$e = \alpha - \hat{\alpha} \tag{8}$$

Given a set of N training data samples, the Root Mean Squared Error (RMSE) is defined as the:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\alpha_i - \hat{\alpha}_i)^2} \tag{9}$$

The process of learning algorithm includes following several steps:

Step 1: Calculate prediction error RMSE in Eq. (9);
Step 2: Compare the error: if RMSE $\leq \varepsilon$ then quit, otherwise go to the next step;
Step 3: Find out all the rules are used in FNN, and identify the rule make greatest contribution for the output values in Eq. (4), in other word, determine the corresponding fuzzy rule with highest weights, max(w), and identify the fuzzy sets involved in membership function of all input variables;
Step 4: Equally divide these fuzzy sets into two parts, which means split fuzzy area and replace each fuzzy set with two new one, for each run of the learning algorithm, 2^5 new rules are created in the rule base;
Step 5: Construct new Takagi–Sugeno inference system, use improved LSE method in Eq. (7) to update optimal parameters, and then predict new values of steering angles in FNN, then go to the Step1 and Step 2.

4. Experiments

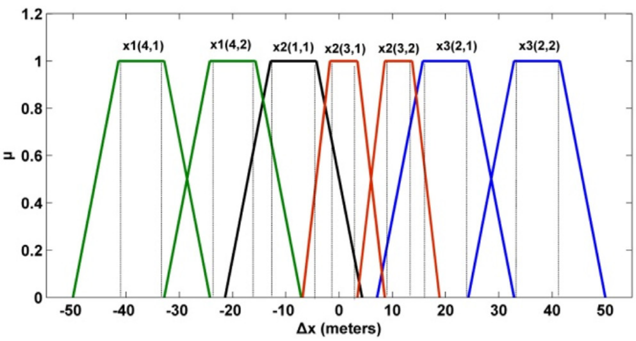
4.1. Data collection

The experiments are conducted in a driving simulator shown in Fig. 3, which is installed sensors to collect dynamic data of subject vehicle, such as acceleration, braking and steering. The simulator is also equipped with a sound system which can simulate sounds from vehicle engine, tires. The body of the simulator is supported by hydraulic cylinders to allow six degrees of freedom. Three screens projecting the virtual environments are placed in front of the cab with a visual angle of 48° wide and 36° high. Two additional screens are located behind the cab so that subjects can view vehicles traveling behind them by scanning the mirror. The projector has a resolution of 1280 × 768 pixels and a frame rate of 60 Hz to ensure a smooth and delicate simulating environment. A total of 47 experienced drivers (22 female and 25 male) ranging from 29 to 47 years old are recruited for the experiments. Each experienced driver has held a driving license more than 5 years with an average annual driving distance of at least 8000 km.

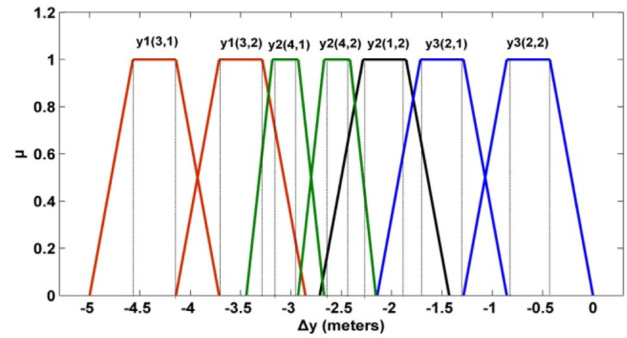
A van (6915 mm in length, 2150 mm in width and 2260 mm in height) serves as the lead vehicle. The driving behavior takes place on a simulated road with two lanes, and each lane is 3.5 m in width. In addition, traffic signs, buildings, guardrails and trees

Table 2
Sensibility analysis of variables to prediction results.

