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Abstract: Inappropriate speed in negotiating curves is the primary cause of rollovers and sideslips. In this study, the authors proposed an improved curve speed model considering driving styles, as well as vehicle and road factors. On the basis of a vehicle–road interaction model, the driver behaviour factor was introduced to quantify driving styles of curve speed choices. Firstly, the fuzzy synthetic evaluation method was utilised to classify the driving styles of 30 professional drivers into three different types (i.e. cautious, moderate and aggressive). Secondly, the classification results using fuzzy synthetic evaluation were compared to and verified with the *K*-means clustering method resulting over 60% the similarities. Finally, the proposed curve speed model was built and compared with four existing models. The authors' model has the following promising advantages: (i) it reflects the speed preferences of three different types of drivers on the premise of driving safety on curves; and (ii) it shows a stationary speed transition when the road adhesion coefficient exceeds 0.8, which indicates that rollover, instead of sideslip, becomes the primary cause for lateral instability crashes on curves. Therefore, this proposed curve speed model could be applied in a curve speed warning system to improve both driving safety and comfort.

1 Introduction

Over the past few years, both the amount and the severity of curve accidents in China have been maintaining a high rate. There were 35,000 curve crashes in 2014, accounting for 17.8% in all crashes. Moreover, the fatality rate in curve accidents reached up to 0.8, i.e. 0.8 people were killed in each curve incident, which was much higher than 0.3 the average fatality rate among all crashes [1].

Curve crashes are caused by many factors, including road conditions, vehicle dynamics and driver behaviours. Inappropriate choice of driving speed is a major cause of curve accidents [2]. Vehicles in high speed are exposed to lateral instability hazards like rollovers and sideslips. Naturally, the adjustment of the vehicle speed during curve negotiation becomes one of the effective solutions. A common method that has always been used for drivers to adjust curve speed is to set roadside speed limit signs along curves. The speed limits on roadside are mainly obtained using standards and empirical data from the highway engineering. This method, however, cannot rectify drivers' inappropriate speed effectively. First, the roadside speed limits cannot fully take into account some dynamic and individual factors, such as vehicle structural parameters and driver behaviors. Moreover, drivers may ignore the speed limit signs intentionally because their values are derived from the conservative conditions which are probably below drivers' expectations.

Curve speed warning (CSW) is an on-board driver assistance system that can calculate appropriate speed based on the driver–vehicle–road interactions and send warning signals if the driver drives over the calculated speed limit. However, in a situation where drivers lose the trust to the warning system, inappropriate speed selection can occur and lead to more dangerous situation. Therefore, it is important to improve the system to reduce wrong warnings.

This paper proposes an improved curve speed model for calculating the safe speed during curve negotiation by combining multiple factors from drivers, vehicles and roads. Specifically, the influence of driving behaviour is described by driver behaviour factor which can vary as driving styles differ. Several indices are selected to make the classification according to their properties of reflecting driving style. The simulation studies show that the vehicle would be out of sideslip and rollover risks if a driver drives at a speed within the improved curve speed model proposed. Furthermore, it is substantiated that the improved curve speed model not only meets the safety requirements, but also adapt to the drivers' expected speed on a curve.

2 Literature review

The vehicle lateral instability crashes, such as rollovers and sideslips, are always related to road surface conditions, road geometry features, vehicle dynamics and so on. Some previous studies have focused on road and environment impacts on the driving safety on curves [3–5].

As drivers characteristics vary, the curve negotiation speed preferences would be distributed around a range of values. Therefore, the analysis of driver behaviours is indispensable to avoid inaccurate predictions of curve speeds. MacAdam [6] identified human driver as the primary control element within the long-established driver–vehicle system. Driver models including human traits were proved to be useful in predicting the performance of the combined driver–vehicle system. Salvucci [7] developed a rigorous computational model of driver behaviour in a cognitive architecture that incorporate basic properties and limitations of human, which could be applied to predict and recognise driver behaviour and distraction.

Most existing curve speed models were established based on the analysis of vehicle–road interactions. Glaser *et al.* [8, 9] proposed a more comprehensive model than previous ones. The road geometry was fully used. Chen *et al.* [10] proposed a BP neural network-based model to represent the motion states of vehicles on curves. Unfortunately, these models neglected driver behaviours which could largely influence the curve negotiating process.

Some researchers intended to introduce human factors to conventional curve speed models. Bosetti *et al.* [11] concluded that one important aspect of the curve driving was the driver speed choices. Zhang *et al.* [12] concluded that the curve speed was related to the drivers' preferred velocity and the initial velocity on a curved road. Lee *et al.* [13, 14] added three different gain factors

Table 1 General information of 30 studied drivers

Driver number	Gender	Age	Driving years	Driver number	Gender	Age	Driving years
D01	male	52	23	D16	male	42	16
D02	male	53	16	D17	male	48	22
D03	male	33	6	D18	male	48	18
D04	male	50	16	D19	male	57	21
D05	male	36	15	D20	male	34	3
D06	male	55	21	D21	male	35	8
D07	male	52	16	D22	male	50	12
D08	male	47	20	D23	male	53	9
D09	male	47	16	D24	female	51	17
D10	male	52	27	D25	male	37	6
D11	male	46	9	D26	male	49	17
D12	female	49	17	D27	male	49	20
D13	male	42	10	D28	male	43	17
D14	female	49	25	D29	male	48	26
D15	female	36	10	D30	male	47	14

associated with vehicles, roads and drivers to the curve speed model to represent how these factors affect the curve speed. However, the process of determining the appropriate gain values was carried out without any on-field experiment for further verification.

Currently, curve speed models mainly consider the coupling effects of vehicles and roads with little efforts on the quantitative analysis of the driver behaviour characteristics. As drivers have different expectations and preferences of the curve speed, it is necessary to obtain appropriate curve safety speed with the consideration of individual differences, otherwise drivers would lose the trust to CSW system, which might increase the risks of traffic crashes.

