Hindawi
Journal of Advanced Transportation
Volume 2020, Article ID 7878656, 11 pages
https://doi.org/10.1155/2020/7878656

Research Article

Study and Simulation Analysis of Vehicle Rear-End Collision Model considering Driver Types

Qiang Luo,[1] Xinqiang Chen ,[2] Jie Yuan ,[1] Xiaodong Zang ,[1] Junheng Yang,[1] and Jing Chen[3]

[1]*School of Civil Engineering, Guangzhou University, 230 Wai Huan Xi Road, Guangzhou Higher Education Mega Center, Guangzhou 510006, China*
[2]*Institute of Logistics Science and Engineering, Shanghai Maritime University, 1550 Haigang Ave, Shanghai 201306, China*
[3]*Merchant Marine College, Shanghai Maritime University, Shanghai 201306, China*

Correspondence should be addressed to Jie Yuan; yuanj@gzhu.edu.cn

Received 20 June 2019; Accepted 28 December 2019; Published 23 January 2020

Academic Editor: Shamsunnahar Yasmin

The reasonable distance between adjacent cars is very crucial for roadway traffic safety. For different types of drivers or different driving environments, the required safety distance is different. However, most of the existing rear-end collision models do not fully consider the subjective factor such as the driver. Firstly, the factors affecting driving drivers' characteristics, such as driver age, gender, and driving experience are analyzed. Then, on the basis of this, drivers are classified according to reaction time. Secondly, three main factors affecting driving safety are analyzed by using fuzzy theory, and the new calculation method of the reaction time is obtained. Finally, the improved car-following safety model is established based on different reaction time. The experimental results have shown that our proposed model obtained more accurate vehicle safety distance with varied traffic kinematic conditions (i.e., different traffic states, varied driver types, etc.). The findings can help traffic regulation departments issue early warnings to avoid potential traffic accidents on roads.

1. Introduction

Private car has become affordable for public with the quick development of economic and promotion of manufacture technique. An adverse effect of is increasing traffic accidents on roadways which greatly imperil traffic safety and efficiency. The previous studies have shown that drivers are assumed to the take the major responsibility for the traffic accidents (i.e., a few accidents are triggered by vehicle defects). Indeed, over 80% traffic accidents on roads can be ascribed to driver misconduct (e.g., answering cell phone, smoking, and taking naps) [1, 2]. It is observed that varied driver characteristics (e.g., age, gender, experience, and speed of response) can impose different impact on individual vehicle maneuver procedure. The driver response time for different driver types for taking actions against dangerous driving situations is varied, which has attracted a lot of research attentions [3–5]. More specifically, the aggressive drivers require smaller displacement between neighboring vehicles when traveling on road, while the mild drivers are likely to keep sufficient vehicle headway for the purpose of avoiding potential traffic accidents. Note that quantifying such vehicle rear end displacement considering driver types is not easy, which is indeed a hot topic in the transportation safety research community.

Several studies have been conducted to establish minimum safety following distance model with vehicle kinematic data (i.e., driver types, vehicle acceleration/decelerations distributions, etc.). Zhang and Hao deeply analyzed the resistance influence on the minimum safety distance, which was involved with air resistance, road resistance, vehicle wheel rolling resistance, etc. [6]. Xu et al. proposed a minimum safety car-following model under different driver states by considering the vehicle acceleration/deceleration in vehicle braking process [7]. Spyropoulou proposed a novel vehicle safety distance model which considered the constraints of vehicle speed variation, minimal safety distance, etc. [8]. Hu et al. firstly studied driver behavior differences and empirical judgment ratio distributions in an abnormal traffic scenario and then proposed a car-following model for estimating the minimum safety distance for the emergency evacuation vehicle [9]. Similar research studies can be found in [10–14].

Many studies have been conducted to analyze the relationship between traffic safety and drivers characteristic, including driver personality, physical fitness, driver distraction, etc. [15–18]. Tang and Xia implemented a series of experiments to measure the reaction time of four different driver types and further studied its impact on the minimal safety distance of preventing rear-end collision [17]. Tang and Xia analyzed a variety of factors that affect the driver reaction time by using fuzzy mathematics theory and then proposed a novel model to estimate driver reaction time [17]. By considering influence of driver individual differences, vehicle braking performance, and driving states, Zhang et al. established a car-following model with minimum safety distance for three typical traffic states [19]. Similarly, Xue et al. proposed a rear-end collision behavior model considering the individual differences of drivers [20]. Some scholars analyzed the relationship between other influencing factors and car safety, such as the speed relation among adjacent vehicles [21, 22].

Fuzzy relevant models have been proposed to simulate real-world traffic situations considering varied driver types and thus provide optimal traffic control strategies for the purpose of ensuring traffic safety and efficiency (i.e., with minimal waiting time, short queue length, etc.). Chai et al. proposed a simulation-based approach to measure driver cognitive failures, which was implemented with fuzzy logic and cellular automata model [23]. Azimirad et al. proposed a novel fuzzy traffic controller to formulate and optimize traffic control at isolated signalized intersection [24]. Li proposed a dynamic fuzzy neural networks traffic flow prediction model to accurately obtain traffic flow prediction under chaos traffic state [25]. Bocklisch et al. proposed an adaptive fuzzy pattern classification model for simulating nonlinear, multidimensional transition processes, which aims to identify the lane change intentions for varied driver types [26].

The previous studies focusing on vehicle rear-end collision analysis mainly employed the kinematic data to estimate minimal neighboring vehicle distance with the quantitative indicators (i.e., speed, displacement, etc.), which did not consider the qualitative indicators (e.g., driving behavior differences influence) and mainly led to biased results. The advantages of fuzzy theory can help us quantify the physiological and psychological characteristics of vehicle drivers and thus provide us a more holistic view of the car-following model. The paper is organized as follows. Driver features were deeply analyzed in Section 2, and the proposed safety model was illustrated in Section 3. The experimental results were described in Section 4, and Section 5 concluded the paper.

2. Driving Characteristics and Reaction Time

2.1. Driving Characteristics Analysis. The vehicle controlling procedure consists of environment perception, potential risk judgment and traveling decision making, and vehicle maneuver, which can be found in Figure 1. In the perception stage, the driver's control of car speed and perception of surrounding environment have a close bearing on the driver's reaction speed to the unexpected situation. In the judgment and decision-making stage, the driver makes control decisions based on driving experience to ensure driving safety. In the operation stage, the driver controls the car accelerating, decelerating, turning, and braking according to the decision. Note that over 80% traffic accidents are triggered due to the driver errors [16, 27, 28]. To avoid the potential traffic accidents, drivers are supposed to take early and correct maneuver activities (i.e., identify risky behaviors, decide the suitable travel behavior, take maneuver activities, etc.) for each of vehicle maneuver steps.

