Study of the Hazard Perception Model for Automated Driving Systems

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Abstract. Automated and human-driven vehicles will coexist for a long time. It would be helpful to improve user experience of automated vehicles by considering drivers' psychological model of hazard perception. This work attempts to build a hazard perception model of a typical traffic scenario for automated driving systems. Seventeen drivers were recruited as participants for the driving simulation experiment to investigate the effects of different road conditions on drivers' subjective assessment of danger level and risk acceptance. A nonlinear regression model of hazard perception was built based on the experimental results. A case study has shown that the model can effectively reflect the quantitative relationship between drivers' perceived danger level and the relevant road conditions. It will provide theoretical basis for the development of future automated driving systems for users with different risk preferences.

Keywords: Automated driving · Hazard perception · Driving simulation · Nonlinear regression

1 Introduction

With the development of technologies such as the Internet of Things (IoT), artificial intelligence, and computer vision, the research and application of automated vehicle technologies has developed rapidly in recent years. The United States, Japan, and Germany have gradually started legislation to regulate road testing of automated vehicles since 2016, and China also issued a management regulation for road testing of automated vehicles in 2018 [1]. It is believed that more and more human-driven vehicles will be replaced by automated vehicles in the near future.

An automated driving system can perceive the surroundings of the vehicle from various sensors, and control the steering and speed of the vehicle according to the road, vehicle position and obstacle information, so that the vehicle can drive on the road safely and reliably [1]. The research work in the field of automated driving mainly focuses on engineering issues such as the path planning method for obstacle avoidance [2], the traffic logic at intersections for automated vehicles [3], and the vehicle control model [4]. Such models or algorithms usually

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take traffic efficiency, cost, and safety as the optimization goals, and rarely consider the psychological needs of drivers and passengers. For example, there are two vehicles passing through an intersection at the same time. The automated driving system can make the vehicles pass through the intersection quickly and safely by calculating the vehicle driving data and applying coordination strategies. With automation in L4 or L5, vehicles are assumed to drive safely and independently, and thus the mental demand from human driver decreases significantly [5]. However, passenger' perception of danger should not be ignored. In other words, the road conditions deemed safe by the automated driving system may not necessarily be safe for the driver and passengers. Moreover, there are large differences in the perception of safety among different individuals. Although there have been significant advances in fully autonomous driving in recent years, it has not achieved the large-scale commercial applications due to a wide range of limitations such as social dilemma, high costs and public trust [6]. Human-driven vehicles will coexist with automated vehicles for a long time before being completely replaced. The solutions designed for fully automated driving scenarios are likely not suitable for the transition period [7]. Therefore, it is crucial for the development of automated driving to consider drivers' and passengers' psychological factors in system solutions at present and for a long time in the future.

Driving simulation is an effective method to carry out experimental research on traffic safety, with which various hazard scenarios can be created in virtual environments [8,9]. Participants' safety is guaranteed in driving simulation experiments. This study investigated drivers' behaviors and subjective assessment of danger level and risk acceptance under given traffic conditions. A hazard perception model was built based on the experimental results. The results and findings of this study will help to improve the driving behavior of automated vehicles, so that they will meet the safety expectations of their drivers and passengers as well as other road users.

2 Method

2.1 Participants

Seventeen participants were recruited for the experiment. All participants have (corrected to) normal vision. Those with vision correction needed to wear optical lenses during the experiment. Two participants quit the experiment due to virtual reality (VR) sickness, and 15 participants (10 males and 5 females, 22–27 years of age) completed the experiment.

2.2 Apparatus

The driving simulation application was developed based on Unity 3D and Steam VR. The virtual environment was rendered by Dell Precision 7820 Tower workstation (Intel Xeon Silver 4110, NVIDIA Quadro P4000). HTC Vive

(2160 × 1200@90 Hz) HMD was used for VR display. Betop steering wheel and pedals (BTP-3189K) were used as input devices. The virtual scene was a 1-km urban road with buildings and transportation facilities. The subject vehicle was on a two-way four-lane road with a lane width of 3.75 m, and there was an intersection 700 m ahead. Participants sat in the driver's seat to observe the road conditions in the virtual environment. The driving simulation system can provide sound effects, such as engine sound and ambient sound through earphone. Steering wheel, brake pedal and gas pedal can be used for driving control. Figure 1 shows the participant practicing the virtual driving operation.