3 Curve speed model based on driving style clustering

3.1 Improved curve speed model considering driver behaviours

For light vehicles, the critical value of the curve safety speed should focus on the prevention of sideslips because they are more likely to skid than overturn on the same curve conditions due to their lower centre of gravity compared to heavy trucks. However, rollover risks of heavy trucks should not be neglected in the analysis of the curve safety speed. Therefore, the curve safety speed is defined as the minimum value $v_{\rm sr}$ between the critical sideslip speed $v_{\rm s}$ and the critical rollover speed $v_{\rm r}$, which is stated in [15]

$$v_{\rm sr} = \min\{v_{\rm s}, v_{\rm r}\} \tag{1}$$

where

$$v_{\rm s} = \sqrt{\frac{\mu + i_y}{1 - \mu i_y} \cdot gR}, \quad v_{\rm r} = \sqrt{\frac{B + 2hi_y}{2h - Bi_y} \cdot gR} \tag{2}$$

where B and h are the vehicle track width and the height of centre of gravity, respectively. g denotes the gravity, R, μ and i_y are the curve radius, the road adhesion coefficient and the superelevation, respectively.

The above model contains the factors of road conditions and vehicle states. However, driver behaviours, which can significantly influence the adaptation of the curve speed to different drivers, have not been included. Therefore, the curve speed model should be improved through the introduction of the influence of driver behaviours which is represented by the following factor $k_{\rm d}$.

$$v_{\rm safe} = k_{\rm d} \cdot v_{\rm sr} \tag{3}$$

where $k_{\rm d}$ represents the influence factor of driver behaviours.

In (3), $k_{\rm d}$ describes drivers' impact on speed choices quantitatively and is related to driving skills, speed preferences and even driving mood. Though driver behaviours are difficult to describe through a mathematical model, their driving styles normally stay steady for a long time, which provides a novel idea by adding a constant coefficient to the theoretical speed. As changing the coefficient for each driver behaviour is difficult to implement, it is more practical to classify the drivers according to their driving styles. In this way, the appropriate values of $k_{\rm d}$ to indicate the accurate curve speed that fits drivers themselves can be derived. Moreover, the results of driving style classifications directly influence the accuracy of curve safety speed.

3.2 Classifications of driving styles

The study divides the driving styles into three typical types: cautious driving, moderate driving and aggressive driving. A cautious driver would drive more carefully and avoid high speed and hard acceleration. In contrast, aggressive drivers prefer exciting driving experiences. Moderate drivers would drive vehicles with relative steady motions that are neither too cautious nor too aggressive.

3.2.1 On-field test for driving style classifications: A driving behaviour experiment was carried out. Before recruitment of participants, a sample of taxi drivers were surveyed through interview and questionnaires. It was found that more than 85% of them were male and their ages ranged from 30 to 60 years old. Based on the survey, 30 professional drivers were recruited to complete the experiment. Their driving experiences ranged from 3 to 27 years (mean = 15.8, STD = 6.2) with ages ranging from 34 to 55 years old (mean = 46.3, STD = 6.6). Also, the gender ratio was controlled around 85% (see Table 1).

The experiment was conducted on the Hanshi Freeway from Wuhan to Xiangyang and the total distance was about 600 km, as shown in Fig. 1. It took each driver 5–7 h to finish the whole experiment. However, there is a service area in Suizhou (approximately in the half section of Hanshi Freeway), as shown in Fig. 1. Before the experiment, each participant took a trial drive through the experimental route in order to get used to the road conditions. Besides, all subjects were not allowed to start experimenting until they were reported to get used to on-board driving assistance devices so that they could drive in a naturalistic way. During the experiment, all participants were asked to drive with a safe and comfortable speed that reflected their real driving style.

Data acquisition equipment includes vehicle-mounted CAN bus, Mobileye C2–270 system, smartphones, angle sensors and HD video cameras. The information about the collected experimental data is listed in Table 2. Steering wheel angle data was acquired

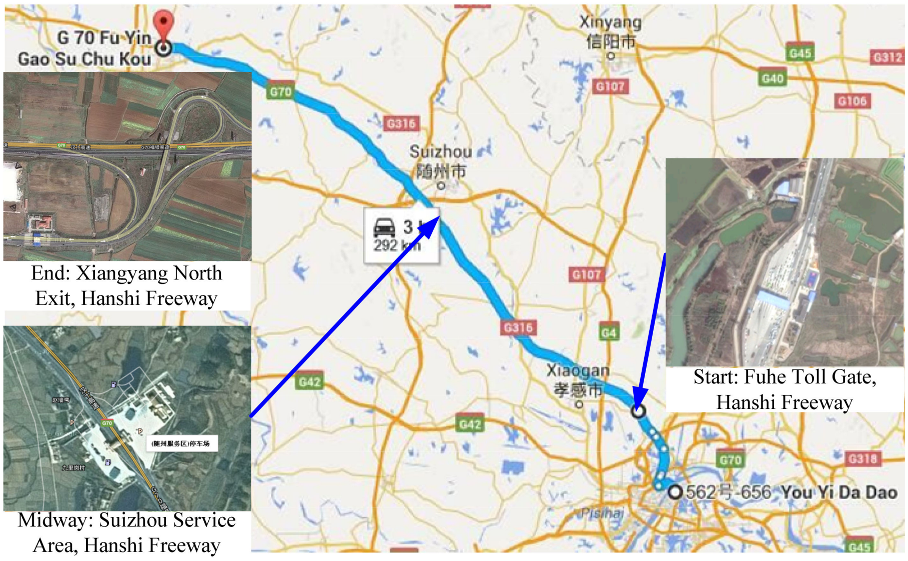


Fig. 1 *Driving route for the experiment*

Table 2 Some data collected during the field experiment

Parameter types	On-board equipment	Sampling frequency, Hz
speed, km h^{-1}	Smartphone	16
steering wheel angle, deg.	Angular transducer	77
acceleration, ms^{-2}	Smartphone	16
lane departure, m	Mobileye C2–270	5–15

using angular transducer. Smartphones were used to collect dynamic data such as vehicle speeds and accelerations.

Mobileye C2–270 is an image processing product provided by the company Mobileye. It could sense moving or fixed objects and determine positions between host vehicles and surrounding traffic signs. A camera and a display screen are included in the system. The camera is used to collect the traffic information, like lane lines and relative time headway. In this experiment, Mobileye C2–270 system was used to collect time headways (within 2.5 s) and lane departure displacements. This device has been used to collect vehicle motion states for the research of driving behaviour in many researches [16, 17].

3.2.2 Driving style classification using fuzzy synthetic evaluation: Fuzzy-logic based mechanism has been utilised to identify driving styles for evaluating energy-saving performance [18] and driver profiling [19]. In this paper, fuzzy synthetic evaluation is applied to classify the driving styles by analysing the evaluation indexes reflecting each driver's characteristic. The chosen indices include the following driving parameters.