The driver's individual characteristics can be analyzed from physiological and psychological factors, for example, the driver's age, gender and driving age, fatigue and emotions while driving, the driver's own driving style and safety attitude, traffic regulations awareness level, and so on. These research studies show that [29–31] (1) the reaction speed to the emergency situation will be significantly reduced with age; (2) in terms of emergency response capacity and the ability to cope with the complex external environment, the female drivers are worse than the male drivers; (3) the experienced driver has the faster reaction in the emergency situation; and (4) the adventure driver is more likely to be in danger of rapid acceleration, deceleration, and changing lanes than the cautious driver. Based on the above analysis, it is necessary to quantify the driving characteristics into quantifiable parameters, such as reaction time, which can be introduced into the modeling process of the improved car-following model.

2.2. Relationship Analysis between Driver Characteristics and Reaction Time. The driver age, driving experience duration, and fatigue level are considered as crucial elements for quantifying analysis on the relationship between driver characteristics and reaction time [32, 33]. Previous studies have evaluated the reaction time variation under different traffic flow density constraints by building three kinds of traffic flow density scenarios, which suggested that the driver reaction time tends to be shorter in higher traffic flow density. Factually, the driver in a conservative driving style (intends to obtain much larger distance) has the longest reaction time regardless of the vehicle braking manner. The driver age has a significant interference to driver reaction time which is obviously observed in the emergency traffic situations. The statistical distributions of empirical traffic data suggested that the average and variance of collision avoidance reaction time of 18 to 30 years old drivers are the smallest and the drivers over 51 years old have the longest collision avoidance reaction time. Previous studies suggested that aging drivers need more reaction time because they require longer time to think carefully about various potential travel strategies [18, 34, 35]:

$$t_r = 1 + (1 - C)^{1-Q}, \quad (1)$$

where t_r is the driver's reaction time, C is the response degree of different types of drivers under different conditions, and Q is vehicle braking type.

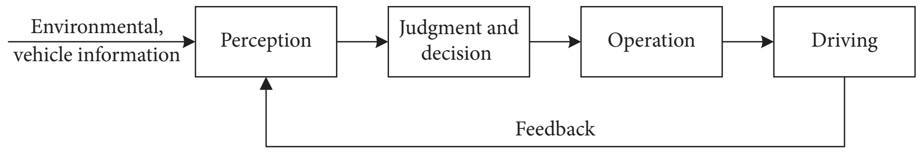

Figure 1: Control flow for vehicle maneuver procedure.

According to the formula, the reaction time of several representative driver types is obtained which is shown in Table 1 (for details, see [9]).

3. Analysis and Improvement of Safety Distance Model

The reaction time of various types of drivers is different when they face the same situation, so the required safety distance is also different. The improvement of safety distance model mainly researches on driver's reaction time and confirms a more reasonable safety distance. When establishing the model, the driver's reaction time varies from different influencing factors. Some researchers discovered that these influencing factors are not absolutely independent, but have a certain intersection, and they have characteristics of fuzziness [36, 37]. Therefore, this study uses the fuzzy mathematics principle to calculate reaction time of different types of drivers.

3.1. Reaction Time Analysis. There are many factors affecting the driver's driving behavior, and the impact of these factors can be measured by the reaction time of drivers. Through in-depth analysis and comparative research, three main factors affecting response time were selected in this manuscript: age, driving age, and fatigue. Other factors will be considered in future research.

In the fuzzy inference system, there are three variables including input variables, fuzzy rules, and fuzzy output, as shown in Figure 2. After determining the influencing factors, the fuzzy distribution method is used to determine membership function, and the Gaussian or semi-Gaussian distributions are selected which include small, large, and intermediate types that correspond exactly to the conservative, adventurous, and conventional types of driver classification [38, 39].

(1) Membership function of age:

The driver's age can be roughly divided into three parts including youth, middle, and old age, which are denoted as A1, A2, and A3, respectively. The legal driver age in China ranges from 18 to 70 which are supposed by China traffic regulations. Following such rule, the driver age interval is set as [20, 70]. The membership function of driver's age is trapezoidal membership function.

(2) Membership function of driving age:

As for the driver's driving age, it can be roughly divided into three levels including low, medium, and high, which are denoted as B1, B2, and B3, and the interval [0, 50] is selected. More specifically, we set the driving age interval from 0 to 50 considering that a driver can hold a driver license without longer than 50 years. The membership function of driving age is the Gaussian membership function.

(3) Membership function of fatigue degree:

The driving time is used to express the driver's fatigue. It can be roughly divided into mild, moderate, and high fatigue magnitude, respectively, which are marked as C1, C2, and C3. Note that driver fatigue interval is set as [0, 10] following the rules suggested by the Chinese traffic regulations. The driver fatigues the membership function is the Gaussian membership function.

(4) Reaction time variable:

The inference system finally derives the driver's reaction time according to fuzzy theory. Based on a large number of survey results, it is generally believed that the driver's response time interval is [0.2, 3.0], which can be roughly divided into short, medium, and long. Therefore, the Gaussian-type function is used for the membership function.

After inputting the driver's age, driving age, and fatigue level, the fuzzification process can be performed to obtain the approximate value of the driver's reaction time, and then the center of gravity defuzzification method is used for antifuzzification, and the precise value of the reaction time can be obtained. Its expression is

$$y_0 = \frac{\int u_c(y) y \,\mathrm{d}y}{\int u_c(y) \mathrm{d}y}, \tag{2}$$

where $\int$ is the integral of all subsets in the continuous domain y and y_0 means that the area of left and right sides is the same.

3.2. Improved Safety Distance Model Establishment. The reaction time is used to distinguish different types of drivers and is used as a parameter in the process of model building. In order to analyze different driving conditions comprehensively, three states of static, uniform, and deceleration of the preceding car were analyzed in order to establish the safety distance model.

(1) Static state of the front car:

When the front vehicle is stationary, the positional relationship between the two vehicles is shown in Figure 3.

Table 1: Reaction time of different types of drivers (s).

Driver types	Conservative $C = 0.1$	Cautious $C = 0.3$	Conventional $C = 0.5$	Radical $C = 0.7$	Adventurous $C = 0.9$
Hydraulic brake/$Q = 0.15$	1.91	1.74	1.55	1.36	1.44
Barometric brake/$Q = 0.4$	1.94	1.81	1.66	1.49	1.25

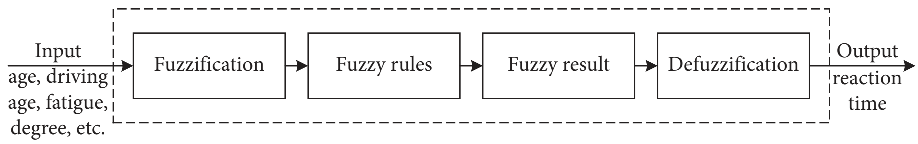

Figure 2: Fuzzy inference system.