Fig. 1. Experiment setting.

2.3 Scenarios

In order to fully understand different types of road traffic hazards and their mechanisms, a total of 208 collision video clips were collected from video websites including traffic surveillance videos and driving recorder videos. After screening and classifying the collision videos, a hazard scenario library consisting of 20 categories was obtained finally. A typical traffic scenario was chosen for experimental study, in which the subject vehicle is approaching to an intersection while the opposite vehicle is about to turn left through the intersection. As shown in Fig. 2, the white car is the subject vehicle and the traffic light is green, and the black car is in the opposite inner lane with the left turn signal flashing.

2.4 Experimental Design

This study investigated drivers' behavior and hazard perception in a specific traffic scenario. In vehicle collision accidents, the driving speed and the distance

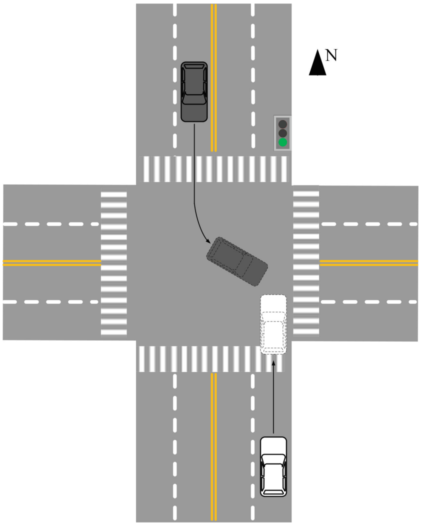


Fig. 2. Traffic scenario of the experiment. (Color figure online)

are two key factors, so speed of subject vehicle (SSV), speed of opposite vehicle (SOV), and travel distance between two vehicles when either one reached the intersection point (distance to collision) were selected as independent variables (Table 1). Both SSV and SOV had two levels, low speed and high speed. Considering the speed limit of urban roads and the speed limit of passing intersections required by the Road Safety Law of China, the low speed was set to 30 km/h, and the high speed was set to 60 km/h. As shown in Fig. 3, O is the intersection of the extension lines of the two vehicles' travel trajectories. There are three cases in the sequence of the two cars arriving at point O: the subject vehicle arrives at the intersection first, the two vehicles arrive at the same time, and the opposite vehicle arrives first.

In order to understand the relationship between hazard perception and distance to collision more accurately, it was subdivided. For the case of the subject vehicle arriving at O first, there must be a certain point A on the driving trajectory of the opposite vehicle, so that when the subject vehicle reaches O and the opposite vehicle has not yet reached A, the subject thinks that it is safe to pass through the intersection, while when the opposite vehicle has reached A, the subject thinks that it is dangerous. The driving distance from A to O is called the psychological safety distance. Due to individual differences in hazard perception, the psychological safety distance was determined through a pilot test including 5 participants. The participants drove straight through the intersection at a constant speed in the virtual environment and met with opposite vehicle turning into the intersection. Different safety distances were set for each test to allow the subjects to conduct safety assessments. Considering the influence of driving speed on hazard perception, low-speed and high-speed test conditions were used for both the subject vehicle and the opposite vehicle. The average value of the test results of the 5 participants was finally obtained, and the psychological safety distance AO was 14.73 m. The driving distance of AO was divided into 3 sections evenly, and the distances from B and C to O were obtained as 9.82 m and 4.91 m respectively (Fig. 3). Following the same way, the psychological safety distance GO was 21.00 m for the case of the opposite vehicle arriving at O first. The driving distance of the GO was divided into 4 sections evenly, and the distances from D, E, F to O were obtained as 5.25 m, 10.50 m, and 15.75 m respectively (Fig. 3).