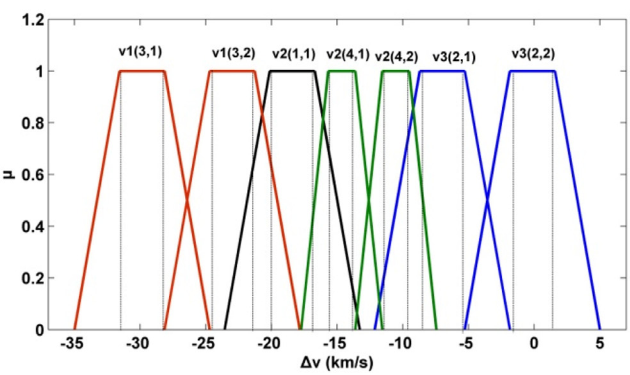
Speed variables removed	60 km/h			80 km/h			100 km/h		
	RMSE	MAE	MPAE (%)	RMSE	MAE	MPAE (%)	RMSE	MAE	MPAE (%)
Θ	4.8687	3.9752	15.5852	4.8433	3.5254	15.6263	4.4918	3.3484	11.3987
Acc	4.7698	3.5490	13.5736	4.1347	3.0127	13.7168	4.1277	3.2724	10.6726
θ and *acc*	5.4451	4.5543	16.4923	5.9743	4.5707	19.9665	5.3622	4.1475	15.0216



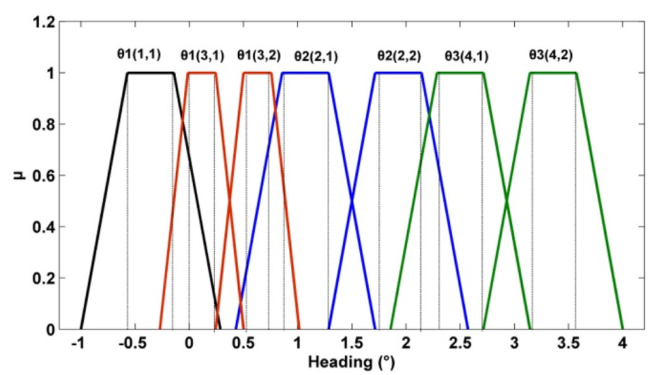
a Difference of distance in the horizontal coordinate



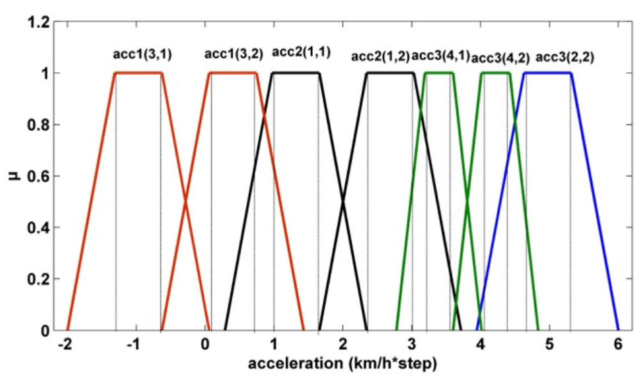
b Difference of distance in the vertical coordinate



c Relative velocity



d Heading angles



e Acceleration

Fig. 7. Final membership functions of five input variables after four times iterations.

are designed to construct a realistic driving environment. In the simulation of lane change, a lead vehicle is traveling in the front of subject vehicle with constant speed, and the experiments are conducted under different speed levels of lead vehicle: 60 km/h, 80 km/h and 100 km/h respectively.

Before the experiment, every subject needs to fill out a questionnaire about their age, date when they have had a drivers' license and driving mileage. Then, a member of our research team presents the driving simulator and the driving task. A practice session is conducted prior to the experiments to ensure subjects becoming familiar with the driving simulator. Then each subject will directly finish the driving task in scenarios where the lead vehicle runs at speed levels of 60 km/h, 80 km/h and 100 km/h respectively. For each scenario, drivers need to successfully complete three valid

