Received June 16, 2020, accepted July 1, 2020, date of publication July 6, 2020, date of current version July 20, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3007151

Determination of Risk Perception of Drivers Using Fuzzy-Clustering Analysis for Road Safety

DINGAN NI, FENGXIANG GUO, YANNING ZHOU, AND CHENGUANG SHI
School of Transportation and Engineering, Kunming University of Science and Technology, Kunming 650500, China

Corresponding author: Fengxiang Guo (20050062@kust.edu.cn)

This work was supported by the National Natural Science Foundation of China under Grant 71961012 and National Key Research and Development Program of China under Grant 2018YFB1600500.

ABSTRACT This study aims at investigating drivers' risk perception ability. To achieve this objective, the risk sensitivity and risk judgment thresholds of drivers of different ages were calculated. Five scenarios of intersections with risks were established for the driving simulator experiment. The driving behavior data of fourteen younger drivers and fourteen elderly drivers during the risky event and the subjective evaluation of risk by an expert driver were collected. The expert driver's conflict degree and subjective feeling were combined to classify the risk level of driving scene; then, fuzzy signal detection was used to calculate the driver's risk sensitivity (d') and judgment threshold (β). The β with the greatest difference was selected for cluster analysis and drivers were divided into four types according to the threshold. Finally, a driver classification discriminant model was constructed based on Fisher discriminant analysis. The results show that d' and β of younger drivers are both better than those of elderly drivers, younger drivers can detect and respond risks in time, while elderly drivers need be closer to risks and have intuitive feelings to make judgments. The results of the cluster analysis showed that younger drivers account for a large proportion of the sensitive type, indicating that younger drivers can find risks more sensitively in risk scenarios than elderly drivers, while elderly drivers easily ignore risks due to physical and psychological weakness. The correlation analysis showed that age, saccade amplitude and heart rate are the main factors that affect the risk judgment threshold.

INDEX TERMS Driver behavior, elderly driver, risk sensitivity, risk judgment threshold, cluster analysis.

NOMENCLATURE

ABBREVIATIONS

UFOV	useful field of view
VL	very low
L	low
M	medium
H	high
VH	very high
RLS	risk level of the scene
ROC	receiver operating characteristic
AUC	area under the curve
SRD	situational risk degree
HI	hit report
FA	false report
MR	missing report
CN	correct negation
RJT	risk judgment threshold
DS	driver's sex
DA	driving age
SA	saccade amplitude
FT	fixation time
HRA	heart rate
V	velocity
BPD	brake pedal depth

SYMBOLS

R_{LOW}	the lower limit of the fuzzy value range
R_{HIGH}	the upper limit of the fuzzy value range
I	driver's value of response
I_{mean}	the average response
HR	the probability that the driver records a response
FAR	the probability that the driver falsely reports
H_i	the fuzzy response value of the driver's hit response in scene i

The associate editor coordinating the review of this manuscript and approving it for publication was Lorenzo Ciani.

FA_i	the false response value of the driver in scene i
S_i	the situational risk of experimental scene i
d'	the risk sensitivity
β	the risk judgment threshold
C	the distance of an incomplete braking instance
S	the expert's subjective evaluation of risks
P	the critical conflict value
D	the average deceleration of a small vehicle
T	the braking coordination time
x_i	the standardized value of the expert driver's four-dimensional subjective evaluation
$D(t)$	the distance between the test vehicle and the risk conflict
v_0	the initial speed of test vehicle
v_1	the initial speed of conflict vehicle
θ_0	the test vehicle's directions of movement in terms of angles with the x-axis
θ_1	the conflict vehicle's directions of movement in terms of angles with the x-axis
t	the movement time
(x_0, y_0)	the position of the test vehicle
(x_1, y_1)	the position of the conflict vehicle
$x1, x2, x3, x4, x5$	the risk judgment threshold of the drivers in scenes 1-5
y	the discriminant score

I. INTRODUCTION

China is becoming an aging society. By 2030, it is expected that the proportion of elderly people (aged 65 years and older) will be 15.8%. For better mobility and flexibility, increasingly more elderly people are choosing to continue driving, which has led to an increasing number of traffic crashes involving elderly drivers [1]. Traffic accidents are most likely to occur at intersections [2]–[4]. Age-related deterioration in the physiology of elderly drivers leads to a decline in responsiveness and operational capacity [5]. The effects of low risk perception ability on driving behavior in a risky driving environment were studied to provide a theoretical basis for the safe driving of elderly drivers. At present, there are some methods for testing the risk perception of elderly drivers, such as the picture test [7]–[8], driving simulator tests [9]–[13] and vehicle test [14]–[16]. The driving simulator test and vehicle test are used widely, but the driving simulator test is safer and more convenient. Therefore, the main method for testing the risk perception ability of elderly drivers is the driving simulator test.

The driving behavior of elderly drivers is influenced by changes in the road environment. Elderly drivers rely heavily on road signals to detect risks, reflecting the situation of elderly drivers who have mastered traffic environments through rich driving experience [17]. The driving behavior of elderly driver is differing greatly across different environments. The driving behaviors of elderly drivers differ on urban, suburban and rural roads; for example, elderly drivers cannot stop in emergency situations due to poor visibility and other issues on rural roads without shoulders [18]. There has differences on drivers' scanning behavior at signalized and unsignalized intersections [19]. Both environmental and personal factors affect the occurrence of traffic accidents. The main factors affecting traffic accidents involving elderly drivers through a summarization of the causes of traffic accidents were personal and environment factors, while the personality attitude and self-evaluation affected driving behavior [20]. Elderly drivers ignore the risk of surrounding objects due to their concentration on the road ahead, resulting in traffic accidents [21]. The relationship between the physical conditions of intersections and pedestrian safety related to elderly drivers was investigated; a multivariable logistic regression model was constructed to determine the pedestrian collision factors associated with elderly drivers [22]. Elderly drivers are vulnerable to impact when they turn left at crossroads [23]. Traffic congestion negatively affected driver behavior on the post-congestion roads and will easily led to accidents [24]. Drivers can understand themselves objectively and avoid traffic accidents by testing their risk perception ability; the driving simulator test is more realistic and safer than other methods. The skin potential reflex was found to be useful as an evaluation index for the risk response ability of elderly drivers through the driving simulator test [25]. Through a driving simulator test, it was found that drivers' consciousness of lifeless obstacles is lower than that of living obstacles [26]. Elderly drivers maintained a longer distance from the vehicle and showed instability in the distance and the velocity through a driving simulator experiment [10]. In driving simulator experiment, elderly drivers were more dependent on in-vehicle assistance systems and chose a larger gap to pass through intersection than younger drivers [27]. In addition, risk perception can also be detected by watching a video. There is a correlation between the risk perception ability of elderly drivers and accident incidence, which is discoverable through watching videos [28]. The vehicle test method has more traffic safety risks than other methods, but it has the highest authenticity. Drivers of different ages have different fatigue conditions and fatigue accumulation speeds during driving, and the optimal driving times are different [29]. Drivers of different ages have different risk perception abilities; the difference between elderly drivers and younger drivers is obvious. In an experiment involving elderly drivers and younger drivers, the elderly drivers were inclined to scan the routes they already paid attention when turning at T-intersections or four-legged intersections; this behavior leads to ignoring the risk of turning and entering risky areas [21]. The risk perception of elderly drivers is slower than that of younger drivers, and the risk perception behavior of drivers is significant correlated in the useful field of view (UFOV) test [8]. Fuzzy signal detection method is an effective method to compare the perception difference between younger and elderly drivers. There is a difference in risk perception between new drivers and experienced drivers based on fuzzy signal detection theory [30], [31]. Experienced and trained drivers respond faster than novices in a hazard perception test based on fuzzy signal detection theory [32].