Finally, the independent variable distance to collision had eight levels, namely the three positions A, B, C for the opposite vehicle, the four positions D, E, F, G for the subject vehicle and the intersection point O for the two vehicles arriving at the same time. A 2 SSVs $\times$ 2 SOVs $\times$ 8 distances within-group experimental design was adopted in this experiment. The order of the SSV and SOV conditions was counter-balanced and the order of the distance conditions was randomized to minimize the influence of the experimental sequence on the test results.

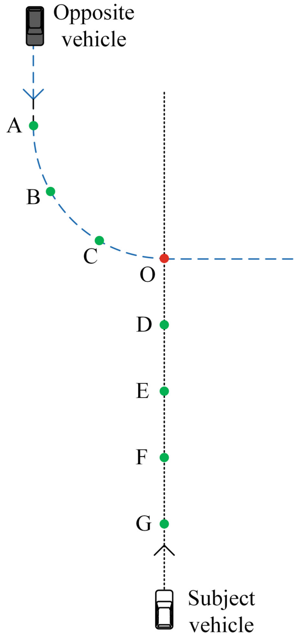


Fig. 3. Eight vehicle positions when the other one arriving at the intersection point. A, B, C is for the opposite vehicle and D, E, F, G is for the subject vehicle.

2.5 Procedure

The driving simulation experiment included two parts: warm-up practice and formal experimental test. The participants were briefed on the research objec-

Table 1. Independent variables.

Independent variables	Levels
Speed of subject vehicle (SSV)	Low: 30 km/h; High: 60 km/h
Speed of opposite vehicle (SOV)	Low: 30 km/h; High: 60 km/h
Distance to collision	A, B, C, O, D, E, F, G (Fig. 3)

tives and precautions. Afterwards, they provided their consent to the experimenter. The experimenter helped the myopic participants choose and install the optical lenses, and then the participants wore the HMD with the assistance of the experimenter. The interpupillary distance of the HMD was also adjusted for each participant if necessary. It was ensured that each participant wore the HDM comfortably and can see the virtual environment clearly.

All participants were asked to take a warm-up practice for at least 3 min before the formal experimental test. They can use the steering wheel, accelerator pedal and brake pedal to control the vehicle to drive in the virtual environment. They were required to experience visual and auditory feedback at different driving speeds through acceleration and deceleration operations. The warm-up practice can help participants become familiar with the virtual environment and the handling characteristics of the driving simulation system.

For each trial of the formal experimental test, the subject vehicle was driving at a predetermined speed approaching to the intersection while the opposite vehicle was about to turn left through the intersection. The subject vehicle can maintain the constant speed and direction, so the participant did not need any operation until he/she had to avoid a dangerous situation. The participant was asked to complete an assessment questionnaire regarding the scenario just experienced after each trial. In order to avoid the inconvenience caused by wearing the HMD repeatedly, the questionnaire was displayed in the virtual environment directly after the driving simulation test, and the participant simply said the rating option for each question, which was then recorded by the experimenter. One trial was performed under each test condition, and each participant need to complete 2 SSVs $\times$ 2 SOVs $\times$ 8 distances = 32 trials totally. The whole experiment took around an hour, with a break of five minutes every eight trials. Each participant received 50 Chinese yuan as a reward.