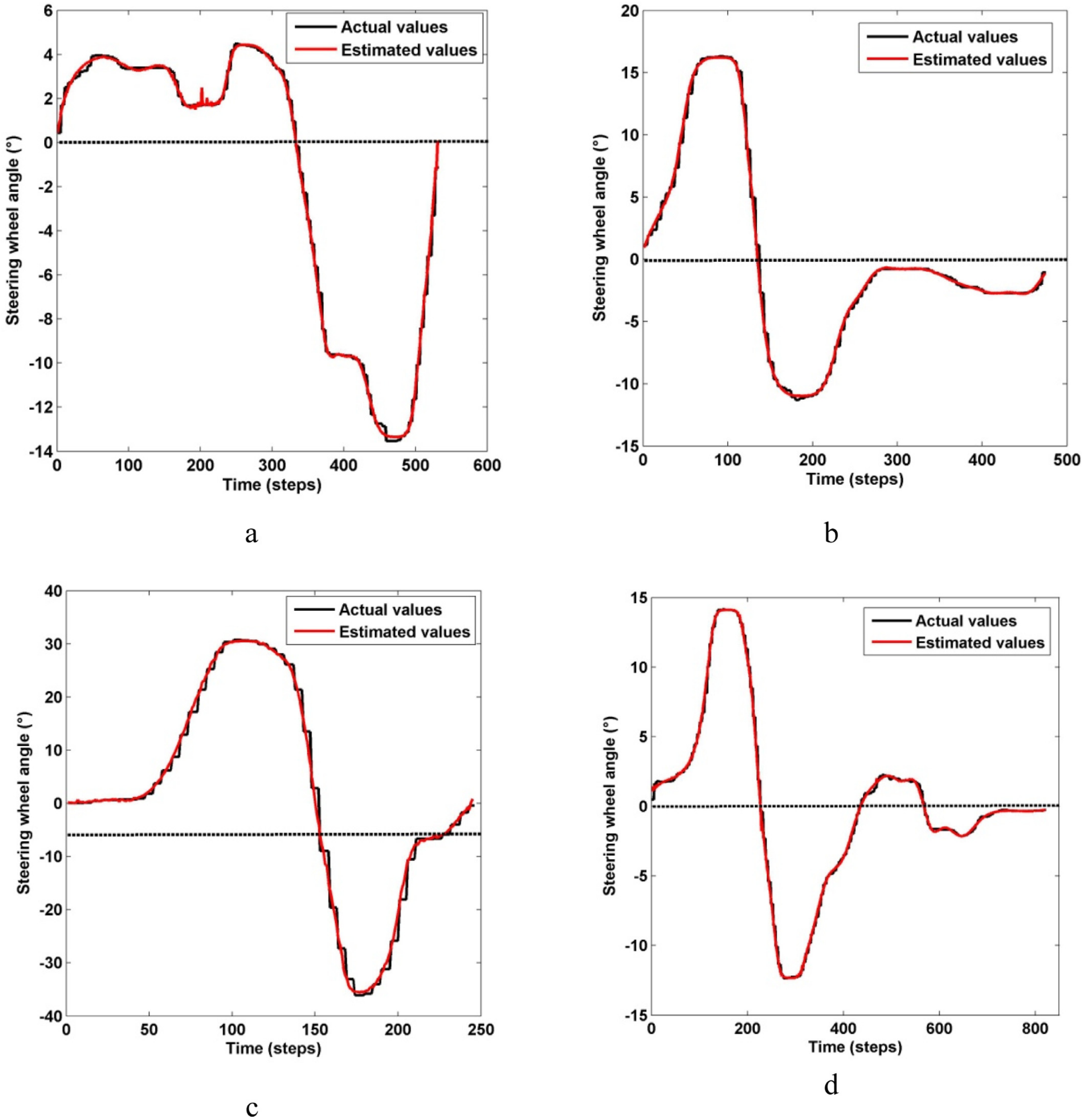


Fig. 8. Prediction results of steering angles for four drivers in scenario with speed of 60 km/h.

lane changing tasks. Finally, we can obtain totally 141 lane changing data samples under each scenario. Fig. 4 shows an actual data sample. Fig. 4a expresses a lane changing trajectory in a relative coordinate system, dash line represents the center of lanes, and the maximum left position is near the center line of left lane. Fig. 4b, c, d, e, f show the distribution of five input variables: Δx, Δy, Δv, θ, *acc*. Fig. 4g expresses data distribution of output variable: steering angle α. As the data were recorded with a frequency of 60 Hz, thus, 1 time step in this study equals 0.017 s. In the simulation, the lead vehicle is stationary before the experiment starts, and it will accelerate to the designed speed and keep unchanged until the experiment ends. The subject vehicle firstly follows the lead vehicle at a safe and comfortable distance. Based on the previous designed tasks, the subject vehicle then will accelerate to finish lane changing behavior on the premise of ensuring safety.