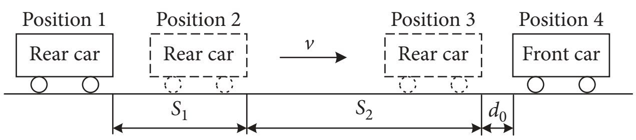

Figure 3: Positional relationship (in the static state of the front car).

At position 1, the rear car begins to realize the danger. After the reaction time t, the rear car will arrive at position 2. The rear car maintains a constant speed v_1 during the whole process, and traveling distance in reaction time t is

$$S_1 = v_1 t. \tag{3}$$

At position 2, the rear car starts to brake at the maximum deceleration, and its speed drops to 0 at position 3. At this time, the distance between the front and rear cars is d_0, and the distance traveled by rear car during this time is

$$S_2 = \frac{v_1^2}{2a_1}. \tag{4}$$

To avoid collision of two cars, the minimum safety distance needed to maintain is

$$D_1 = S_1 + S_2 + d_0 = \frac{v_1 t + v_1^2}{2a_1 + d_0}, \tag{5}$$

where a_1 is the maximum braking deceleration of the rear car and d_0 is the minimum safety distance required for the two cars.

(2) Uniform state of the front car:

When two cars are driving at a constant speed, a collision occurs only when the speed of the following vehicle is faster than the speed of the preceding vehicle. The positional relationship is shown in Figure 4.

Assume that the rear car is in position 1 and the front car is in position 3. The rear car will reach position 2 after reaction time t, and then it starts to brake. During the reaction time, the rear car maintains a constant speed, and the distance traveled is

$$S_1 = v_1 t. \tag{6}$$

At position 2, assume that the rear car begins to decelerate until its speed is the same with the front car; meanwhile, the front car arrives at position 5 and the rear car arrives at position 4. In this process, the distance traveled by the rear car and the front car is, respectively,

$$S_3 = v_2 t_2 = \frac{v_2 (v_1 - v_2)}{a_1} = \frac{v_1 v_2 - v_2^2}{a_1}. \tag{7}$$

To avoid collisions of two cars, the minimum safety distance needed to maintain is

$$D_2 = S_1 + S_2 - S_3 + d_0 = v_1 t + \frac{v_1^2 - v_2^2}{2a_1} - \frac{v_1 v_2 - v_2^2}{a_1} + d_0. \tag{8}$$

(3) Deceleration state of the front car:

When the speed of the rear car is faster than that of the front car, the two cars have the possibility of collision. In order to prevent this collision, the speed of the two cars is equal or the speed is zero when the distance between two cars is d_0. The position relationship is shown in Figure 5.

With the previous analysis, the rear car travels from position 1 to position 2 within the reaction time t. The distance traveled is

$$S_1 = v_1 t. \tag{9}$$

At position 2, the rear car begins to brake. When the speed of two cars is equal (set as v), the rear and the front car

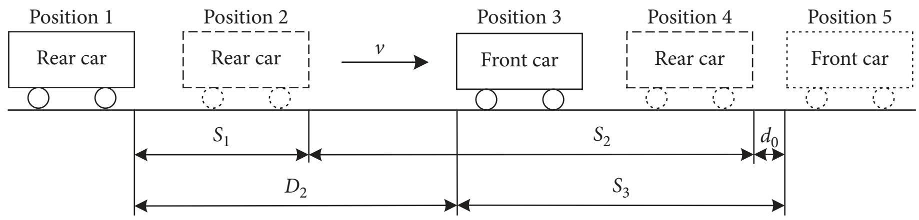

Figure 4: Positional relationship (in the uniform state of the front car).

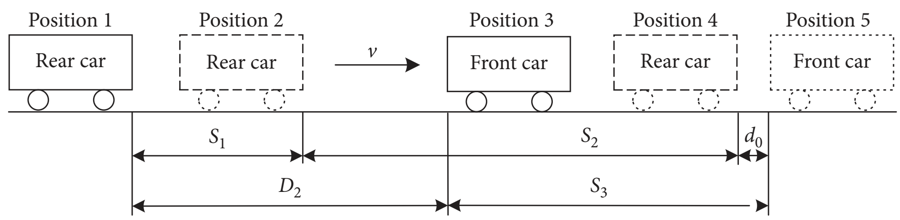

Figure 5: Positional relationship (in the deceleration state of the front car).

will arrive the position 4 and 5, respectively. The travel distances are as follows:

$$S_2 = \frac{v_1^2 - v^2}{2a_1},$$
$$S_3 = \frac{v_2^2 - v^2}{2a_2}. \tag{10}$$

To avoid collisions, the minimum safety distance to be maintained is

$$D_3 = S_1 + S_2 - S_3 + d_0 = v_1 t + \frac{(a_2 - a_1)v^2 + a_1 v_2^2 - a_2 v_1^2}{2a_1 a_2} + d_0, \tag{11}$$

where a_2 is the braking deceleration of the front car and the remaining parameters have the same meaning as mentioned above.

4. Model Simulation and Analysis

4.1. Improved Model Simulation. When the front car is in three different states, the established model is simulated. Due to the combination of three factors (age, driving age, and fatigue degree) and limited space, representative combinations are selected for simulation. For example, the age is 30, 45, and 60, the driving age is 5, 10, and 15, and the values of fatigue degree take 2, 5, and 8. These numbers are arranged and combined randomly. Table 2 shows the driver reaction time obtained by substituting three groups of factors into the fuzzy system.

Table 2: Reaction time in different combinations.

Age, driving age, and fatigue degree	Reaction time (s)
(30 5 2)	1.21
(30 5 5)	1.58
(30 5 8)	1.69
(30 10 8)	1.83
(30 10 5)	1.52
(30 10 2)	1.28
(45 5 2)	1.39
(45 5 5)	1.92
(45 5 8)	2.10
(45 10 8)	1.99
(45 10 5)	1.73
(45 10 2)	1.32
(45 15 8)	1.91
(45 15 5)	1.62
(45 15 2)	1.38
(60 5 2)	1.94
(60 5 5)	2.58
(60 5 8)	2.75
(60 10 8)	2.71
(60 10 5)	2.53
(60 10 2)	1.81
(60 15 8)	1.91
(60 15 5)	1.61
(60 15 2)	1.34

From Table 2, some conclusions can be obtained as follows. (1) When the driver's age and driving age are constant, the driver's reaction time is directly proportional to the fatigue degree. (2) When the driver's age and fatigue degree are constant, the driver's reaction time is directly proportional to the driving age. (3) When the driver's driving age and fatigue value are constant, the driver's reaction time is directly proportional to the age. And, between the ages of 30 and 45, the driver's reaction time grows slowly, and after the age of 45, the growth rate accelerated.