3 Results

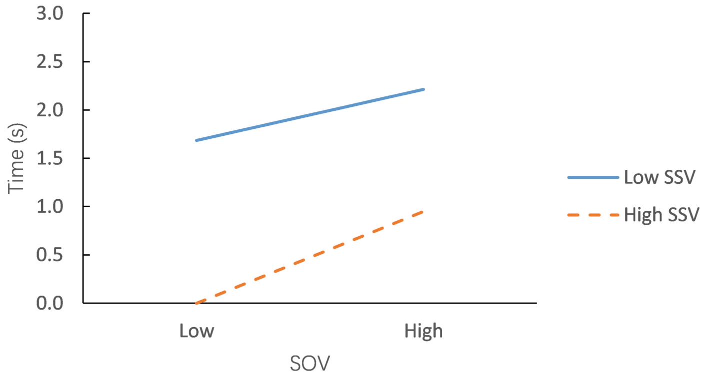
3.1 Time to Intersection

In order to study the driving behavior of the subject vehicle when the opposite vehicle turned left through the intersection at different speeds and different timings, the experimental results were analyzed in three cases: the subject vehicle arrived at the intersection first, the two vehicles arrived at the same time, and the opposite vehicle arrived first. For the first case (A, B, C in Fig. 3), the time when the participant braked was recorded. The average time to reach the intersection was calculated for the two conditions of SSV and the two conditions of SOV correspondingly. As shown in Fig. 4(a), when the subject vehicle passed through the intersection at low speed, the participants reserved longer response time, and when the speed of the opposite vehicle was higher, the participants tended to reserve a longer response time as well. Figure 4(b) shows the result of the two vehicles arriving at the same time. The difference from the first case is that the subject vehicle would take hazard avoidance actions in advance when it passed through the intersection at high speed and found the opposite vehicle turning left slowly. The average time to reach the intersection is about 1.0 s. While for the last case, the subject vehicle tended to take hazard avoidance actions earlier than the first two cases when passing at low speed. If the subject vehicle was passing at high speed and encountered a high-speed vehicle turning left, the actions would be taken later (0.9 s) as shown in Fig. 4(c).

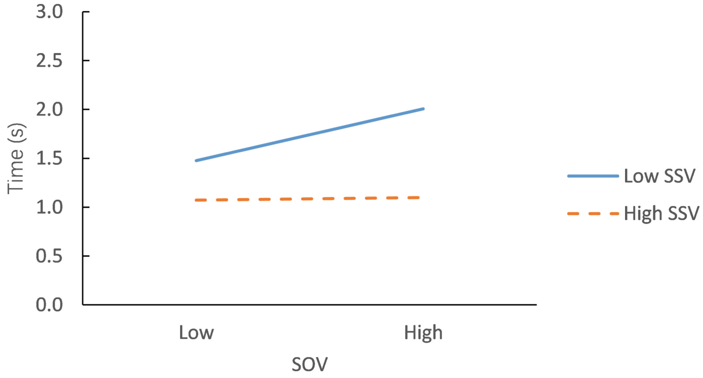
3.2 Danger Level Assessment

The danger level for each test scenario was rated on a 7-point Likert scale, with 1 to 7 representing from not at all dangerous to extremely dangerous. The results are shown in Table 2. Figure 5 shows the relationship between the perceived danger level and distance to collision when the subject vehicle and the opposite vehicle were driving at different speeds. The perceived danger level increased as the distance to collision decreased in general, no matter the subject vehicle passed first or the left-turning vehicle passed first. However, it is likely to be biased due to the influence of traffic rules. The subjective assessment of the danger level tended to be lower when participants were observing traffic rules, while it tended to be higher when the danger was caused by violating traffic rules by themselves.