4.2. Model validation and results discussion

In the validity test of the model, we divide lane changing data samples into two parts: two-thirds of samples from each driver are integrated as the training dataset, and the other one-third of samples are composed as testing dataset. Additionally, we define three

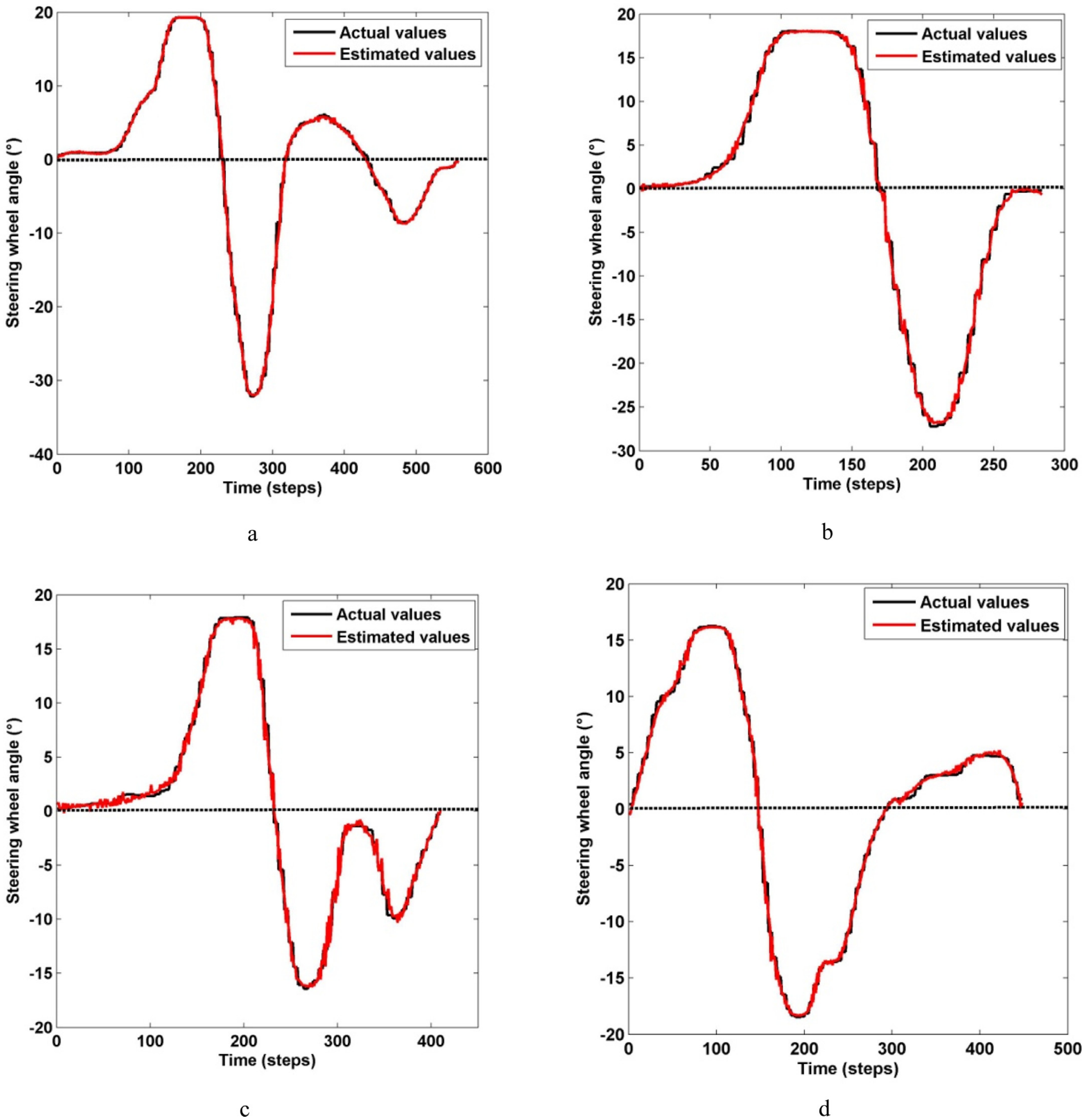


Fig. 9. Prediction results of steering angles for four drivers in scenario with speed of 80 km/h.

indicators as the criteria for evaluating the effect of the prediction: mean absolute error (MAE), the mean absolute percentage error (MAPE) and the root mean square error (RMSE), the definition of RMSE can be seen in Eq. (9).

$$\text{MAE} = \frac{\sum_{i=1}^{N} |\alpha_i - \hat{\alpha}_i|}{N} \tag{10}$$

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \frac{|\alpha_i - \hat{\alpha}_i|}{\alpha_i} \times 100\% \tag{11}$$

Here, we take the lane-changing data samples collected in the scenario with speed of 60 km/h as an example to introduce the learning process and prediction results of the proposed method. Fig. 5 shows the initial membership function for the five input variables, and the μ indicates degree of membership. For each input variable, we define three fuzzy subsets to represent its values from low level to high level. As we mentioned before, all the fuzzy subsets use trapezoid function to present membership degree. Fig. 6 shows the distribution of training errors using the proposed learning algorithm. We use the RMSE to evaluate errors. The number of iterations represents the running number of learning