In the research of behavior characteristics and risk perception ability of elderly drivers, researchers seldom further subdivide the type of driver based on factors which affect the risk perception ability of elderly drivers and analyze the characteristic of drivers based on the type of driver. The paper takes the difference in the drivers' risk perception as the starting point, and the risk perception ability of different types of drivers was analyzed. Then, fuzzy signal theory was used to calculate risk sensitivity and risk judgment threshold; the risk sensitivity and risk judgment threshold were used to analyze the difference between younger drivers and elderly drivers. Cluster analysis was used to classify drivers and obtain a driver classification discriminant model. At last, the correlation analysis was used to found that some factors have significant correlation with drivers' risk judgment threshold. The experiment showed that the driver classification type has a certain reliability based on the risk judgment threshold. Driver classification discriminant model brings more accurate self-assessment to drivers, which is helpful to correct their own shortcomings, and reducing the occurrence of traffic accidents.

II. EXPERIMENT

A. PARTICIPANTS

In total, 39 drivers with driving licenses were recruited to participate the experiment. Six drivers did not finish the experiment due to dizziness in the simulator and five drivers' data were missing. Finally, 28 drivers' operating data were selected (15 male drivers and 13 female drivers). To avoid the influence of objective factors such as driving age and driving experience on the experimental results, all the drivers had more than three years of driving experience and more than 10,000 km of actual driving mileage. Among them, fourteen drivers were younger drivers (average age of 34.3±7.5 years old), and fourteen drivers were elderly drivers (average age of 66.0±3.5 years old). All the participants were recruited in Yunnan Province of China for age diversity.

B. APPARATUS

A KMRTDS driving simulator, which was developed independently by the School of Transportation, Kunming University of Science and Technology (KUST), was used in the experiment (Fig. 1). The driving simulator system platform is composed of six subsystems: a cockpit system, vehicle dynamics simulator system, visual image generation system, traffic microsimulation system, sound simulation system and

FIGURE 1. KMRTDS driving simulator.

computer control system. The simulator is composed of a real car cab with an automatic transmission gearshift and three large screens that create a visual angle of 140°. The roadway was virtually projected onto the screens and was refreshed at 60 Hz. PsyLAB was used to collect the drivers' physiological data and psychological data, iView HED4 eye tracker was used to collect the saccade and fixation data. The output parameters of driving simulation system are shown in Table 1.

TABLE 1. Output parameters of driving simulation system.

Apparatus	Output parameters
Driving simulator	Velocity (km/h), Brake pedal (mm), Gas pedal (mm), Wheel steering (Deg), Longitudinal acceleration (m/s2)
PsyLAB	ECG, EDA, EMG
IView HED4	Saccade amplitude (°), Fixation time (s)

C. EXPERIMENTAL SCENARIOS

VS-Design software (developed by the School of Transportation, KUST) was used to design and establish 3D virtual experiment scenarios. According to the traffic risk situations that often take place in urban road intersections, five intersections scenarios with traffic risks were designed and connected into one experimental section. To avoid the objective impact of the signal on the experiment, the five risk scenarios in the experiment involve no signal intersections on urban roads. Traffic conflicts were triggered by setting the trigger zones. Vehicles, bicycles and pedestrians moved according to the designed routes and speeds when the test vehicle entered into the trigger zone. The description of specific intersection risks is shown in Table 2.

D. PROCEDURE

The KMRTDS driving simulator, including basic driving operation such as starting, throttle, braking, steering, etc., was introduced to the driver before entering the driving simulator

TABLE 2. Design of the dynamic risk scenarios.

Scenario	Simulation	Test vehicle direction	Risk situation
Scene 1		Straight	When the test vehicle drives through the trigger zone from the south to the north, the pedestrian crosses the road at a speed of 10 km/h from west to east.
Scene 2		Straight	A motorcyclist on the right side of the road driving from south to north appears and remains still. When the test vehicle drives past the trigger zone, the motorcyclist enters the nonmotor vehicle lane at 50 km/h and goes straight.
Scene 3		Straight	The left side of the road is full of vehicles. When the test vehicle drives from west to east through the trigger zone, a cyclist drives from north to south at a speed of 18 km/h.
Scene 4		Turn left	When the test vehicle turns left, a vehicle driving straight from south to north at 35 km/h.
Scene 5		Straight	When the test vehicle drives from west to east through the trigger zone, a vehicle from the south turns right (to the east) at 40 km/h into the lane of the test vehicle.

cabin. After the driver entered the simulator cabin, he or she was assisted in adjusting the seat and safety belt for optimal driving. After the driver adapted to the driving in the simulator, a formal simulated driving experiment was conducted in which the drivers were required to follow daily driving habits and road signs in five scenarios (the velocity limit is 60 km/h). After the experiment finished, the drivers filled out a subjective questionnaire.

III. RISK DISCRIMINATION OF DRIVING SCENARIOS

In the experiment, the severity of the risk in the driving situation was defined as the "driving scene risk level" and was used to sort and segment the different scenarios in the experiment. The risk level division needs to apply the traffic conflict information and the result of the driver's subjective evaluation. The situational risk based on traffic conflicts is a value greater than 0, and the value of the situational risk based on the subjective evaluation is between [0, 1]. The risk will be more significant with a higher level of driving scene risk, and there will be more danger to the driver.

The "driving situation risk assessment method" based on a driving simulator experiment was proposed in [6]. Through the conflict degree and subjective questionnaire obtained from the real-time operational data of the simulator, the driver's subjective feelings of the risk scene were calculated and adjusted to obtain an effective driving scene risk rating. In the paper, the driving scenario risk level was defined as the risk level of the scene (RLS):

$$RLS = C \cdot S \tag{1}$$

In (1), C is the distance of an incomplete braking instance. The main role of C in the formula is to quantify the number of conflicts. S is the expert's subjective evaluation of risks. The expert driver indicates that a driver who has rich driving experience, solid driving theory knowledge and subjective evaluation ability, so that they can evaluate risks subjectively and has a certain degree of credibility.

C is mainly related to the speed and distance in the conflict process and is affected by vehicle deceleration due to braking. The severity of conflict through the above variables can be determined with (2):

$$C = P/T = D/VT = 0.175 + 0.08V/T \tag{2}$$

P is a critical conflict value, and the critical conflict value is mainly determined by the braking condition of the vehicle. D is calculated from the "Safety Technical Conditions for Motor Vehicle Operation" (GB7258-2012), which indicates that the average deceleration of a small vehicle is 6.2 m/s^2 or more (the value used in this paper is 6.2 m/s^2) and the braking coordination time for a vehicle with hydraulically brakes is less than or equal to 0.35 s (the value used in this paper is 0.35 s).

T is the time that the conflict occurred between the test vehicle and the risk. The idea of two-dimensional space was used to calculate the conflict time. The coordinates and motion trajectory of the test vehicle and the conflict object are shown in Fig. 2. The initial speeds are v_0 and v_1, the directions of movement in terms of angles with the x-axis are θ_0 and θ_1. At time t, the position of the test vehicle and the conflict object are $x_0(t) = 0$, $y_0(t) = v_0 t$; $x_1(t) = x_1(0) + v_1 t \cdot \cos\theta_1$, and $y_1(t) = y_1(0) + v_1 t \cdot \sin\theta_1$.