4.2. Comparative Analysis of Different Models

4.2.1. Traditional Safety Distance Model. So far, there are many classic car safety distance models, such as, the Mazda model, the Honda model, and the models proposed by the domestic research institutes and various universities [14], as follows:

(a) The Mazda model:

$$d = \frac{a_2 v_1^2 - a_1 v_2^2}{2a_1 a_2} + v_1 t_1 + v_r t_2 + d_0. \quad (12)$$

(b) The Honda model:

$$D = (1.2 + l)v_1 + \frac{v_1^2 - v_2^2}{2a} + d. \quad (13)$$

(c) Research institutes' model:

$$S_0 = 0.3195v_1 + 0.034v_r + \frac{v_r(2v_1 - v_r)}{254.06\varphi} + 5. \quad (14)$$

(d) Universities' models:

$$d_w = \tau v_c + \frac{v_c^2}{2a_c} + d_{\text{off}},$$
$$D_x = \frac{v_c^2}{2(0.0826v_c + 0.6177)} + 3.6. \quad (15)$$

In the formulas, d, D, S_0, d_w, and D_x represent the safety distance, v_1 and v_2 represent the speed of the leading and following car, a_1 and a_2 represent the acceleration of the leading and following car, v_r is the relative speed, d_0 and d represent the minimum safety spacing, l is the length of car, τ is the response time of driver, and the remaining parameters are the same as before.

4.2.2. Model Comparison and Analysis. The reaction time deduced by the fuzzy theory is substituted into different safety distance models. Under different reaction times, the safety distances calculated by different models are different. Four groups of data are randomly selected as comparisons.

(1) Static state of the front car:

D_1 represents the safety distance of modified model when the leader car is in the anchoring state. In such traffic state, the parameters are set as follows: the initial speed of the rear car is 60 km/h and the deceleration is 4 m/s^2. The safety distance between the two cars is 50 m. More specific parameter settings are shown in Table 3.

(a) We employ MATLAB to implement experiment when the driver reaction time is set to 1.21 s, and the corresponding results are shown in Figure 6. The comparison result of safety distances for different models is shown in Figure 7.

From Figure 6, we can see that the two curves intersect at 50 m, which proves that setting the safety distance to 50 m is not enough and a collision will occur. Under this condition, the safety distance of rear-end collision model is 54.89 m by calculation. From Figure 7, it can be found that in all the models, the improved model D_1 is the closest to the minimum safety distance.

(b) We employ MATLAB to implement experiment when the driver reaction time is set to 1.58 s, and the corresponding results are shown in Figure 8. The comparison chart of safety distances for different models is shown in Figure 9.

From Figure 8, the safety distance is 61.06 m. From Table 3, it can be seen that the models D_1 and D are close to the minimum safety distance. However, due to the need of keeping a certain distance between two cars when they are still, the model D_1 is more appropriate.

(2) Uniform state of the front car:

D_2 represents the safety distance of the modified model when the front car is in the uniform state. In such traffic state, the parameters are set as follows: the speed and deceleration of the rear car are 80 km/h and 4 m/s^2 and the speed of the front car is 40 km/h. The safety distance between the two cars is 50 m. More specific traffic parameters for obtaining safety distance in the traffic state are shown in Table 4.

(a) We employ MATLAB to implement experiment when the driver reaction time is set to 1.39 s, and the corresponding results are shown in Figure 10. The comparison chart of safety distances for different models is shown in Figure 11.

It can be seen from Figure 10 that since there are no intersections between the two curves, it can be seen that the safety distance of 50 m is sufficient, and the calculated safety distance to prevent rear end is 31.37 m. Figure 11 shows that the safe distance of model D_2 is closest to 31.37 m, so the model D_2 is most suitable.

(b) We employ MATLAB to implement experiment when the driver reaction time is set to 1.73 s, and the corresponding results are shown in Figure 12. The comparison of the safety distances of different models is shown in Figure 13.

It can be seen from Figure 12 that since there are no intersections between the two curves, it can be seen that the 50 m safety distance is sufficient. According to MATLAB calculations, the safety distance is 34.78 m if there is no collision. From Figure 13, it is found that the safe distance of model D_2 is closest to 31.37 m, so the model D_2 is most suitable.

(3) Deceleration state of the front car:

D_3 represents the safety distance of the modified model when the front car is in the deceleration state. In this driving condition, the parameters are set as follows: the speed and deceleration of the rear car are 100 km/h and 5 m/s^2 and the speed and deceleration of the front car are 60 km/h and 3 m/s^2. The safety distance between the two cars is 50 m. The safety distance of different models (in the deceleration state) is shown in Table 5.

Table 3: Safety distance of different models (in the static state).

Age, driving age, and fatigue degree	(30 5 2)	(30 5 5)	(30 5 8)	(30 10 8)
Reaction time (s)	1.21	1.58	1.69	1.83
D_1	59.89	66.06	67.89	70.22
d	63.22	69.39	71.22	73.56
D	59.82	61.95	67.42	70.53
S_0	96.26	96.26	96.26	96.26
d_w	61.37	69.87	72.36	75.96
D_x	70.12	70.12	70.12	70.12

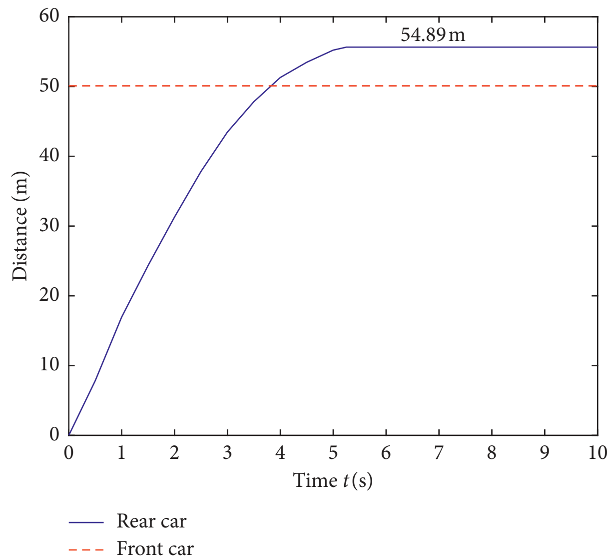

Figure 6: Distance change (in the static state on front car).