Mean speed ($\bar{v}$) differs when driving style changes. Aggressive drivers prefer to drive faster to reach the destination while the cautious ones would choose lower speed with more safety concerns. In this field experiment, participants drove their vehicles in freeway, where driving style was hardly influenced by traffic flow, therefore, driving speed could reflect their driving styles in a large extent.

Speeding is a kind of common driving behaviour especially when driving in wide road. Aggressive drivers are inclined to drive over the speed limits to shorten travel time, leading to higher speeding frequency than cautious drivers. The number of speeding ($\boldsymbol{n}_s$) is selected as an indicator for classification of driving style. In this experiment, speeding is defined when driving speed is over 120 km/h which is the speed limit in Chinese freeway.

Acceleration is an indirect measure of the acceleration pedal position and it can reflect the driving smoothness. Aggressive drivers tend to depress acceleration pedal harder to get higher speed during a short period, resulting in higher acceleration. Therefore, maximum positive acceleration ($a_{\max}^{+}$) is selected as a parameter for fuzzy evaluation.

Standard deviation of speed ($\boldsymbol{v}_{\text{std}}$) represents the stability of driving speed, which is able to reflect the fluctuation of driver's operations. Aggressive drivers generally keep their speed at a high level and reduce it under complex traffic environment, which, inevitably, leads to a wide range of driving speed. Thus, standard deviation of speed differs between aggressive and cautious drivers.

Driving style reflects comprehensive performance of longitudinal and lateral control to the vehicle. Steering angle and driving speed are important parameters in two directions. Generally, drivers will slow down the vehicle when making a turn in case of unstable lateral accidents. However, aggressive drivers are likely to take risks pursuing high speed. Based on this assumption, we define maximum product of the steering wheel angle and vehicle speed ($\boldsymbol{k}_{\max}$) as a new parameter.

Besides, many literatures are based on the parameters mentioned above to study the modelling and classification of personal driving style [20–22].

The following four steps are used to determine a driver's driving style:

Step 1: Define appropriate membership functions for the five chosen indices. In fuzzy mathematics, membership function of a research is first roughly obtained from subjective knowledge and then determined according to distributions of the experiment data. In this study, drivers' temperament test which psychologically reflects their driving styles is combined with on-field tests to determine membership functions.

In [23], Chen proposed a '60 questions' temperament test to help people to understand their temperament types. The temperament test consisting of 60 questions is very popular, and it has been widely used in various fields in China, such as education, medicine and sports. The research divided the personality into four types: choleric, sanguineous, phlegmatic and melancholic temperaments.

Human behaviours are directly influenced by their psychological characteristics. Drivers' driving styles are psychologically related to the intrinsic temperament types of their own. For example, as displayed in Fig. 2, the average speed profiles show apparent differences as personal characteristics change of recruited drivers who did temperament test [23].

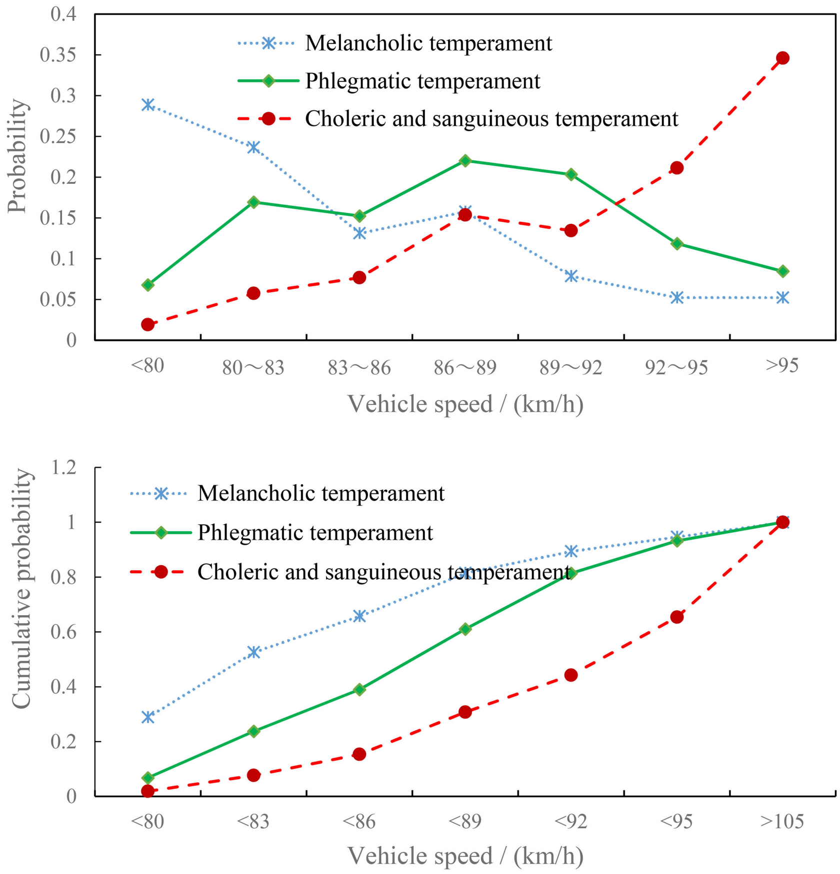
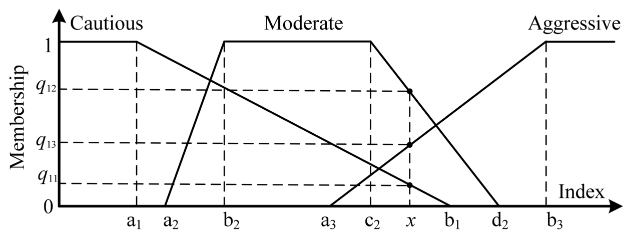


Fig. 2 *Probability and cumulative probability distributions of vehicle speeds for the divers with different temperaments*



	(a_1, b_1)	(a_2, b_2, c_2, d_2)	(a_3, b_3)
$\bar{v}$	(80, 92)	(80, 83, 85, 95)	(83, 95)
v_{std}	(20, 28)	(20, 21, 25, 30)	(21, 30)
n_s	(1, 12)	(0, 10, 30, 50)	(1, 60)
a^{+}_{max}	(1, 1.6)	(1, 1.1, 1.6, 1.9)	(1.1, 1.9)
k_{max}	(500, 2000)	(500, 660, 2000, 5000)	(1000, 5000)

Fig. 3 *Membership functions for five indices of three driving styles*

The cumulative probability distributions of vehicle speeds were presented to indicate the speed preferences of drivers with different personal characteristics and then determine the interval points in the membership functions of the fuzzy synthetic evaluation, i.e. a_i, b_i and c_i in Fig. 3. The conclusions could be drawn from the changes of slopes.