At this time, the distance D(t) between the test vehicle and the risk conflict is expressed as:

$$D^2(t) = x_1^2(t) + [y_1(t) - y_0(t)]^2 \tag{3}$$

D^2(t) is derived as follows:

$$t_m = \frac{y_1(0) \cdot (v_0 - v_1 \sin\theta_1) - x_1(0) \cdot v_1 \cos\theta_1}{v_1^2 + v_0^2 - 2v_1 v_0 \sin\theta_1} \tag{4}$$

When $t = t_m$, D(t) is minimized. When there is a conflict, the collision time is $T = t_m$.

When $0 < C < 1$, the conflict is not serious; when $C \geq 1$, the conflict is very serious; the closer the value of C is to 1, the more serious the conflict. When $T > 5$s, it can be considered that there is no conflict, and $C = 0$.

The driver's subjective evaluation was derived from the four-dimensional subjective risk assessment method, and an expert driver was invited to subjectively evaluate the risk in the driving situation based on four dimensions (perception, decision, manipulation and consequences) and with a level between 0 and 10. After the simulated driving experiment was

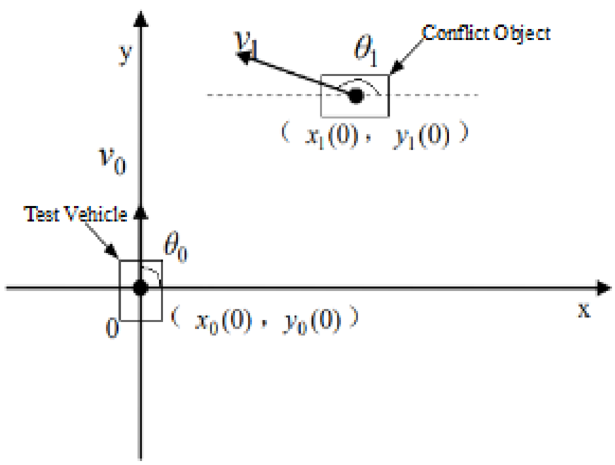

FIGURE 2. Schema of traffic conflict.

TABLE 3. Risk levels of the driving scenes.

	Scene 1	Scene 2	Scene 3	Scene 4	Scene 5
C	0.34	0.93	1.98	0.75	1.43
S	0.36	0.49	0.77	0.46	0.60
RLS	0.12	0.46	1.50	0.35	0.86
Rank	L1	L3	L5	L2	L4

completed, the expert driver provided a subjective evaluation from the four aspects of perception, decision, manipulation and consequence, and a four-dimensional hierarchical subjective evaluation function was constructed:

$$S = \frac{1}{2}\left(\sqrt[4]{\prod_{i=1}^{4} x_i} + \frac{1}{4}\sum_{i=1}^{4} x_i\right) \tag{5}$$

In (5), x_i ($i = 1,2,3,4$) is the standardized value of the expert driver's four-dimensional subjective evaluation of the risk level.

Vehicle motion data and subjective evaluation data were obtained through the driving simulator experiments and the expert driver's evaluations. The above comprehensive traffic risk rating function based on traffic conflicts and subjective evaluations was applied to calculate the risk level values of the five scenarios in the risk scenario experiment (Table 3). The five risk scenarios were ranked according to the RLS from low to high: L1 is the lowest, L5 is the highest.

IV. MATHEMATICAL METHOD

A. FUZZY SIGNAL DETECTION

To explore the perception of younger drivers and elderly drivers in the risk scenarios, the fuzzy signal recognition method was used to calculate the driver's risk sensitivity and judgment threshold, and the risk response ability of drivers was analyzed at different risk levels.

The perception of the operational judgment after the driver received the traffic information was divided into the following levels: very low (VL) = (0,1,2,3), low (L) = (2,3,4,5), medium (M) = (4,5,6), high (H) = (5,6,7,8), and very high (VH) = 7,8,9,10) [33]. The membership function can describe as Fig.3 based on fuzzy signal detection theory.

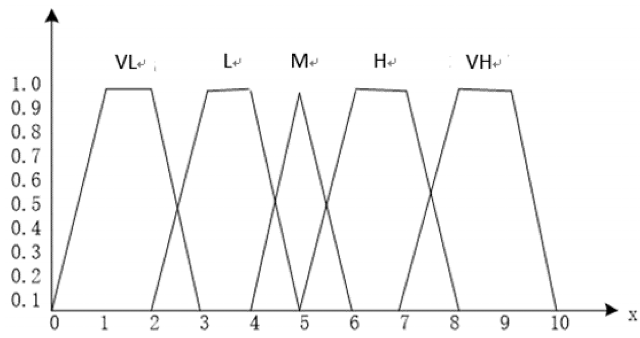

FIGURE 3. Fuzzy evaluation variables correspond to membership functions.

TABLE 4. Correspondence of the fuzzy numbers and fuzzy value ranges.

Fuzzy number	Fuzzy value range
P_{VL}= (0, 0.1, 0.2, 0.3)	[0.1λ+0, 0.1λ+0.3]
P_{L}= (0.2, 0.3, 0.4, 0.5)	[0.1λ+0.2, 0.1λ+0.5]
P_{M}= (0.4, 0.5, 0.6, 0.7)	[0.1λ+0.4, 0.1λ+0.7]
P_{H}= (0.6, 0.7, 0.8, 0.9)	[0.1λ+0.6, 0.1λ+0.9]
P_{VH}= (0.8, 0.9, 1)	[0.1λ+0.8, 0.1λ+1]

The maximum membership degree was applied to grade the fuzzy numbers of the subjects' subjective choices. After grading, the fuzzy number was reselected through a formula to obtain the range and to defuzzify the fuzzy value. The subjective rate was expressed as (6) and the fuzzy value range was assigned to a fuzzy number as in Table 4.

$$p^{\lambda} = \begin{cases} [(p_2-p_1)\lambda+p_1, (p_2-p_3)\lambda+p_3] \cdots\cdots \bar{p}=(p_1,p_2,p_3) \\ [(p_2-p_1)\lambda+p_1, (p_3-p_4)\lambda+p_4] \cdots\cdots \bar{p}=(p_1,p_2,p_3,p_4) \end{cases} \tag{6}$$

The lower limit of the fuzzy value range is defined as R_{LOW}, the upper limit is defined as R_{HIGH}, and the defuzzification formula was defined as:

$$\begin{cases} I = \frac{1}{2}\left[(1-k)\sum_{\lambda=0.1}^{1} R_{LOW}\Delta\lambda + k\sum_{\lambda=0.1}^{0.9} R_{HIGH}\Delta\lambda\right] \\ \lambda = 0, 0.1, 0.2 \ldots\ldots, 1;\ \Delta\lambda = 0.1 \end{cases} \tag{7}$$

In (8), I is the driver's value of response, the average response I_{mean} of the subject in each scenario was calculated, and I_{mean} was used as a comprehensive experimental response value for each driver.

$$I_{mean}\frac{1}{n}\sum_{i=1}^{n} I_i \quad (i = 1, 2, \ldots, n) \tag{8}$$

B. CALCULATION OF THE RISK SENSITIVITY AND THRESHOLD

The formula of the implication function [34] was applied to represent fuzzy set members. The values of the hit response (HI) and false report (FA) were calculated, and then the rates of driver's HI and FA were calculated from (9).

$$\begin{cases} HR = \sum_{i=1}^{N} H_i / \sum_{i=1}^{N} S_i \\ FAR = \sum_{i=1}^{N} FA_i / \sum_{i=1}^{N} (1 - S_i) \end{cases} \tag{9}$$

In (9), HR represents the probability that the driver records a response in a risk scene (a ''hit''), FAR represents the probability that the driver falsely reports a risk of the risk scene. H_i represents the fuzzy response value of the driver's hit response in scene i; FA_i represents the false response value of the driver in scene i; S_i is the situational risk of experimental scene i.