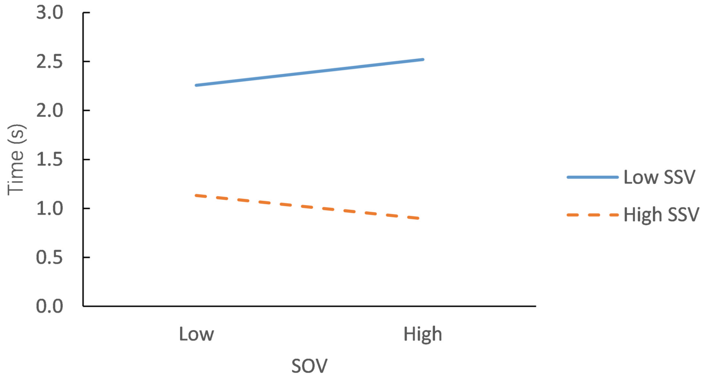
When the speed difference between the two vehicles was large and they maintained a relatively large distance, the danger level perceived by the driver of the subject vehicle was low and did not change significantly with the distance, such as A, B, C under L/H speed condition and E, F, G under H/L speed condition. When comparing the left and right sides of point O of each curve, it is found that the left part is concave downward except for H/L. That means in the case where the subject vehicle passed first, the perceived danger level decreased rapidly with the increase of the distance to collision as long as no collisions occurred. The above psychological perception of danger is likely to be caused by the traffic rules for left-turning vehicles to yield to straight vehicles. The post-experiment interviews also confirmed this. The reason for the shape difference between H/L and other speed conditions on the left is probably due to the influence of violating the speed limit at an intersection. The right part of curve H/L is concave and lower than most of other speed conditions, which is determined by the participants' high controllability of the dangerous situation. Since the opposite vehicle turned through the intersection at low speed and the subject vehicle was driving at high speed, collision can be avoided by slowing down. Based on the observation of the highest danger level area as shown in the dotted circle in Fig. 5, there are two



(a) Subject vehicle arrived first



(b) Two vehicles arrived at the same time



(c) Opposite vehicle arrived first

Fig. 4. The average time to reach the intersection point when the participants started braking.

types of situations in which participants perceive a higher risk except for the situation where the two vehicles arrived at the same time and collided. The first case is that the subject vehicle passed first at high speed, and the left-turning vehicle passed at low speed. The second case is that the subject vehicle passed behind, and it was at low speed or both vehicles were at high speed.

Table 2. The results of danger level assessment.

SSV/SOV		A	B	C	O	D	E	F	G
H/H	M	2.13	2.53	3.93	6.67	6.00	4.73	3.73	2.80
	SD	1.25	1.36	1.58	0.49	1.00	1.49	1.79	1.70
L/H	M	1.67	1.33	1.93	5.80	5.33	4.13	3.00	2.07
	SD	1.11	0.62	1.22	1.21	1.35	1.25	1.69	1.44
H/L	M	2.53	2.87	5.47	6.47	4.07	2.67	2.33	2.13
	SD	1.68	1.81	1.51	0.74	1.53	1.35	1.54	1.46
L/L	M	1.80	2.40	4.20	6.07	5.60	3.20	2.33	1.60
	SD	1.01	1.50	1.78	1.28	1.18	1.37	1.54	0.83

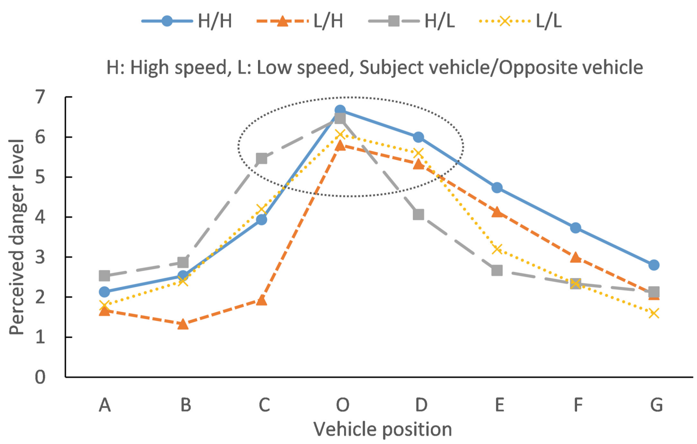


Fig. 5. The relationship between perceived danger level and distance to collision under different speed conditions.