For example, as speed points of melancholic temperament drivers are mainly distributed in the low speed interval, the driver is more likely to be melancholic temperament if the driving speed is <83 km/h. For phlegmatic drivers, their speed points are almost linearly distributed from 80 to 95 km/h, so it is reasonable to set the starting and terminal points as 80 and 95, respectively, in the speed membership function. Those driving at higher speed (i.e. >89 km/h) are more likely to be choleric or sanguineous, so the membership function of aggressive drivers could be determined. These turning points indicate the speed preferences of drivers with different personal characteristics and could help to determine the interval points in the membership functions of the fuzzy synthetic evaluation. Interval points of other four indices have been determined in the same way. Based on the analysis of the relationship between driving style and driver characteristics, we can get the membership functions for five selected driving parameters of three driving types as presented in Fig. 3.

There is a reason for combining choleric and sanguineous temperaments as one group. In [23], Chen made a correlation analysis of the number of people with four different temperaments. The result showed that there was no significant variation ONLY between people of choleric and sanguineous temperaments, which indicates that these two kinds of people are very similar in personality. Besides, driving styles are usually divided into three categories in many previous literatures [24, 25], which is also an important reason for our decisions.

Table 3 Statistics of driving styles indices

Driver no.	Indices				
	$\bar{v}$, km·h^{-1}	v_{std}, km·h^{-1}	n_s	a^{+}_{max}, m·s^{-2}	k_{max}, °·km·h^{-1}
D01	93.6	25.64	80	1.58	1050.4
D02	82.74	37.28	33	2.09	3274.8
…	…	…	…	…	…
D30	91.49	20.34	1	1.78	2017.2

Table 4 Membership degree of 30 studied drivers

Membership degree	Cautious	Moderate	Aggressive	Membership degree	Cautious	Moderate	Aggressive
B^*_{D01}	0.147	0.463	0.39	B^*_{D16}	0.37	0.329	0.301
B^*_{D02}	0.098	0.35	0.552	B^*_{D17}	0.375	0.522	0.103
B^*_{D03}	0.314	0.344	0.342	B^*_{D18}	0.116	0.382	0.502
B^*_{D04}	0.15	0	0.85	B^*_{D19}	0.345	0.504	0.151
B^*_{D05}	0.238	0.452	0.31	B^*_{D20}	0.508	0.283	0.209
B^*_{D06}	0.098	0.506	0.396	B^*_{D21}	0.174	0.598	0.228
B^*_{D07}	0.036	0.52	0.444	B^*_{D22}	0.471	0.412	0.117
B^*_{D08}	0.07	0.477	0.453	B^*_{D23}	0.254	0.447	0.299
B^*_{D09}	0.053	0.497	0.45	B^*_{D24}	0.313	0.456	0.232
B^*_{D10}	0.253	0.395	0.352	B^*_{D25}	0.261	0.516	0.223
B^*_{D11}	0.292	0.409	0.299	B^*_{D26}	0.584	0.324	0.092
B^*_{D12}	0.305	0.249	0.299	B^*_{D27}	0.54	0.404	0.056
B^*_{D13}	0.544	0.222	0.525	B^*_{D28}	0.641	0.31	0.049
B^*_{D14}	0.243	0.232	0.525	B^*_{D29}	0.359	0.567	0.074
B^*_{D15}	0.367	0.451	0.182	B^*_{D30}	0.374	0.213	0.413

Step 2: Determine weighing values of assessment indices. If the five indices equally affected by driving behaviours, we can set the weight values for all of them as 0.2 averagely. However, the impact of driving behaviour on these indicators is comparatively different. The reasons for the weighting values are based on their relations with driving style. If the index is affected more by driving style than traffic environment, the weighting will be higher than the average one. For example, average speed $\bar{v}$ and standard deviation of speed v_{std} are more vulnerable to the traffic condition because drivers have to keep speed in a reasonable range considering driving safety. Other indicators such as maximum positive acceleration a^{+}_{max}, as well as the maximum product of the steering wheel angle and vehicle speed k_{max} are easier to be affected by driver behaviours because drivers are free to depress the accelerator pedal intensely or gently. Therefore, we decrease the weight values of $\bar{v}$ and v_{std} by 25%, then conversely increase those of a^{+}_{max} and k_{max} by 25% from the average. Finally, based on comprehensive comparisons of the five indices, we determine the weighting value of $\bar{v}$, v_{std}, n_s, a^{+}_{max} and k_{max} as 0.15, 0.15, 0.2, 0.25 and 0.25, respectively.

If the weighting is made differently, the membership degree B_{Di} in Step 3 will change and the classification results will also vary. However, it is impossible to determine the exact weighting value of each index because fuzzy evaluation method is a kind of subjective system based on human experience in most cases. All we can do is setting appropriate range of weighting values through reasonable demonstrations.

Step 3: Calculate membership degree values of each driver. First, we calculate the values of five indices for each driver during the whole drive cycle on the freeway, as presented in Table 3.

As the membership function is described in the form of graphs, the membership degree could be determined by substituting the average values of evaluation indices into the abscissa. For example, if one index value of a driver is x, the corresponding membership degree will be q_{j1}, q_{j2} and q_{j3} which reflect the driver's tendencies of cautious, moderate and aggressive styles, respectively, as shown in Fig. 3. Therefore, the membership degree q_{jk} of the above five indices $\bar{v}$, v_{std}, n_s, a^{+}_{max} and k_{max} in turn could also be determined, where $j = 1, 2, \ldots, 5$ and $k = 1, 2, 3$. The evaluation matrix $\boldsymbol{Q}$ is then defined to describe the fuzzy relationship consisting of q_{jk}, where

$$\boldsymbol{Q} = \begin{bmatrix} q_{11} & \cdots & q_{13} \\ \vdots & \ddots & \vdots \\ q_{51} & \cdots & q_{53} \end{bmatrix} \tag{4}$$

Then the relation matrix can be calculated in terms of $\boldsymbol{Q}$. Finally, each driver's membership degree B_{Di} is calculated through the following equation:

$$B_{Di} = w \cdot Q, \quad i = 01, 02, \ldots, 30 \tag{5}$$

where $\sum_{j=1}^{5} w_j = 1$, and $w = [0.15, 0.15, 0.2, 0.25, 0.25]$, which is described in Step 2.