The risk sensitivity (d') is a parameter that measures the sensitivity of the driver. In signal detection, the degree of separation between noise distribution and signal distribution. The larger the degree of separation is, the higher the corresponding sensitivity; the smaller the degree of separation is, the lower the sensitivity. A PZO conversion table was used to calculate the risk sensitivity, the PZO conversion table is a kind of normal distribution table, P is the area of $(-\infty, Z)$, Z and O are abscissa and ordinate of curve's point. As in (10).

$$d' = \phi^{-1}(HR) - \phi^{-1}(FAR) = Z_{HR} - Z_{FAR} \tag{10}$$

In signal detection theory, β is an indicator of the risk judgment threshold; it is the ratio between the conditional probability of a particular sensation caused by a signal plus noise and the conditional probability caused by noise. A PZO conversion table was used to calculate the risk judgment threshold. Specifically, the ratio of the distribution of the signal and the noise distribution on the vertical axis is calculated with (11).

$$\begin{aligned} \beta &= \frac{1}{\sqrt{2\pi}} \exp^{-Z(HR)^2/2} \Big/ \frac{1}{\sqrt{2\pi}} \exp^{-Z(FAR)^2/2} \\ &= O_{HR}/O_{FAR} \end{aligned} \tag{11}$$

V. RESULTS

The comprehensive response value of each driver was calculated in both age groups. The risk sensitivity and judgment threshold were calculated through the probability of hit response and false report. The accuracy of the experiments was determined based on the probability of a hit response and false report, and a difference analysis of the risk sensitivity and judgment threshold was performed.

A. DETECTION OF THE ROC CURVE

A receiver operating characteristic (ROC) curve was used to test the accuracy of the experiment, the diagnostic indicator for the ROC curve is the area under the curve (AUC).

TABLE 5. Area of curve.

Area	Standard error [a]	Progressive Sig. [b]	Asymptotic 95% confidence interval	
			Lower limit	Upper limit
0.788	0.09	0.009	0.612	0.964

The greater the AUC is, the stronger the diagnostic ability of the indicator to the target. The range of the AUC is (0, 1). In general, AU C $\leq$ 0.7 means that the indicator has a low differential diagnostic value; 0.7 < AUC $\leq$ 0.9 means that the indicator has a moderate differential diagnostic value; AUC > 0.9 means that the indicator has a high differential diagnostic value.

According to the experimental results, the driver's false report rate and hit response rate were used as the horizontal axis and vertical axis, respectively, of the ROC plot (Fig. 4). If the curve is convex and close to the upper-left corner, then the accuracy of the test results is high, and the diagnostic value is high.

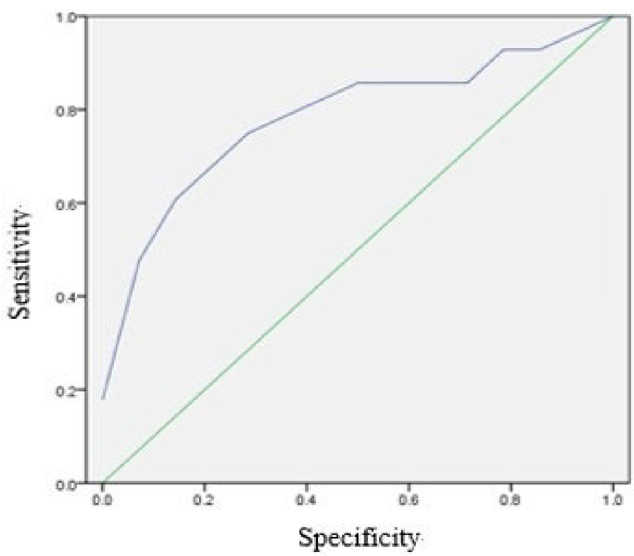

FIGURE 4. Driver ROC curve.

The ROC curve reflects the risk perception ability of the different age groups. From Table 5, an AUC of 0.788 indicates that the curve has 78.8% efficiency to distinguish the risk perception of younger drivers and elderly drivers.

B. ANALYSIS OF THE DRIVER'S RISK SENSITIVITY AND JUDGMENT THRESHOLD

The risk sensitivity was calculated through a PZO conversion table and (10). Then, a difference analysis of the risk sensitivity between younger drivers and elderly drivers was performed, and the results are shown in Table 6.

From Table 6, the risk sensitivities of younger drivers and elderly drivers in the five scenarios are 1.283 and 1.176, and P = 0.044 indicates that there is a significant difference between the two groups of drivers.

TABLE 6. Differences in the risk sensitivity.

	d' mean					
	Scene1	Scene2	Scene3	Scene4	Scene5	Mean
Younger Drivers	-0.372	1.541	2.301	1.089	1.854	1.283
Elderly Drivers	-0.231	1.390	1.938	1.184	1.598	1.176
P	0.059	0.068	0.052	0.032*	0.01**	0.044*

*: P≤0.05, **: P≤0.01

The judgment threshold was calculated through a PZO conversion table and (11). Then, a difference analysis of the judgment threshold between younger drivers and elderly drivers was performed, and the results are shown in Table 7.

TABLE 7. Differences in the risk judgment threshold.

	β mean					
	Scene1	Scene2	Scene3	Scene4	Scene5	Mean
Younger Drivers	0.951	7.504	11.011	6.381	10.635	7.296
Elderly Drivers	1.049	9.437	9.331	7.425	11.254	7.699
P	0.048*	0.045*	0.042*	0.015*	0.044*	0.038*

*: P≤0.05

From Table 7, the risk judgment threshold of younger drivers and elderly drivers in the five scenarios is 7.296 and 7.699, and P = 0.038 indicates that there is a significant difference between the two groups of drivers.

C. DRIVER CLASSIFICATION DISCRIMINANT MODEL BASED ON RISK PERCEPTION

To have a clearer understanding of the differences in risk perception between younger drivers and elderly drivers, cluster analysis was used to classify the 28 drivers based on the risk sensitivity and judgment threshold. Cluster analysis is a multivariable statistical method for classifying samples [35]; the essence is to classify samples with similar attributes or characteristics into the same group according to the standard. The difference between the two types of drivers' risk perception ability can be discerned more objectively through classification.

1) CLUSTER ANALYSIS OF DRIVERS

Because the risk judgment threshold β is significantly different between younger drivers and elderly drivers, this parameter was selected for driver classification. K-means clustering was used to classify the drivers into four categories. Among them, ten drivers belong to driver category 1 (e.g., driver 1); six drivers belong to driver category 2 (e.g., driver 7); five drivers belong to driver category 3 (e.g., driver 3); seven drivers belong to the driver category 4 (e.g., driver 9). The comparative results are shown in Fig. 5.