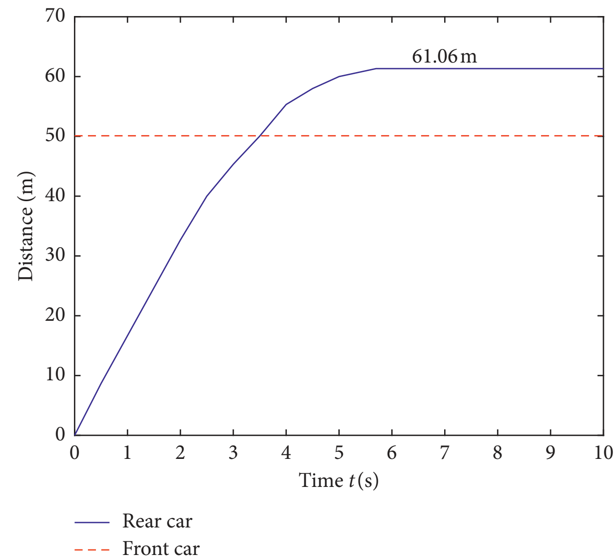

Figure 8: Distance change (in the static state of front car).

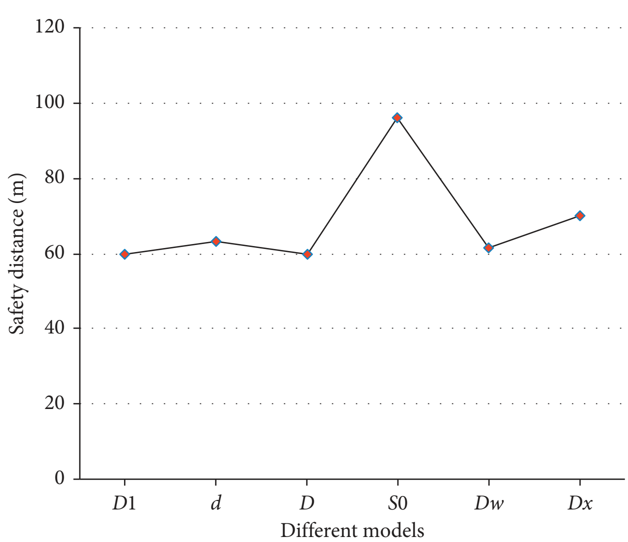

Figure 7: Safety distance comparison (in the static state on front car).

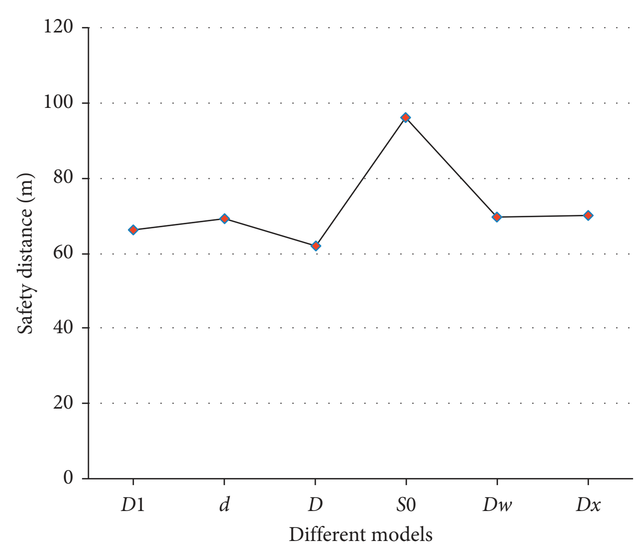

Figure 9: Safety distance comparison (in the static state of front car).

(1) When the driver's reaction time is 1.21 s, use MATLAB simulation to obtain results as shown in Figure 14. The comparison of the safety distance of different models is shown in Figure 15.

From Figure 14, there are intersections between the two curves, which proves that it is not enough to set the safety distance to 50 m, and there will be a collision. After the simulation calculation, the

Table 4: Safety distance of different models (in the uniform state).

Age, driving age, and fatigue degree	(45 5 2)	(45 10 5)	(60 15 8)	(60 5 8)
Reaction time (s)	1.39	1.73	1.91	2.75
D_2	51.32	58.88	62.88	81.54
d	99.84	107.40	111.40	130.06
D	69.82	71.95	77.42	80.53
S_0	134.37	134.37	134.37	134.37
d_w	109.37	116.87	123.36	138.96
D_x	108.40	108.40	108.40	108.40

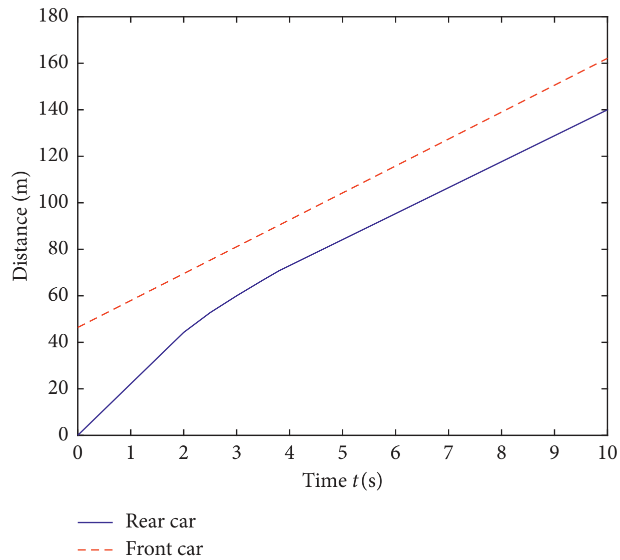

Figure 10: Distance change (in the uniform state of front car).

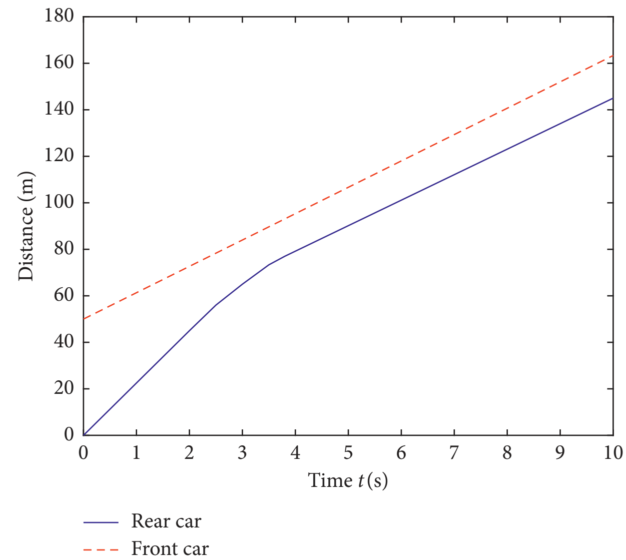

Figure 12: Distance change (in the uniform state of front car).