After the normalised processing of membership values, the result of membership degree of 30 drivers described by B_{Di}* is shown in Table 4.

Step 4: Determine driving styles according to the principle of the maximum membership degree. As the principle describes, though each object gets three membership degrees, the maximum one determines which group the object belongs to. Therefore, the final classification results are shown in Table 5.

3.2.3 Driving style verification using K-means clustering: Fuzzy synthetic evaluation is often used to describe the ambiguous things in nature, like driving styles in this case. In fact, it is hard to accurately distinguish the boundaries of different driving styles. Therefore, we use K-means clustering with different evaluation indexes to classify drivers' driving styles. This method is further used to verify the above classification results of fuzzy synthetic evaluation.

K-means clustering is often used in clustering analysis of large amounts of data. In this study, we choose three driving parameters for clustering analysis which reflect the differences of driving styles.

Table 5 Comparisons of fuzzy synthetic evaluation and *K*-means clustering

Fuzzy synthetic evaluation		*K*-means clustering analysis		Similarity, %
Driving style	Driver no.	Cluster	Driver no.	
cautious	**D13**, **D16**, D17, **D20**, **D22**, **D26**, D27, D28, **D30**	I	D06, D13, D14, D16, D20, D22, D26, D30	66.7
moderate	**D01**, **D03**, **D05**, D06, **D07**, D08, D09, **D10**, **D11**, **D15**, **D19**, **D21**, **D23**, **D24**, **D25**, **D29**	II	D01, D03, D05, D07, D08, D10, D11, D12, D15, D17, D19, D21, D23, D24, D25, D27,D28, D29	87.5
aggressive	**D02**, **D04**, D12, D14, **D18**	III	D02, D04, D9, D18	60

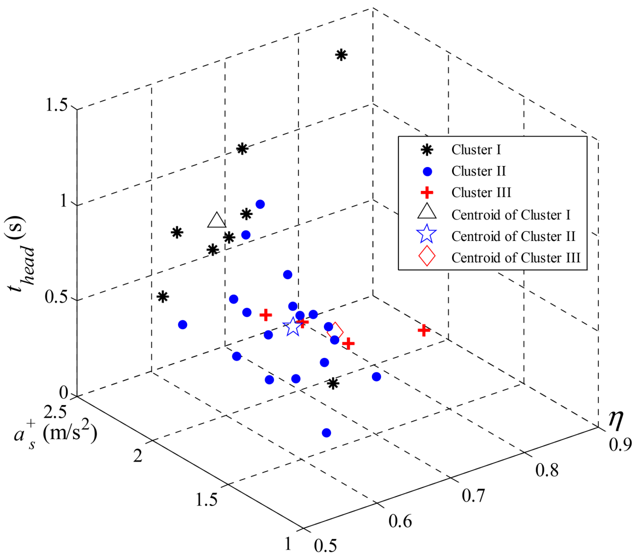


Fig. 4 *Driving styles classification based on K-means clustering*

The first parameter, represented by $\boldsymbol{\eta}$, is the proportion of time when the driving speed is over 80% of the limited speed. Aggressive drivers usually tend to drive faster. In contrast, the ratio when the speed is at high level is lower for cautious drivers. Hence, the proportion $\boldsymbol{\eta}$ reflects the speeding tendency of drivers with different driving style. Due to the choice of highway traffic situation, 80% of the limited speed is 96 km/h.

Standard deviation of the positive acceleration $\boldsymbol{a_s^+}$ is the second chosen parameter. Acceleration reflects the control of the accelerator pedal and the brake pedal, while standard deviation of the acceleration reflects the discrete degree of acceleration. Positive acceleration results from the control of the accelerator pedal and is closely related to the traffic and driving behaviour characteristics. For aggressive drivers, positive acceleration often shows the driving characteristics that include opening or closing level of the accelerator and sudden changes of acceleration and deceleration.

The third parameter is minimum time headway $\boldsymbol{t}_{\text{head}}$. Time headway refers to the time interval that two consecutive vehicles in the same lane need to go through a section. It reflects the risk of collision between two vehicles. Under car-following scenarios, aggressive drivers tend to maintain high-speed state, and look for the chances for overtaking which usually result in small values of the time headway. Therefore, time headway could be the index of driving style characterisation.

As shown in Fig. 4, 30 participants are divided into three types. For each type, there is a centroid which represents the average characteristics of the corresponding cluster. Compared with Cluster II (56.9, 1.41, 0.77) and Cluster III (75.1, 2.02, 0.23), the centroid of Cluster I (42.5, 1.21, 1.6) has much lower η (= 42.5) and a_s^+ (= 1.21), as well as higher t_{head} (= 1.6), which conforms to the characteristics of the group of cautious drivers. Similarly, it could be seen that Clusters II and III represent moderate and aggressive drivers separately according to the locations of their centroids.

Comparison of driving style results classified by fuzzy synthetic evaluation and *K*-means clustering is shown in Table 5. When comparing the cautious type with Cluster I, six drivers (i.e. D13, D16, D20, D22, D26, D30 which are the underlined bold texts in Table 5) always belong to the same classification analysed by both two methods. Hence, the similarity is calculated on 66.7% (i.e. six drivers in common divided by nine drivers in total). Similarly, the similarities are 87.5 and 60% for the other two types. The resemblances are all over 60% through the verification of *K*-means clustering analysis indicating that the fuzzy synthetic evaluation can be used for the driving styles classification.

3.2.4 Driving style impact on curve speed model: To calibrate the influence factor of driver behaviors k_d for different drivers in the curve speed model, vehicle speeds of entering the exit ramps on the freeway are sampled because curve radius in those conditions are small enough to reveal drivers' styles classified by the above fuzzy synthetic evaluation. The statistical results are listed in Table 6.