Drivers were divided into four types through the line chart: "sensitive", "negligent", "emotional" and "composite" (Table 8).

TABLE 8. Driver classification based on the judgment threshold.

Driver type	Driver category	Driver number
Sensitive	Category 1, Category 3(except driver 4)	1, 2, 3, 5, 6, 10, 12, 14, 16, 18, 22, 24, 27, 28
Negligent	Category 4(except driver 13)	9, 17, 19, 20, 21, 26
Emotional	Category 2	7, 8, 11, 15, 23, 25
Composite	Driver 4 in category 3, driver 13 in category 4	4, 13

2) DRIVER CLASSIFICATION DISCRIMINANT MODEL BASED ON FISHER DISCRIMINANT ANALYSIS

Based on the classification result of drivers, the fisher discriminant method was applied to fit the parameters, and then obtained the discriminant model. The basic principle of fisher discriminant analysis is to project the independent variable combination in various categories of high-dimensional space to low-dimensional space, so that the coincidence of various categories in the low-dimensional space is minimized [36]. The coefficient of discriminant model as Table 9.

TABLE 9. Coefficient of the discriminant model.

	Sensitive	Negligent	Emotional	Composite
Scene 1	10.026	15.181	12.446	9.574
Scene 2	1.383	1.536	0.6	0.945
Scene 3	1.353	-0.21	-0.009	1.187
Scene 4	1.006	1.808	2.177	1.195
Scene 5	2.446	3.325	2.82	1.784
(Constant)	-38.415	-45.596	-35.01	-27.08

The driver classification discriminant function based on the driver's risk judgment threshold in five risk scenarios as (12), as shown at the bottom of the page.

In (12), x_1, x_2, x_3, x_4, and x_5 represent the risk judgment threshold of the drivers in scenes 1-5, and y represents the discriminant score.

$$y = \begin{cases} 10.026x_1 + 1.382x_2 + 1.353x_3 + 1.006x_4 + 2.446x_5 - 38.415 \text{ (Sensitive)} \\ 15.181x_1 + 1.536x_2 - 0.210x_3 + 1.808x_4 + 3.325x_5 - 45.596 \text{ (Negligent)} \\ 12.446x_1 + 0.600x_2 - 0.009x_3 + 2.177x_4 + 2.820x_5 - 35.010 \text{ (Emotional)} \\ 9.574x_1 + 0.945x_2 + 1.187x_3 + 1.195x_4 + 1.784x_5 - 27.080 \text{ (Composite)} \end{cases} \quad (12)$$

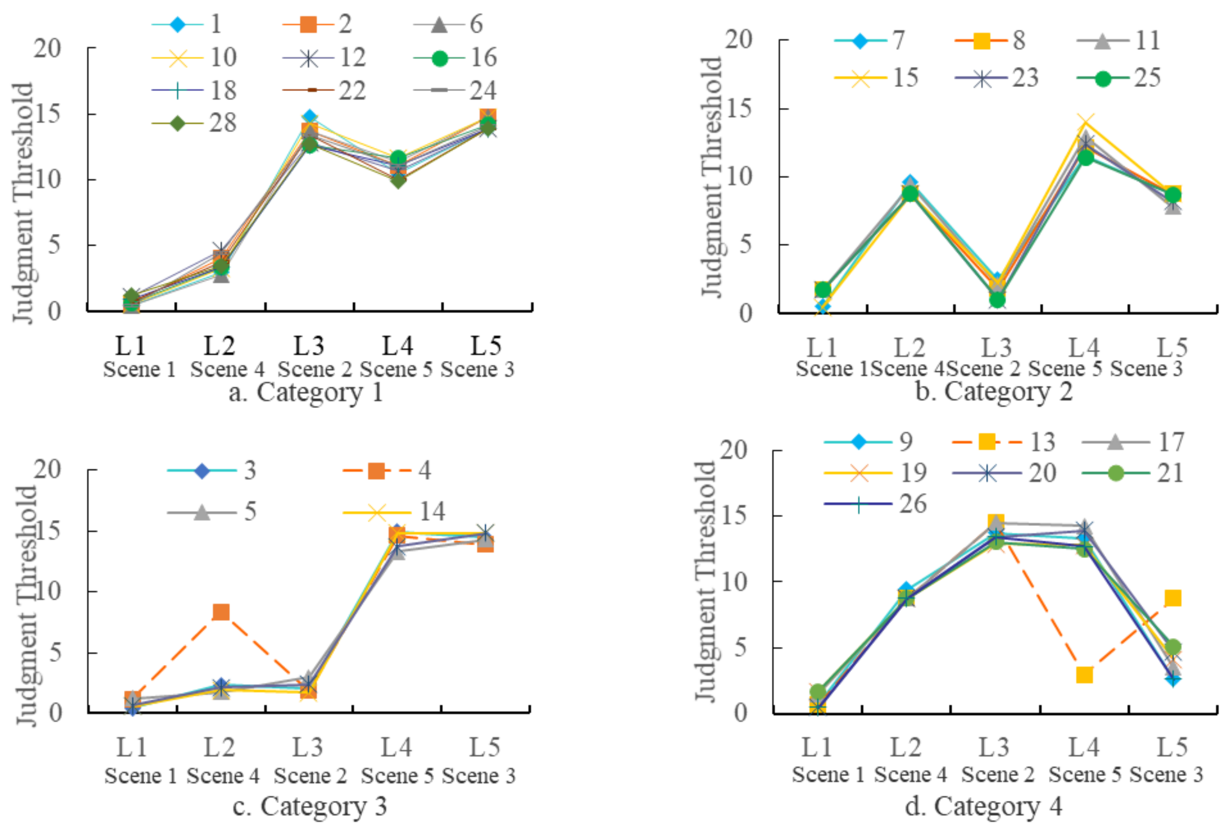

FIGURE 5. Comparative analysis of the drivers.

A driver's score can be calculated into four types through (12), then the driver can be categorized based on the score.

VI. DISCUSSION

A. RLS AND FUZZY METHOD

VS-Design software was used to design five traffic risk scenarios, including three common intersection risk scenarios: vehicle to vehicle, vehicle to nonmoving vehicle, and vehicle to pedestrian. The RLS was proposed to indicate the risk, there has study defined the traffic risk at an intersection as the situational risk degree (SRD) [6]; the higher the SRD is, the greater the driving risk in the driving situation. Both of these metrics are static and dynamic: static indicates the risk level in a risk scene at a particular moment, and dynamic represents the set of static risks over time; these concepts can reflect the change in traffic risk during driving more comprehensively than previous metrics. A driving simulator was applied to calculate C, which was combined with the S of the expert driver to obtain the risk scene level values under five risk scenarios. Scene 3 has the highest risk level value, indicating that scene 3 brings the most intuitive risk to the driver.

Considering that drivers' judgments of risk during driving are rather vague, vague judgment words such as "some risk" or "feel some risk" are generally used, and this vagueness led to an inability to accurately judge the drivers' risk perception abilities. For this purpose, fuzzy signal recognition was used to process the driver's operational judgment. The operation judgment was divided into five language levels after the driver accepted the traffic information. The maximum membership degree was applied to defuzzify the language level, the formula was used to obtain the fuzzy value range, and the comprehensive response value was calculated. To evaluate the driver's risk perception ability quantitatively, the implied function was used to calculate the HI, FA, missing report (MR) and correct negation (CN) of the fuzzy set members. The MR and CN were not used because they do not usually provide new information. The HI and FA were used to calculate the probability of the driver hitting the risk and falsely reporting the risk, respectively, in the driving risk scenarios. The risk sensitivity and risk judgment threshold, which can reflect the driver's risk perception ability to a certain extent, these values were obtained through the PZO conversion table.