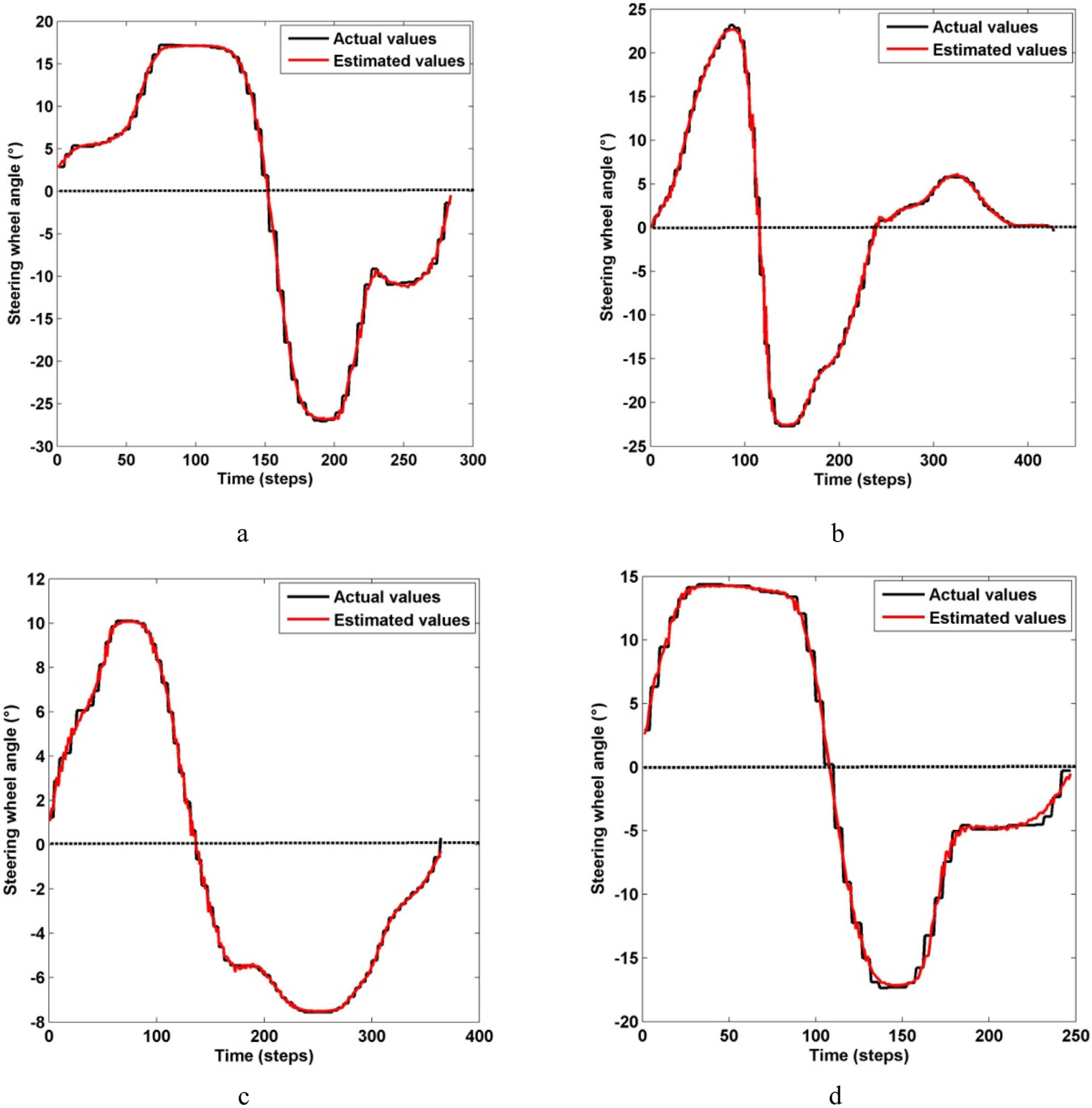


Fig. 10. Prediction results of steering angles for four drivers in scenario with speed of 100 km/h.

algorithm introduced in Section 3.3. As the figure shows, with the increase of the number of iterations, the training error decreases. Furthermore, this decreasing pattern contains two parts: when the number of iterations is less than four, the error declines rapidly; when the number of iterations is higher than four, the error decreases slowly and gradually tends to be stable. We can conclude that the improvement of model predicting ability is limited after learning algorithm implementing four iterations. Therefore, we choose the model with four learning iteration as optimal system to predict steering angles. Fig. 7 provides the distribution of the membership function of five input variables after four iterations, and the μ indicates degree of membership. In each iteration, an involved fuzzy subset will be split into two sets. There are two numbers in the bracket for each subset. The first one indicates the number of iterations, and the second one represents the number of the divided subset. For example, $x1$ (4,1) means the first part of fuzzy subset $x1$ belongs to variable Δx was split in the fourth iteration. Fig. 8 shows the prediction results of steering driver using trained AFNN model, and we only display perdition performance of four drivers. In the figure, black line represents the actual data collected from simulator, and the red line means the predicted steering angles. As we can see, the prediction model proposed in this study can successfully and accurately follow the pattern of actual data, which indicates strong predicting ability of AFNN model.