The scatter diagram in Fig. 5 shows the actual speed v_{safe} chosen by drivers and the theoretical velocity v_{sr} calculated by (1). The driver behaviours influence factor can be obtained by calculating the slopes of each driver presented in (3). In this way, we obtain the mean value of k_d in three driving styles, where $k_{d\_\text{cautious}} = 0.475$ (STD = 0.065), $k_{d\_\text{moderate}} = 0.554$ (STD = 0.123) and $k_{d\_\text{aggressive}} = 0.636$ (STD = 0.152).

Obviously, the more aggressive a driver is, the greater the value of k_d would be. This kind of tendency suggests that aggressive drivers would drive faster than those who drive cautiously when entering segment of a curve.

3.3 Numerical study of the improved curve speed model

To evaluate the proposed curve speed model, we designed a series of simulation tests in TruckSim and MATLAB/Simulink, and we detected the lateral stability indices that could reflect the safety performance of the vehicle. Lateral load transfer ratio (LTR) is an evaluating indicator that estimates the risk of rollover. Generally, the vehicle could be in a safe state if its LTR is under 0.6 [26]. Another indicator sideslip gradient (SSG) is used to evaluate the risk of sideslips. If SSG > 0, the vehicle is in the understeering state; and if SSG < 0, the vehicle is in the oversteering state [8]. SSGs of the left and right side of the vehicle are represented as SSG_L and SSG_R, separately.

Table 6 Driver behaviours influence factors of 30 studied drivers

Driver no.	Style	R, m	v_{safe}, km/h	v_{sr}, km/h	k_d
D01	moderate	172	78	106.7	0.731
D02	aggressive	172	89.6	106.7	0.84
D03	moderate	196	75	113.9	0.67
D04	aggressive	662	90	209.3	0.43
D05	moderate	196	77.5	113.9	0.681
D06	moderate	172	82.8	106.7	0.776
D07	moderate	196	80.7	113.9	0.709
D08	moderate	172	62	106.7	0.581
D09	moderate	662	85.4	209.3	0.408
D10	moderate	303	62.2	141.6	0.439
D11	moderate	303	61.8	141.6	0.437
D12	aggressive	196	78.8	113.9	0.692
D13	cautious	196	55.1	113.9	0.484
D14	aggressive	172	60	106.7	0.566
D15	moderate	303	62.2	141.6	0.439
D16	cautious	196	61.7	113.9	0.542
D17	cautious	662	90.3	209.3	0.432
D18	aggressive	303	92	141.6	0.65
D19	moderate	303	64.9	141.6	0.458
D20	cautious	303	47.1	141.6	0.333
D21	moderate	303	81.1	141.6	0.573
D22	cautious	303	76.3	141.6	0.539
D23	moderate	303	73.6	141.6	0.52
D24	moderate	303	72.1	141.6	0.509
D25	moderate	303	74	141.6	0.523
D26	cautious	303	66.3	141.6	0.468
D27	cautious	303	72.4	141.6	0.511
D28	cautious	303	72.2	141.6	0.51
D29	moderate	172	43.9	106.7	0.412
D30	cautious	303	65	141.6	0.459

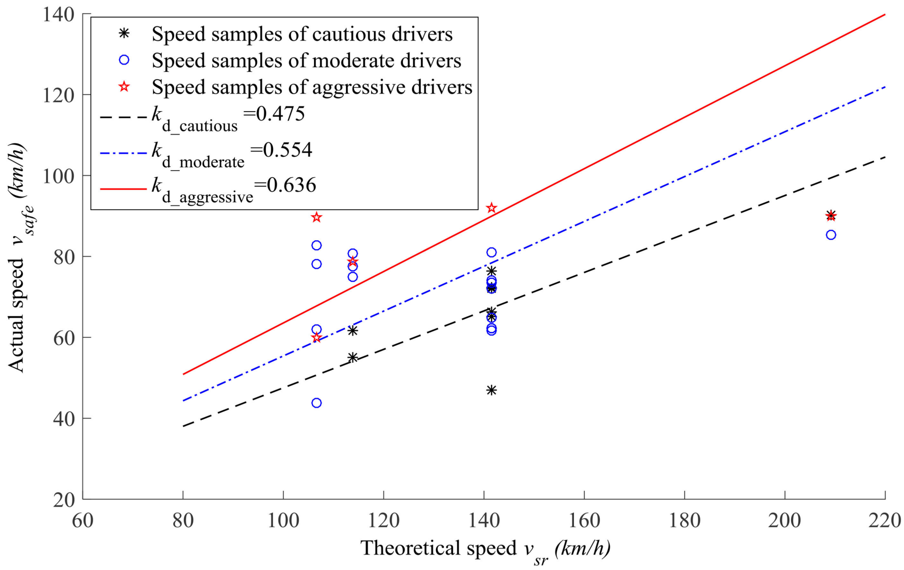
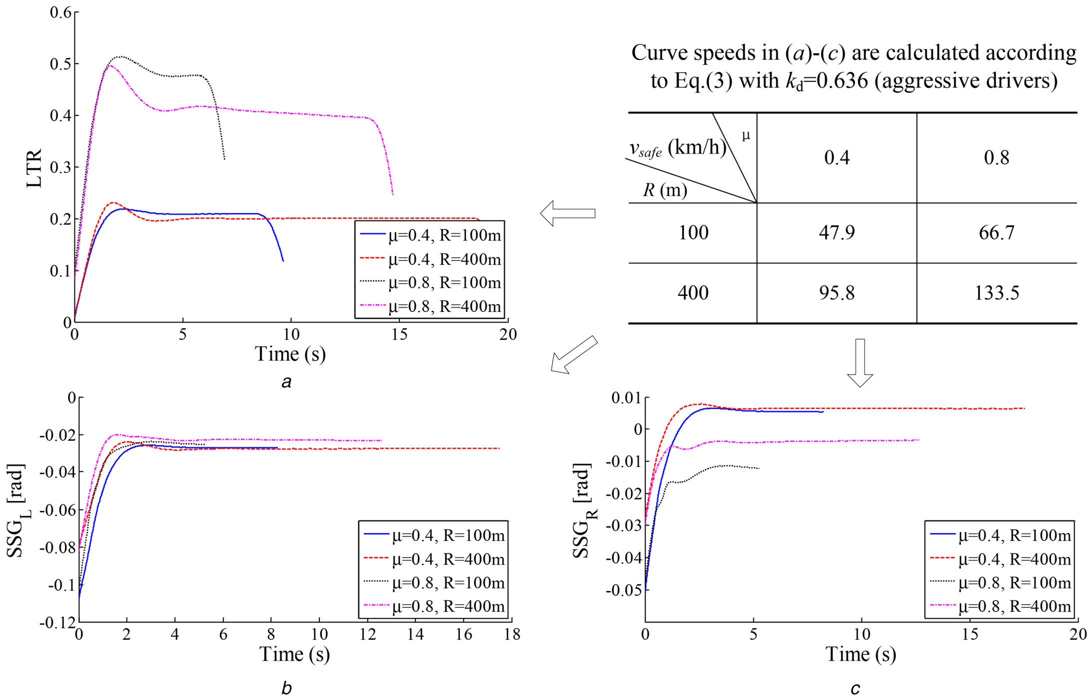