B. SENSITIVITY AND THRESHOLD

The risk sensitivity is the degree of separation between a hit response and a false report. The larger the degree of separation, the higher the risk sensitivity, and the better the driver's ability to distinguish and respond to risks. In scene 1, the risk sensitivity of younger drivers and elderly drivers is less than 0, indicating that both sets of drivers were tense at the beginning of the experiment and had more false reports of risk. After adapting to the experiment, the participants resumed stable driving. The peak risk sensitivity of both sets of drivers appeared in scene 3, which is had highest level, indicating that both drivers can capture risks and react more accurately in scenarios with more obvious risks. In five risk scenarios, the values of the risk sensitivity of younger drivers and elderly drivers are 1.283 and 1.176, respectively; the higher risk sensitivity of younger drivers indicates that younger drivers can more accurately identify risks in the scenarios and respond in a timelier manner. Younger drivers can maintain a more cautious driving state during driving and have higher risk identification ability. The value of P was maintained at approximately 0.05 in the five risk scenarios, indicating a significant difference between the younger drivers and elderly drivers.

The risk judgment threshold reflects the driver's subjective perception of risk. For a larger threshold, the driver's judgment ability will be weaker, and the response will be slower with larger threshold. In the five risk scenarios, the risk judgment thresholds of the younger drivers were lower than those of the elderly drivers, indicating that younger drivers drive more conservatively in risky environments and make risk judgments in advance. The risk judgment ability of an elderly drivers would decrease with increasing age, which will cause the elderly drivers judge the risk when they closer to the risk and have a more intuitive feeling in the driving process. The risk judgment thresholds of the younger drivers and the elderly drivers in the five scenarios showed significant differences ($P < 0.05$), the risk judgment threshold ($P = 0.038$) can show the difference between younger drivers and elderly drivers better than the risk sensitivity ($P = 0.044$).

C. ANALYSIS OF DRIVER CLASSIFICATION

The risk judgment threshold with a higher difference was used to classify the drivers; the study showed that the risk judgment threshold can more accurately determine the driver's risk perception ability than the sensitivity [28]. In Fig. 5, a and c show that the risk judgment threshold increased as the risk level increased, which shows that these drivers can still drive cautiously under low-risk conditions, and there will be tension and panic that results in an error in the judgment of the risk when the risk level increase, causing an increase in the judgment threshold. This type of person is classified as a sensitive driver, and driver 4 in c was not classified first because his judgment threshold suddenly increased in scene 2. In Fig. 5b, the driver's judgment threshold showed a repeated increase and decrease trend and did not have a certain regularity with the change in the risk level. In scene 3, which has the highest risk level, a relatively low judgment threshold can be maintained, indicating that such a driver has a higher risk perception capability than other drivers. In scene 4 and 5, which have the lower risk levels than scene 3, a higher judgment threshold was displayed, indicating that such drivers were relaxed in the low-risk situation and driving more casually, which led to the risk judgment. Therefore, the driver was classified as an emotional driver. In Fig. 5d, the driver's judgment threshold showed an increasing trend first and then decreased as the risk level increase, indicating that such drivers can maintain certain judgment ability in high-risk situations but ignore some risks in low-risk situations. Therefore, this type of drivers was classified as a negligent driver; driver 13 was not classified first because his judgment threshold changed suddenly in scene 5. Driver 4 and driver 13 experienced a sudden change in their risk judgment thresholds during the driving process, but they only experienced a sudden change in one scene, so they were classified as composite drivers.

From Table 8, in the sensitive category, there are eight younger drivers and six elderly drivers, which were half of the test drivers. This finding indicates that drivers who have a certain driving experience can maintain cautious driving in a risky scene and are relatively sensitivity to risk. The relatively large proportion of younger drivers indicated that younger drivers had a more accurate risk judgment than elderly drivers. One younger driver and five elderly drivers were classified as negligent drivers. Elderly drivers made up a high proportion of negligent drivers, indicating that elderly drivers are assess risks slower than younger drivers due to issues such as weak eyesight and slow nerve reflexes in risk scenarios, and it is easy to ignore some risks, resulting in higher judgment thresholds. Three younger drivers and three elderly drivers were classified as emotional, indicating that there is a certain proportion of emotional drivers in both groups. This type of driver had the ability to full judge risks, but the external environment and the behavior of other vehicles may cause emotional changes in such drivers and lead to a large change in risk judgment, which would result in the inaccurate evaluation and analysis of this kind of driver. Two younger drivers were categorized as composite drivers, indicating that they can maintain the same driving characteristic of other drivers, but there are occasional unpredictable factors that led to errors in judgment. According to the four types of classification, the risk judgment ability of younger drivers is indeed better than that of elderly drivers. Elderly drivers easily ignore risks due to physical and psychological weaknesses.

D. ANALYSIS OF CORRELATION

Four classification discriminant functions were calculated based on the fitting parameters of the Fisher discriminant function. The function type was used to characterize the driver's type to reflect the driver's risk perception ability.

To reflect the characteristic of drivers intuitively, correlation analysis was performed between the risk judgment threshold (RJT) and driver's sex (DS), age, driving age (DA), saccade amplitude(SA), fixation time(FT), heart rate (HRA), EDA, velocity (V), EMG and brake pedal depth (BPD). The results are shown in Table 10.

From Table 10, a high correlation was shown in the risk judgment threshold with age, saccade amplitude and heart

TABLE 10. Correlation analysis of the risk judgment threshold.

	RJT	DS	Age	DA	SA	FT	HRA	EDA	V	EMG	BPD
RJT	1	0.038	0.45*	0.145	0.435*	0.227	0.473*	0.316	0.000	0.099	0.011
DS		1	0.203	0.264	0.226	0.009	0.194	0.093	0.384*	0.033	0.03
Age			1	0.704**	0.303	0.404*	0.134	0.562**	0.429**	0.076	0.177
DA				1	0.403*	0.553**	0.184	0.317	0.410*	0.189	0.157
SA					1	0.501**	0.135	0.136	0.338	0.098	0.265
FT						1	0.096	0.126	0.439*	0.091	0.278
HRA							1	0.334	0.191	0.176	0.101
EDA								1	0.260	0.002	0.417*
V									1	0.046	0.279
EMG										1	0.123
BPD											1

*: P≤0.05, **: P≤0.01

TABLE 11. Correlation analysis of the risk judgment threshold.