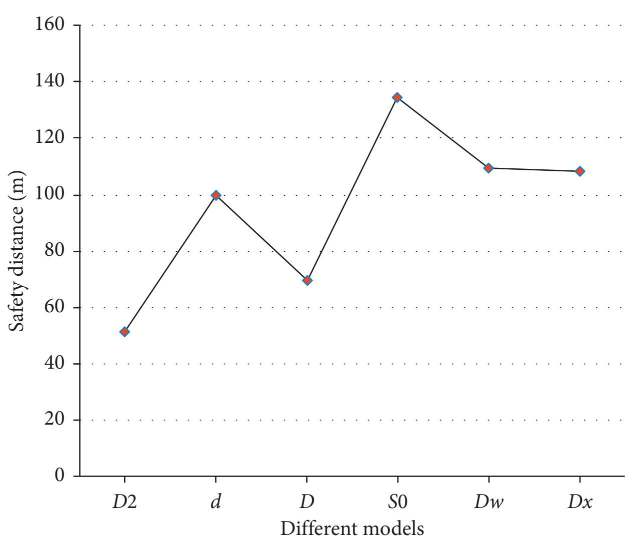

Figure 11: Safety distance comparison (in the uniform state of front car).

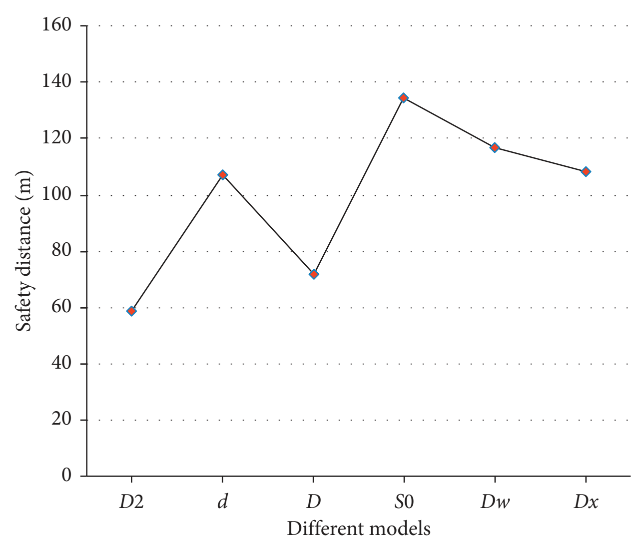

Figure 13: Safety distance comparison (in the uniform state of front car).

safety distance for preventing rear-end collision is 64.5 m. It can be seen from Figure 15 that the safety distance of model D_3 is the closest to 64.5 m. Thus, the model D_3 is most suitable.

(2) We employ MATLAB to implement experiment when the driver reaction time is set to 1.73 s, and the corresponding results are shown in Figure 16.

Table 5: Safety distance of different models (in the deceleration state).

Age, driving age, and fatigue degree	(30 5 2)	(45 10 5)	(60 10 2)	(60 5 5)
Reaction time (s)	1.21	1.73	1.81	2.58
D_3	69.60	84.05	86.27	107.66
d	73.22	91.89	93.22	106.06
D	76.82	93.95	96.42	108.53
S_0	106.26	106.26	106.26	106.26
d_w	81.37	89.87	92.36	105.96
D_x	89.12	89.12	89.12	89.12

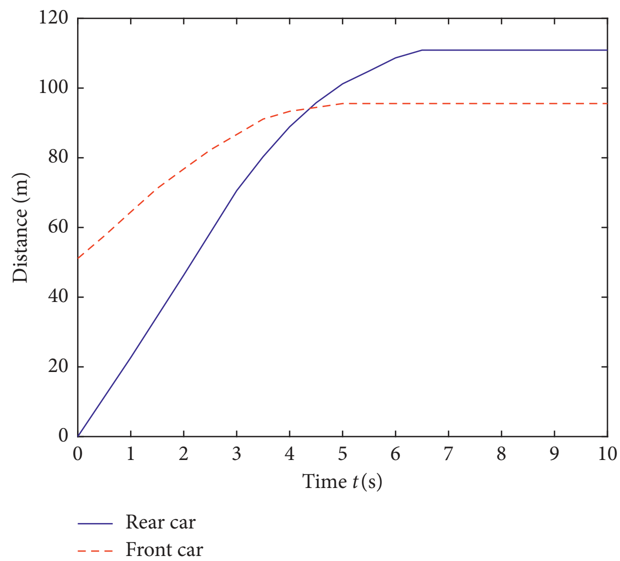

Figure 14: Distance change (in the deceleration state of front car).

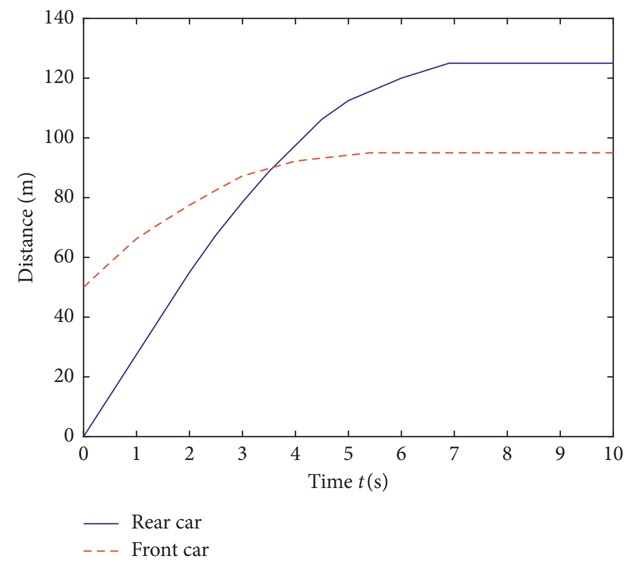

Figure 16: Distance change (in the deceleration state of front car).

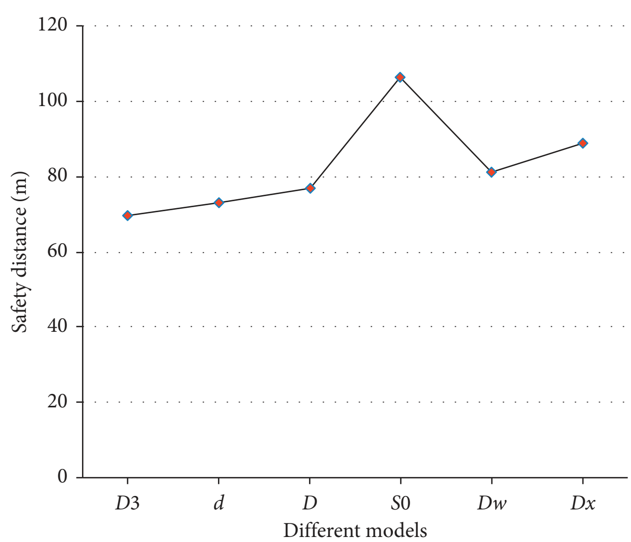

Figure 15: Safety distance comparison (in the deceleration state of front car).