Fig. 5 *Calibration result of k_d for drivers with different driving styles*

Four different scenarios were considered with the variations of the road adhesion coefficient and the curve radius. The route was set in the order of straight road, curve road and straight road. All variables were kept the same except the road adhesion coefficient and the curve radius in each simulation scenario. The data was extracted during the driving process on curves and they are plotted (see Fig. 6).

As shown in Fig. 6, LTR varies when the road condition changes due to the influence of the vehicle speed to the lateral stability. The curve shapes are similar. In the early period, LTR rises from 0 to the peak value; then it is steady during most of the following time; it come down in the end. All peak values are found to be lower than 0.6, indicating that the vehicle is always out of the risk of rollovers on the curve. Similarly, SSG_L and SSG_R are between −0.05 to 0.05 rad most of the time. In accordance with previous finding, this implies that the yaw motion of the vehicle is under control and out of the danger of sideslips [8].



v_{safe} (km/h) / R (m) \ μ	0.4	0.8
100	47.9	66.7
400	95.8	133.5

Fig. 6 *Data was extracted during the driving process on curves*
(a) LTR, ***(b)*** SSG_L and, ***(c)*** SSG_R analysis in four scenarios with the corresponding curve speeds

4 Comparisons with existing curve speed models

In this part, simulation experiments were carried out under different road conditions to analyze the influences of the road adhesion coefficient and the curve radius on the curve speed calculated by the proposed model. Thereafter, the results were compared between different speed models. To make the simulation environment similar to the field test, we chose the road parameters that were common in highways. The superelevation $i_y = 0.04$ rad and four kinds of common road adhesion coefficients are 0.4 (gravel), 0.6(wet asphalt), 0.8(dry asphalt) and 0.85(dry concrete) [27]. The curve radiuses are 100 200, 400 and 1000 m. Based on these conditions, four existing curve speed models including the simplified model [27], Glaser's model [8, 9], Chen's model [10] and Lee's model [13, 14] were compared with the proposed model.

4.1 Impact analysis of road curvature on curve speed threshold

Fig. 7 shows that the value of speed positively correlates to the radius under the fixed friction coefficient. When the radius is small, the curve safety speed would rise quickly with the increasing radius. When the radius becomes bigger, the curve safety speed becomes steady.

The simplified model does not take the driver behaviors and vehicle parameters into consideration, resulting in the apparent larger value of curve safety speed. For example, when the vehicle drives on the gravel road ($\mu = 0.4$) entering a curve of 400 m, the curve safety speed calculated by simplified model is close to 150 km/h, which is too high. Instead, the results calculated by the proposed curve speed model mostly fall between the result of Lee's model and Glaser's model. The reason could be that Lee's model adds three different influence factors to the vehicle-road based calculation.

Specifically, through our analysis and the results shown in Fig. 7, our curve speed model stays the same when the friction coefficient are 0.8 and 0.85 as the curve radius changes. In the meantime, the curve safety speed calculated by other models still changes, although the friction coefficient is big enough. Thus, it can be seen that the improved curve speed model takes the risk of rollover into consideration when the friction coefficient of road surface is high. From this perspective, our improved model performs better.

4.2 Impact analysis of coefficient of road adhesion on curve speed threshold

Fig. 8 shows the variation tendency of safety speed with respect to the road friction coefficient. The value of speed is positively correlated to the friction coefficient under the fixed radius in most models, except Glaser's model whose variation is not completely monotonically increasing. When the friction coefficient is small, the curve safety speed would rise quickly with the increasing friction coefficient. But when the friction coefficient increases, the curve safety remains steady.

When the friction coefficient comes to 0.8, the curve speed calculated by the improved model reaches its saturation point due to rollover's role in our model. When the friction coefficient is over 0.8, rollover becomes the leading factor causing speed growth stagnation that could affect the traffic safety. On the contrary, other speed models have not shown the similar property, which could be the limitations in practical application.

5 Conclusion and recommendations

A curve speed model is proposed with the consideration of vehicle parameters, road conditions and driving styles. The driver behavior factor k_d is introduced to reflect the driving styles. The improvements of driving safety and comfort are the objectives of the curve speed modeling. Driving comfort can be guaranteed when calculated curve speeds are compatible with drivers' psychological expectations of driving speeds when negotiating road curves ahead. On the premise of driving safety, the proposed curve speed model could meet the psychological expectations of drivers in different (cautious, moderate and aggressive) driving styles by quantitatively evaluating the driving features. In this regard, the proposed model could improve both driving safety and comfort on curve negotiations.

A calibration test with 30 participants is conducted to determine the values of k_d. First, the driving style is defined by analyzing five evaluation indexes with fuzzy synthetic evaluation model. The classification is verified by comparing with K-means clustering model. Thereafter, the entry speeds chosen by drivers on the curve of the exit ramp are collected to linear fit the curve speed coefficient of drivers in different driving styles. Through the joint simulation of TruckSim and MATLAB/Simulink, LTR and SSG are chosen to evaluate risks of vehicle lateral instabilities including rollovers and sideslips. The results show that the vehicles are out of