	Sensitive		Negligent		Emotional		Composite	
	SA (°)	HRA (t/m)	SA (°)	HRA (t/m)	SA (°)	HRA (t/m)	SA (°)	HRA (t/m)
Younger drivers	2.21	80.31	1.74	82.78	1.48	94.29	1.09	85.96
Elderly drivers	2.01	83.9	1.95	97.67	1.58	96.24		
Mean	2.11	82.11	1.85	90.23	1.53	95.27	1.09	85.96

rate. From Table 11, the mean saccade amplitude of the four types of drivers (sensitive, negligent, emotional and composite) are 2.11°, 1.85°, 1.53°, and 1.09°, respectively, indicating that sensitive drivers have a greater saccade amplitude when driving than the other types of drivers. They have a comprehensive grasp of the risks of surrounding things and have high risk perception ability. The mean heart rate of the four types of drivers (sensitive, negligent, emotional and composite) are 82.11 times/min (t/m), 90.23 t/m, 95.27 t/m, 85.96 t/m, respectively, which indicates that sensitive drivers can maintain a relatively stable mentality while driving, and negligent drivers have a high heart rate due to late detection of risks; negligent drivers are mainly elderly drivers. Emotional drivers are susceptible to external influences; their mood swings result in faster heartbeats and lead to a higher heart rate. The composite driver group is a mutation based on the sensitive driver group, so the heart rate in this group is slightly lower than that in the sensitive driver group. The saccade amplitudes of younger drivers and elderly drivers are 2.21° and 2.01°, respectively, and the heart rate of sensitive younger drivers and elderly drivers are 80.31 t/m and 83.9 t/m, respectively, because sensitive drivers are mainly younger drivers and their saccade amplitude are larger than those of elderly people, indicating that younger drivers can focus on more information and detect risks earlier and they have better risk perception ability and less stress than elderly drivers, as indicated by lower heart rates. The saccade amplitude and heart rate of the negligent younger drivers are 1.74° and 82.78 t/m, respectively, and those of negligent elderly drivers are 1.95° and 97.67 t/m, respectively, which indicates that the saccade amplitude of elderly drivers is wider than that of younger drivers, but the heart rate of elderly drivers is higher so that they cannot maintain a steady state of mind when driving. Therefore, the risk sensitivity of negligent drivers is lower than that of sensitive drivers. The saccade amplitude and heart rate of emotional younger drivers are 1.48° and 94.29 t/m, respectively, and those of emotional elderly drivers are 1.58° and 96.24 t/m, respectively, which indicates that the risk sensitivity of emotional younger drivers is lower than that of emotional elderly drivers. Emotional younger drivers are more susceptible to their external environment than emotional elderly drivers and their mood changes greatly. Emotional drivers' risk sensitivity is not easily captured. Two of the composite drivers are younger drivers, the saccade amplitude and heart rate are 1.09° and 85.96 t/m, respectively; their saccade amplitudes are narrow than that of other drivers, but they can maintain a steady state to mitigate risks. It can be seen that driver classification based on the risk judgment threshold has an obvious hierarchy and can discriminate the driver's risk perception ability to a large extent through the saccade amplitude and heart rate, which are highly correlated with the risk judgment threshold.

E. APPLICATION

From section E, saccade amplitude is the most influence factor that affected driver's perception ability, so drivers should maintain a wider saccade amplitude while driving so that they can grasp the traffic conditions and then risks can be avoided effectively. In the future, advanced driving assistance systems can incorporate a saccade system which can remind drivers to fully scan the surrounding environment and then ensure driving safety.

VII. CONCLUSION

To explore the differences in the risk perception abilities of drivers of different ages, it was found that the risk perception ability of younger drivers is better than that of elderly drivers based on the risk sensitivity and risk judgment threshold. Different driving personalities will affect drivers' risk response abilities; therefore, cluster analysis was used to divide the participants into four driver types, and a risk perception ability evaluation model was constructed. Then, the drivers' ages, saccade amplitudes and heart rates were compared across the different types that were more relevant to drivers. It was found that the saccade amplitude of younger drivers is larger than that of elderly drivers, and younger drivers' heart rate is relatively stable. This finding strongly indicated that younger drivers are able to deal with risks more calmly than elderly drivers. The disadvantage of the experiment is that no real vehicle experiments were performed. The elderly drivers adapted to the driving simulation system slower than the younger drivers; therefore, it is necessary to use a real vehicle and repeat the experiment to ensure the accuracy.