Similarly, we also show the results of four individual drivers in the environments with speed of 80 km/h and 100 km/h in Figs. 9 and 10. The numbers of iterations for these two experiments are 3 and 4 respectively. Stable and accurate prediction results also verify the effectiveness of the proposed method. As the AFNN model belongs to Machine Learning Method, we compare predicting performance of proposed method with several conventional methods to express learning ability of AFNN: Neural Network (NN), Support Vector Machine (SVM), Hidden Markov Model (HMM) and Multivariable Linear Regression (MLR). For all other methods, we use the same input and output variables, same training and testing dataset with the AFNN. Table 1 shows prediction accuracy of the four methods under different speed conditions according to the three error indicators. As can be seen from the table, because of simple structure and weak learning ability, the prediction accuracy of MLR is lower than the other three methods. Compared to SVM and NN, AFNN improves the results, which because of the learning mechanism used in this study. For one thing, an improved LSE method is adopted to enhance the optimization effect of parameter in Takagi–Sugeno model of FNN. For another thing, through applying adaptive learning algorithm, the fuzzy memberships are updated, the fuzzy rules are enriched, and finally the rationality and accuracy of rule reference are improved. Taking RMSE as example, the prediction accuracy of AFNN increases by approximately 40% compared to NN and about 20% compared to SVM.