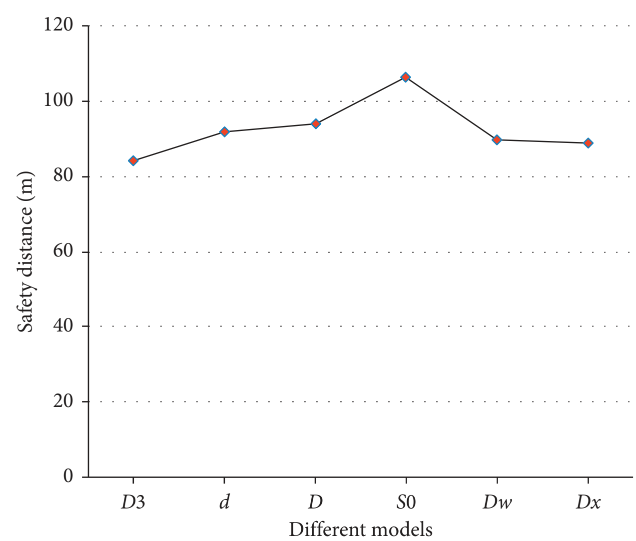

Figure 17: Safety distance comparison (in the deceleration state of front car).

From Figure 16, it can be seen that there are intersections between the two curves, which proves that setting the safety distance to 50 m is not enough and a collision will occur. After simulation calculation, the safety distance of preventing rear-end collision is 78.67 m. As can be seen from Figure 17, the safety distance of model D_3 is the closest to 78.67 m, so the model D_3 is most suitable.

We have evaluated varied minimal car-following distances at different speed variations. For instance, the minimal vehicle headways are 32.04 m and 63.86 m when the following car moves at 60 km/h and 90 km/h with the leading vehicle in the uniform state. The minimal vehicle distance can be shorter when the leading vehicle is in the deceleration state and the following car has same speed constraints (i.e., 60 km/h and 90 km/h). Vehicle speed influence on the simulation model can be summarized as two-folds: (1) the required minimum following distance for the following car is different when the leading car is in different traffic states (e.g., different speeds) and (2) the traveling speed of the following car is in positive relationship to that of the minimal car-following distance (i.e., higher speeds requires larger minimal distance).

5. Conclusions

We have analyzed different driver types' influence on roadway safety and thus quantified the influence by establishing a novel car rear-end collision model. We employed the fuzzy theory to build the reasoning model with the input of typical traffic safety factors (i.e., driver age, driving age, and fatigue degree) and output the driver reaction time. With the aim of obtaining minimum safety following distance, we have deeply analyzed the safety distance between two neighboring vehicles with leading vehicle at varied states. We have estimated minimal safety distances for the two vehicles with the leading car in varied kinematic states (i.e., static, deceleration, and constant speed), which are indeed commonly encountered on the roadway traffic scenarios. Suppose two of the traffic factors are in constant states, driver reaction time is proportional to the variation of the remaining factor (either in negative or positive). Compared with the traditional rear-end model, the proposed safety distance model established can be adapted to different types of drivers, which can better benefit traffic management and control.

Data Availability

All data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was partially supported by the Guangzhou Municipal University Research Project (1201630172), Natural Science Foundation of Guangdong Province (2017A030313293), National Natural Science Foundation of China (51579143 and 51709167), and Shanghai Committee of Science and Technology, China (18040501700, 18295801100, and 17595810300).

References

[1] E. Adell, A. Várhelyi, and M. D. Fontana, "The effects of a driver assistance system for safe speed and safe distance–a real-life field study," *Transportation Research Part C: Emerging Technologies*, vol. 19, no. 1, pp. 145–155, 2011.

[2] J. Lai, P. Zhang, H. Zhou, F. Cheng, and H. Qin, "Study of rules of traffic accidents in expressway tunnels," *Tunnel Construction*, vol. 37, pp. 37–42, 2017.

[3] X. Na and D. J. Cole, "Game-theoretic modeling of the steering interaction between a human driver and a vehicle collision avoidance controller," *IEEE Transactions on Human-Machine Systems*, vol. 45, no. 1, pp. 25–38, 2014.

[4] J. Engström, M. Ljung Aust, and M. Viström, "Effects of cognitive load and anticipation on driver responses to a critical traffic event," in *Proceedings of the 2018 Human Factors and Ergonomics Society Annual Meeting*, vol. 62, no. 1, pp. 1584–1588, Philadelphia, PA, USA, October 2018.

[5] N. Arbabzadeh, M. Jafari, M. Jalayer, S. Jiang, and M. Kharbeche, "A hybrid approach for identifying factors affecting driver reaction time using naturalistic driving data," *Transportation Research Part C: Emerging Technologies*, vol. 100, pp. 107–124, 2019.

[6] H. Y. Zhang and X. L. Hao, "Simulation research on minimum safety distance of automobile rear-end anti-collision," *Computer Simulation*, vol. 16, pp. 146–150, 2014.

[7] L. H. Xu, Q. Luo, J. Wu, and Y. Huang, "Study of car-following model based on minimum safety distance," *Journal of Highway & Transportation Research & Development*, vol. 6, no. 1, pp. 95–101, 2012.

[8] I. Spyropoulou, "Simulation using gipps car-following model—an in-depth analysis," *Transportmetrica*, vol. 3, no. 3, pp. 231–245, 2007.

[9] H. Hu, H. Wei, X. Liu, and X. Yang, "Car-following model featured with factors reflecting emergency evacuation situation," *Journal of Southeast University (English Edition)*, vol. 24, pp. 216–221, 2008.

[10] X. Wang, M. Chen, M. Zhu, and P. Tremont, "Development of a kinematic-based forward collision warning algorithm using an advanced driving simulator," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 9, pp. 2583–2591, 2016.

[11] W. Hönig and T. S. Kumar, "Multi-agent path finding with kinematic constraints," in *Proceedings of the 2016 Twenty-Sixth International Conference on Automated Planning and Scheduling*, London, UK, June 2016.

[12] L. Chai, B. Cai, W. ShangGuan, J. Wang, and H. Wang, "Basic simulation environment for highly customized connected and autonomous vehicle kinematic scenarios," *Sensors*, vol. 17, no. 9, p. 1938, 2017.