REFERENCES

[1] H. M. Qiu and J. G. Gu, "Current situation and countermeasures of traffic safety of older drivers in China," *J. Road Traffic Manage.*, vol. 10, no. 10, pp. 58–60, Oct. 2008.
[2] S. Bao and L. N. Boyle, "Age-related differences in visual scanning at median-divided highway intersections in rural areas," *Accident Anal. Prevention*, vol. 41, no. 1, pp. 146–152, Jan. 2009.
[3] D. D. Clarke, P. Ward, C. Bartle, and W. Truman, "Older drivers' road traffic crashes in the U.K.," *Accident Anal. Prevention*, vol. 42, no. 4, pp. 1018–1024, Jul. 2010.
[4] H. Gstalter and W. Fastenmeier, "Reliability of drivers in urban intersections," *Accident Anal. Prevention*, vol. 42, no. 1, pp. 225–234, Jan. 2010.
[5] F. X. Guo, C. G. Shi, P. Chen, and L. Zhu, "Research on UFOV test for older drivers," *J. Chin. J. Ergonom.*, vol. 25, no. 1, pp. 52–59, 2019.
[6] Y. Q. Qin, H. Q. Zhang, J. Xiong, and L. H. Jiang, "Driver's hazard perception under simulating risk driving scenarios," *J. Jiaotong Yunshu Xitong Gongcheng Yu Xinxi/ J. Transp. Syst. Eng. Inf. Technol.*, vol. 15, no. 2, pp. 142–148, 2015.
[7] G. Underwood, D. Crundall, and P. Chapman, "Driving simulator validation with hazard perception," *Transp. Res. Part F, Traffic Psychol. Behav.*, vol. 14, no. 6, pp. 435–446, Nov. 2011.
[8] M. S. Horswill, S. A. Marrington, C. M. Mccullough, J. Wood, N. A. Pachana, J. Mcwilliam, and M. K. Raikos, "The hazard perception ability of older drivers," *J. Gerontol. B, Psychol. Sci. Social Sci.*, vol. 63, no. 4, pp. 212–218, 2008.
[9] F. X. Guo, C. G. Shi, M. Y. Li, S. Zhang, and P. Chen, "Visual characteristics of older drivers in road intersections situation based on driving simulation," *China J. Highway Transp.*, vol. 31, no. 9, pp. 150–158 and 219, 2018.
[10] M. Y. Jian and J. Shi, "Study on older drivers' car following behavior and influencing factors," *China Saf. Sci. J.*, vol. 27, no. 6, pp. 25–30, 2017.
[11] A. Cuenen, E. M. M. Jongen, T. Brijs, K. Brijs, K. Van Vlierden, and G. Wets, "The effect of a simulator based training on specific measures of driving ability in older drivers," *Transp. Res. Part F, Traffic Psychol. Behav.*, vol. 64, pp. 38–46, Jul. 2019.
[12] M. Kunishige, H. Fukuda, T. Iida, N. Kawabata, C. Ishizuki, and H. Miyaguchi, "Spatial navigation ability and gaze switching in older drivers: A driving simulator study," *Hong Kong J. Occupational Therapy*, vol. 32, no. 1, pp. 22–31, Jun. 2019.
[13] E. Sawula, J. Polgar, M. M. Porter, S. Gagnon, B. Weaver, S. Nakagawa, A. Stinchcombe, and M. Bédard, "The combined effects of on-road and simulator training with feedback on older drivers' on-road performance: Evidence from a randomized controlled trial," *Traffic Injury Prevention*, vol. 19, no. 3, pp. 241–249, Apr. 2018.
[14] A. Borowsky, T. Oron-Gilad, and Y. Parmet, "Age and skill differences in classifying hazardous traffic scenes," *Transp. Res. Part F, Traffic Psychol. Behav.*, vol. 12, no. 4, pp. 277–287, Jul. 2009.
[15] J. Baujon, M. Basset, and G. L. Gissinger, "Visual behaviour analysis and driver cognitive model," *IFAC Proc. Volumes*, vol. 34, no. 1, pp. 47–52, Mar. 2001.
[16] Y. Zhao *et al.*, "Study of older male drivers' driving stress compared with that of young male drivers," *J. Traffic Transp. Eng.*, vol. 6, Jul. 2019, doi: 10.1016/j.jtte.2018.10.011.
[17] A. Borowsky, D. Shinar, and T. Oron-Gilad, "Age, skill, and hazard perception in driving," *Accident Anal. Prevention*, vol. 42, no. 4, pp. 1240–1249, Jul. 2010.
[18] R. Payyanadan, J. Lee, and L. Grepo, "Challenges for older drivers in urban, suburban, and rural settings," *Geriatrics*, vol. 3, no. 2, p. 14, Mar. 2018.
[19] G. Li, Y. Wang, F. Zhu, X. Sui, N. Wang, X. Qu, and P. Green, "Drivers' visual scanning behavior at signalized and unsignalized intersections: A naturalistic driving study in China," *J. Saf. Res.*, vol. 71, pp. 219–229, Dec. 2019.
[20] W. H. Zhang, J. B. Gu, and Z. X. Feng, "Advances in researches on driving characteristics and behavior of older drivers," *China Saf. Sci. J.*, vol. 25, no. 7, pp. 23–28, 2015.
[21] M. R. E. Romoser, A. Pollatsek, D. L. Fisher, and C. C. Williams, "Comparing the glance patterns of older versus younger experienced drivers: Scanning for hazards while approaching and entering the intersection," *Transp. Res. Part F, Traffic Psychol. Behav.*, vol. 16, pp. 104–116, Jan. 2013.
[22] D. Kim, "The transportation safety of elderly pedestrians: Modeling contributing factors to elderly pedestrian collisions," *Accident Anal. Prevention*, vol. 131, pp. 268–274, Oct. 2019.
[23] V. Cantin, M. Lavallière, M. Simoneau, and N. Teasdale, "Mental workload when driving in a simulator: Effects of age and driving complexity," *Accident Anal. Prevention*, vol. 41, no. 4, pp. 763–771, Jul. 2009.
[24] G. Li, W. Lai, X. Sui, X. Li, X. Qu, T. Zhang, and Y. Li, "Influence of traffic congestion on driver behavior in post-congestion driving," *Accident Anal. Prevention*, vol. 141, Jun. 2020, Art. no. 105508.
[25] R. Takahashi, M. Kobayashi, T. Sasaki, Y. Yokokawa, H. Momose, and T. Ohhashi, "Driving simulation test for evaluating hazard perception: Elderly driver response characteristics," *Transp. Res. Part F, Traffic Psychol. Behav.*, vol. 49, pp. 257–270, Aug. 2017.
[26] R. Saryazdi, K. Bak, and J. L. Campos, "Inattentional blindness during driving in younger and older adults," *Frontiers Psychol.*, vol. 10, p. 880, Apr. 2019.
[27] E. Becic, M. Manser, C. Drucker, and M. Donath, "Aging and the impact of distraction on an intersection crossing assist system," *Accident Anal. Prevention*, vol. 50, pp. 968–974, Jan. 2013.
[28] P. Darby, W. Murray, and R. Raeside, "Applying online fleet driver assessment to help identify, target and reduce occupational road safety risks," *Saf. Sci.*, vol. 47, no. 3, pp. 436–442, Mar. 2009.
[29] Y. Pei, Y. Jin, and H. Chen, "Fatigue characteristics in drivers of different ages based on analysis of EEG," *China J. Highway Transp.*, vol. 31, no. 4, pp. 59–65 and 77, 2018.
[30] Z. H. Tang, J. Cheng, and Z. N. Fang, "Causal mechanism of difference between experienced and novice drivers in hazard perception based on fuzzy signal detection theory," *J. Southwest Jiaotong Univ.*, vol. 48, no. 3, pp. 532–538, 2013.
[31] Z. H. Tang, T. Lan, J. Cheng, and C. C. Zhu, "Research on the detection of drivers' hazard perception based on FSDT," *J. Saf. Environ. Eng.*, vol. 20, no. 4, pp. 109–113, 2013.
[32] T. S. A. Wallis and M. S. Horswill, "Using fuzzy signal detection theory to determine why experienced and trained drivers respond faster than novices in a hazard perception test," *Accident Anal. Prevention*, vol. 39, no. 6, pp. 1177–1185, Nov. 2007.
[33] C. D. Wickens, *Engineering Psychology and Human Performance*, 2nd ed. New York, NY, USA: Harper Collins Publishers Inc, 1992, pp. 211–257.
[34] R. Parasuraman, A. J. Masalonis, and P. A. Hancock, "Fuzzy signal detection theory: Basic postulates and formulas for analyzing human and machine performance," *J. Hum. Factors Ergonom. Soc.*, vol. 42, no. 4, pp. 636–659, Dec. 2000.
[35] H. Shirmohammadi, F. Hadadi, and M. Saeedian, "Clustering analysis of drivers based on behavioral characteristics regarding road safety," *Int. J. Civil Eng.*, vol. 17, no. 8, pp. 1327–1340, Aug. 2019.
[36] C. C. Xu, P. Liu, W. Wang, and X. Jiang, "Discriminant analysis based method to develop real-time crash indicator for evaluating freeway safety," *J. Southeast Univ. (Natural Sci. Ed.)*, vol. 42, no. 3, pp. 555–559, 2012.

DINGAN NI received the B.S. degree in traffic engineering from the Huaiyin Institute of Technology, Huaian, China, in 2018. He is currently pursuing the M.S. degree in transportation engineering with the Kunming University of Science and Technology, Kunming, China.

His research interests include driver behavior of elderly drivers and traffic safety.

FENGXIANG GUO was born in Hailin, Heilongjiang, China, in 1979. She received the B.S. degree in transportation engineering from Chang'an University, Xi'an, in 2002, and the M.S. degree in transportation engineering and the Ph.D. degree in vehicle engineering from the Kunming University of Science and Technology (KUST), Kunming, in 2005 and 2019, respectively.

From 2005 to 2007, she was a Research Assistant with the Traffic Driving Simulation Laboratory, KUST. Since 2014, she has been an Assistant Professor with the Transportation Engineering Department, KUST. She is the author of more than 50 articles, and more than ten inventions. Her research interests include traffic safety and simulation, driving behavior, and traffic psychology. She have won the 3rd Prize of Science and Technology Progress in Yunnan Province twice, the 3rd Prize of Science and Technology Invention in Yunnan Province once, and the 2nd prize of Teaching Achievement in Yunnan Province once.

YANNING ZHOU received the B.S. degree in transportation engineering from Chang'an University, Xi'an, China, in 2018. She is currently pursuing the M.S. degree in transportation engineering with the Kunming University of Science and Technology, Kunming, China.

Her research interests include driver behavior of elderly drivers and traffic safety.

CHENGUANG SHI received the B.S. degree in transportation engineering from the Liaoning University of Technology, Jinzhou, China, in 2016, and the M.S. degree in transportation engineering from the Kunming University of Science and Technology, Kunming, China, in 2019.

His research interests include driver behavior of elderly drivers and traffic safety and traffic safety.