In previous studies, researchers generally consider the relative indicators between subject vehicle and other vehicles to analyze lane changing behavior. In this study, the input variables of prediction model include not only relative indicators: Δx, Δy, Δv, but also parameters of subject vehicle: θ, *acc*. Accordingly, we employ a sensitivity analysis to further study the influence of subject vehicle parameters on prediction results. Table 2 provides the prediction results of AFNN by removing input variables θ and *acc*. It can be observed firstly that the removal of any one parameter will result in the deterioration of prediction performance, which shows that the heading and acceleration are two important factors need to be considered in the process of lane change. We can also find that the prediction results of model removing *acc* is worse than that of model removing θ, which shows that heading angles, as a key information for the lane change, is more important than acceleration in steering angle prediction. It can be imagined that vehicle heading plays a significant role when driver controls the steering wheel to finish lane-changing behavior.

5. Conclusion

In this paper, we introduced an adaptive fuzzy neural network to predict driver's lane-changing behavior. In the prediction model, we define the distance between the subject vehicle and lead vehicle in the horizontal and vertical coordinates in the current lane (Δx and Δy), the relative velocity between subject vehicle and lead vehicle (Δv), traveling heading (θ) and acceleration (*acc*) as input variables and steering wheel angles (α) as output variable. The trapezoid function is used as membership function. Furthermore, a first-order Takagi–Sugeno model is used to finish fuzzy inference, in which an improved LSE method is applied to optimize modeling parameters. In the adaptive learning algorithm, according to the prediction errors, membership functions and fuzzy inference are updated to improve prediction performance.

In the experiments, data of input and output variables were collected through vehicle simulator. Three different scenarios were designed with different speed of lead vehicle: 60 km/h, 80 km/h and 100 km/h. Total 47 drivers took part in the experiments, and 141 valid lane changing data samples were collected to train and validate prediction model. In the results analysis, we define three indicators to evaluate prediction performance: mean absolute error (MAE), the mean absolute percentage error (MAPE) and the root mean square error (RMSE). The prediction results indicate effectiveness and stability of the proposed model. Moreover, we further compare the AFNN with three traditional machine learning methods: Neural Network (NN), Support Vector Machine (SVM) and Multivariable Linear Regression (MLR), and the comparison results show that the AFNN can achieve higher prediction accuracy than the other three methods for its strong learning ability. Finally, through sensibility analysis of subject vehicle parameters heading (θ) and acceleration (*acc*), we find that these two input variables play an important role in prediction of steering angles and they are two key factors need to be considered in lane-changing process. The works from this study will be helpful to improve the practical effects of ADAS and enhance lane changing safety.

While, in the future research, we will improve the current work from following several aspects: Firstly, for the vehicle model, we only use a simplified movement model of a four wheeled vehicle. However, in a real environment, the traveling status vehicle will be more complex; Secondly, in the simulation experiments, all the drivers are experienced, and the novice drivers are not considered. Therefore, future research may consider difference of lane changing behavior between experienced and novice drivers; Thirdly, more information extracted from different data source (Tang, Liu, Wang, & Wang, 2015, Tang, Zhang, Wang, Wang, & Liu, 2015, Tang, Zou, et al., 2016, Tang, Jiang, et al., 2016, Tang, Liu, Zou, Zhang, & Wang, 2017; Yan, Zhang, Tang, & Wang, 2017; Zhang, Tang, Wang, Wang, & An, 2017; Zou, Yang, Zhang, Tang, & Zhang, 2017, Zou, Tang, Wu, Henrickson, & Wang, 2017) can help to enhance prediction performance. Finally, in the input variables of prediction model, we consider the relative indicators between the subject vehicle and lead vehicle. However, lane change process is complex, and we should not only consider the safety distance in the current lane but also the safe space in the target lane. In the next step, theses important indicators should be taken into account in the prediction model.

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