3.3 Risk Acceptance

The risk acceptance for each test scenario was rated on a 7-point Likert scale, with 1 to 7 representing from totally unacceptable to perfectly acceptable. The results are shown in Table 3. Figure 6 shows the relationship between the risk acceptance and distance to collision when the subject vehicle and the opposite vehicle were driving at different speeds. It was found that risk acceptance and perceived danger level were roughly negatively correlated when comparing the corresponding curves in Fig. 6 and Fig. 5. That means drivers were less receptive to scenarios that feel dangerous and more receptive to scenarios that feel safe, which is consistent with common sense. However, there are exceptions as shown in Fig. 6. For example, D is the lowest point of curve L/H, which means that although the left-turning vehicle could pass the intersection at high speed before the subject vehicle, the small safe distance caused extreme discomfort to the subject vehicle. In addition, the risk acceptance changes of H/H and L/H at G were inconsistent with the danger level assessment, indicating the subject vehicle's low acceptance of the left-turning vehicle's behavior of rushing through the intersection at high speed.

Table 3. The results of risk acceptance assessment.

SSV/SOV		A	B	C	O	D	E	F	G
H/H	M	6.00	5.80	4.27	1.53	2.27	3.53	4.60	4.20
	SD	1.00	1.32	1.79	0.83	1.58	1.92	1.72	2.08
L/H	M	6.53	6.60	6.07	3.00	2.40	4.60	5.80	6.00
	SD	0.74	0.63	1.16	1.89	1.18	1.64	1.08	1.36
H/L	M	5.73	4.80	3.00	1.80	4.47	5.80	6.20	6.33
	SD	1.10	1.97	1.89	1.57	1.36	1.21	0.86	0.82
L/L	M	6.20	5.73	3.60	2.27	2.87	4.87	5.73	6.33
	SD	1.26	1.33	1.76	1.22	1.55	1.64	1.28	0.72

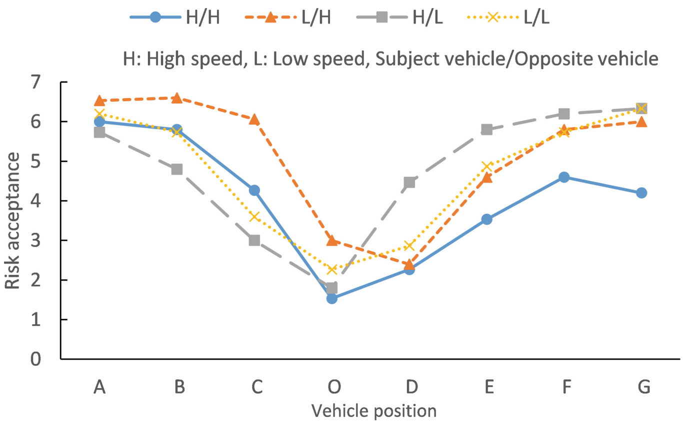


Fig. 6. The relationship between risk acceptance and distance to collision under different speed conditions.

4 Hazard Perception Model

4.1 Model Building

A hazard perception model for this traffic scenario was built to enable the experimental results to be applied in vehicle control of automated driving systems. Two cases were considered according to the order in which the two vehicles passed through the intersection: Case 1, the opposite vehicle passed first; Case 2, the subject vehicle passed first. For the first case, it was observed that the perceived danger level decreased with the increasing distance to collision (see Fig. 5, O to G). In addition, the perceived danger level should be zero when the distance is far enough according to common sense. Based on the observation and analysis of the danger level curves, the relationship between danger level and distance roughly conforms to the asymptotic regression model. The degree of curvature is mainly affected by SOV. Therefore, the model is represented as

$$r = \beta_1 + \beta_2 e^{\beta_3 \frac{d_1}{v_1}} \tag{1}$$

where r is the perceived danger level; d_1 is the distance between the two vehicles when the opposite vehicle is arriving at the intersection; and v_1 is the SOV. The experimental data of r were normalized before nonlinear regression analysis was performed. The parameter estimates, $\beta_1 = 0.117$, $\beta_2 = 0.801$ and $\beta_3 = -2.66$, were obtained ($R^2 = 0.910$). The model expression for Case 1 is

$$r = 0.117 + 0.801 e^{-2.66 \frac{d_1}{v_1}} \tag{2}$$

For the case of the subject vehicle passing first, the shape of the left part of the curve is similar to the right side. The curves H/H and L/L are very close. Based on the observation of the other two curves, the regression model expression for Case 2 is