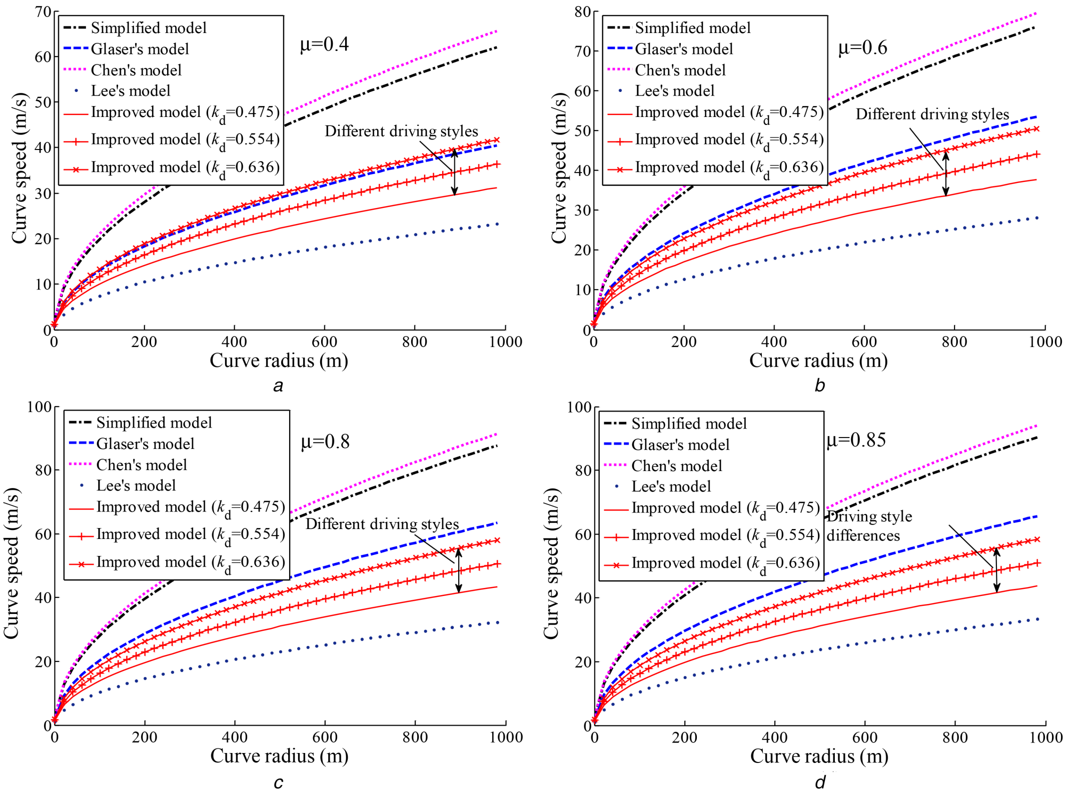


Fig. 7 *Variation of curve speed with respect to the curve radius*

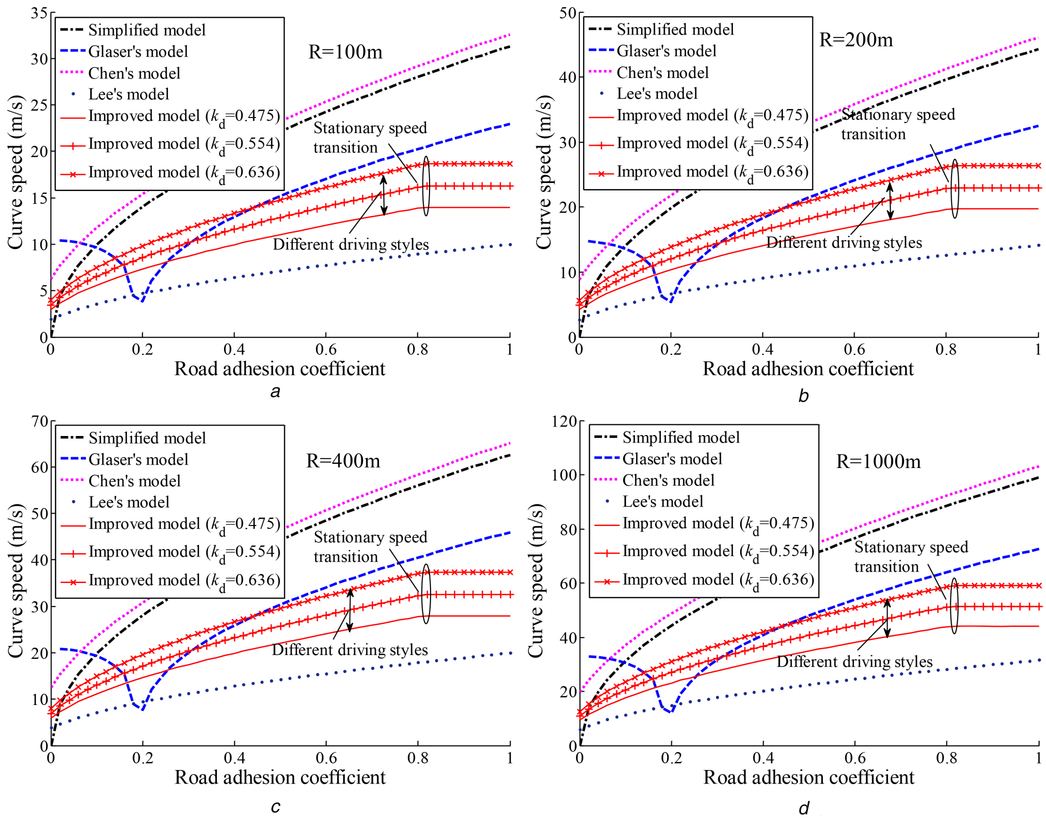


Fig. 8 *Variation of curve speed with respect to the road friction coefficient*

risks of rollover and sideslip after entering the curve roads with the calculated speeds based on the proposed curve speed model.

Although the number of the experiment drivers is 30, which is not enough to draw generalisable conclusions, this study lays the foundation for the speed profiling of the automated driving on curve roads. Nowadays, there is a common view that the human–vehicle cooperation will still be the dominating form in automated driving before autopilot system takes over all aspects of the driving tasks under all traffic scenarios in the foreseeable future [28, 29]. One important aspect in the human–vehicle cooperation is the accurate evaluation of driver behaviour made by driver assistance system when responding to driving tasks because of the variety of drivers' adaptability to it. Therefore, personalised automated driving systems considering drivers' driving styles are more likely to be accepted by different types of drivers or passengers, which will lead to lower driving risks and higher efficiency even in complicated traffic scenarios.

Future studies can be conducted on optimising the driving style classification and its coefficient calibration under more different driving scenarios. More importantly, real-world experiments with CSW systems based on the proposed model could be carried out under real-world traffic scenarios.

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