[13] X. Chen, S. Wang, C. Shi, H. Wu, J. Zhao, and J. Fu, "Robust ship tracking via multi-view learning and sparse representation," *Journal of Navigation*, vol. 72, no. 1, pp. 176–192, 2019.

[14] X. Chen and Y. Yang, "Ship type recognition via a coarse-to-fine cascaded convolution neural network," *Journal of Navigation*, 2020, In press.

[15] H. Liu, H. Wei, Z. Yao, Q. Ai, and H. Ren, "Effects of collision avoidance system on driving patterns in curve road conflicts," *Procedia—Social and Behavioral Sciences*, vol. 96, pp. 2945–2952, 2013.

[16] M. R. R. Shaon, X. Qin, Z. Chen, and J. Zhang, "Exploration of contributing factors related to driver errors on highway segments," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2672, no. 38, pp. 22–34, 2018.

[17] Y. S. Tang and D. H. Xia, "Study the influence of different driver's reaction time to the automobile anti-collision safety

distance," *Science Technology & Engineering*, vol. 16, no. 1, pp. 250–254, 2016.

[18] Q. Xue, Y. Zhang, X. Yan, and B. Wang, "Analysis of reaction time during car-following process based on driving simulation test," in *Proceedings of the 2015 International Conference on Transportation Information and Safety (ICTIS)*, pp. 207–212, Wuhan, China, June 2015.

[19] J. Zhang, Y. Wang, and G. Lu, "Impact of heterogeneity of car-following behavior on rear-end crash risk," *Accident Analysis & Prevention*, vol. 125, pp. 275–289, 2019.

[20] Q. Xue, X. Yan, X. Li, and Y. Wang, "Uncertainty analysis of rear-end collision risk based on car-following driving simulation experiments," *Discrete Dynamics in Nature and Society*, vol. 2018, Article ID 5861249, 13 pages, 2018.

[21] L. Eboli, G. Mazzulla, and G. Pungillo, "Combining speed and acceleration to define car users' safe or unsafe driving behaviour," *Transportation Research Part C: Emerging Technologies*, vol. 68, pp. 113–125, 2016.

[22] Y. Luo, Y. Xiang, K. Cao, and K. Li, "A dynamic automated lane change maneuver based on vehicle-to-vehicle communication," *Transportation Research Part C: Emerging Technologies*, vol. 62, pp. 87–102, 2016.

[23] C. Chai, Y. D. Wong, and X. Wang, "Safety evaluation of driver cognitive failures and driving errors on right-turn filtering movement at signalized road intersections based on fuzzy cellular automata (FCA) model," *Accident Analysis & Prevention*, vol. 104, pp. 156–164, 2017.

[24] E. Azimirad, N. Pariz, and M. B. N. Sistani, "A novel fuzzy model and control of single intersection at urban traffic network," *IEEE Systems Journal*, vol. 4, no. 1, pp. 107–111, 2010.

[25] H. Li, "Research on prediction of traffic flow based on dynamic fuzzy neural networks," *Neural Computing and Applications*, vol. 27, no. 7, pp. 1969–1980, 2016.

[26] F. Bocklisch, S. F. Bocklisch, M. Beggiato, and J. F. Krems, "Adaptive fuzzy pattern classification for the online detection of driver lane change intention," *Neurocomputing*, vol. 262, pp. 148–158, 2017.

[27] M. R. R. Shaon, X. Qin, A. P. Afghari, S. Washington, and M. D. Mazharul Haque, "Incorporating behavioral variables into crash count prediction by severity: a multivariate multiple risk source approach," *Accident Analysis & Prevention*, vol. 129, pp. 277–288, 2019.

[28] K. Wang, T. Bhowmik, S. Yasmin, S. Zhao, N. Eluru, and E. Jackson, "Multivariate copula temporal modeling of intersection crash consequence metrics: a joint estimation of injury severity, crash type, vehicle damage and driver error," *Accident Analysis & Prevention*, vol. 125, pp. 188–197, 2019.

[29] L. I. Gang and H. Han, "Study on classification and identification methods of driver steering characteristics," *Journal of Hebei University of Science & Technology*, vol. 36, pp. 559–565, 2015.

[30] A. Mcdowell, D. Begg, J. Connor, and J. Broughton, "Unlicensed driving among urban and rural maori drivers: New Zealand drivers study," *Traffic Injury Prevention*, vol. 10, no. 6, pp. 538–545, 2009.

[31] H. Hu, X. Liu, and X. Yang, "A car-following model of emergency evacuation based on minimum safety distance," *Journal of Beijing University of Technology*, vol. 33, pp. 1070–1074, 2007.

[32] S. Feng, Z. Li, Y. Ci, and G. Zhang, "Risk factors affecting fatal bus accident severity: their impact on different types of bus drivers," *Accident Analysis & Prevention*, vol. 86, pp. 29–39, 2016.

[33] G. Zhang, K. K. W. Yau, X. Zhang, and Y. Li, "Traffic accidents involving fatigue driving and their extent of casualties," *Accident Analysis & Prevention*, vol. 87, pp. 34–42, 2016.

[34] C. Wu, X. Yan, and X. Ma, "A new car-following model based on multi-agent system," in *Proceedings of the 2007 International Symposium on Distributed Computing and Applications to Business, Engineering and Science (DCABES 2007)*, vol. 2, pp. 101–107, Yichang, China, August 2007.

[35] K. Yi and Y. D. Kwon, "Vehicle-to-vehicle distance and speed control using an electronic-vacuum booster," *JSAE Review*, vol. 22, no. 4, pp. 123–129, 2001.

[36] X. Zhao, S. Wang, J. Ma, Q. Yu, Q. Gao, and M. Yu, "Identification of driver's braking intention based on a hybrid model of GHMM and GGAP-RBFNN," *Neural Computing and Applications*, vol. 31, no. S1, pp. 161–174, 2019.

[37] N. Monot, X. Moreau, A. Benine-Neto, A. Rizzo, and F. Aioun, "Comparison of rule-based and machine learning methods for lane change detection," in *Proceedings of the 2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, pp. 198–203, Honolulu, HI, USA, November 2018.

[38] G. Castignani, R. Frank, and T. Engel, "An evaluation study of driver profiling fuzzy algorithms using smartphones," in *Proceedings of the 2013 21st IEEE International Conference on Network Protocols (ICNP)*, pp. 1–6, Goettingen, Germany, October 2013.

[39] S. Fernandez and T. Ito, "Driver classification for intelligent transportation systems using fuzzy logic," in *Proceedings of the 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, pp. 1212–1216, Rio de Janeiro, Brazil, November 2016.