$$r = \beta_1 + \beta_2 e^{\beta_3 \frac{v_1 d_2}{v_2}} \tag{3}$$

where r is the perceived danger level; d_2 is the distance between the two vehicles when the subject vehicle is arriving at the intersection; v_1 is the SOV; and v_2 is the SSV. The initial parameter estimates of nonlinear regression analysis were $\beta_1 = 0.193$, $\beta_2 = 0.712$ and $\beta_3 = -0.158$. The model was corrected considering the consistency of the two cases. The r values of the two equations should be the same when $d_1 = d_2 = 0$. The regression model for Case 2 is represented as the following equation after correction ($R^2 = 0.951$).

$$r = 0.193 + 0.725 e^{-0.161 \frac{v_1 d_2}{v_2}} \tag{4}$$

4.2 Model Application

The above model can reflect drivers' subjective perception of danger under different road conditions in that traffic scenario. Using this model in automated driving can help the vehicle control system to better understand the driver and passengers' psychological feelings of the hazard scenario, so that the automated driving behavior can not only meet the road safety needs, but also meet the users' psychological safety needs. In addition, it can also be customized according to different risk preferences of users. For example, an automated vehicle is going straight through the intersection at a speed of 30 km/h and meets an oncoming vehicle that is about to turn left at the intersection at a speed of 45 km/h. At this moment, the automated vehicle can determine the relationship between the perceived danger level and the relative position of the two vehicles based on the hazard perception model as shown in Fig. 7. The driving speed can be adjusted by comparing the perceived danger level with the user's risk preference. The customized automated driving system will be able to meet the psychological safety expectations of a specific user. This feature is particularly important in road traffic environments where automated vehicles and human-driven vehicles coexist, and can help improve the user experience of automated vehicles.

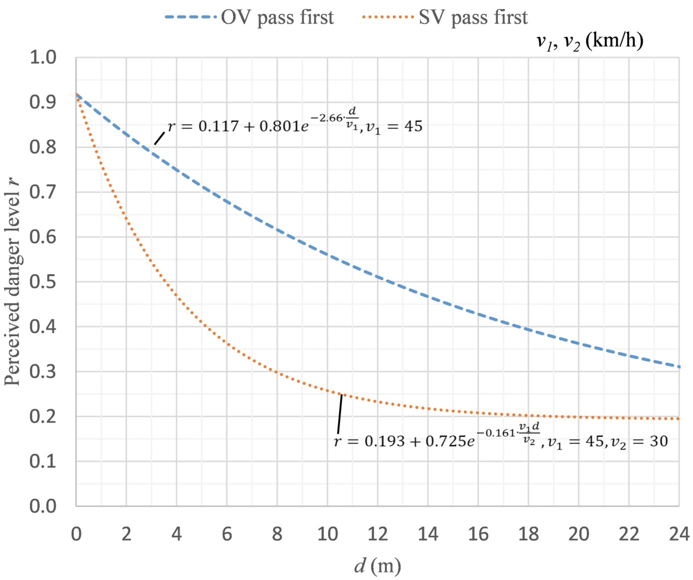


Fig. 7. The application of hazard perception model for the given traffic scenario. OV is short for opposite vehicle and SV is short for subject vehicle.

5 Conclusion

It is crucial to improve user experience of automated vehicles by considering drivers' psychological model of hazard perception. This work takes a typical traffic scenario where a straight vehicle encounters a left-turning vehicle in the opposite lane at an intersection as an example. The effects of the two vehicles' speeds and distance to collision on driving behaviors, perceived danger level, and risk acceptance were investigated through a driving simulation experiment. A regression model of driver hazard perception was built based on the experimental results. The regression model fit the data well, which can effectively reflect the quantitative relationship between perceived danger level and the relevant road condition parameters, so that the automated driving system can better understand users' psychological safety expectations. It makes the customized design based on user's risk preference become possible.

The hazard perception modeling method is also applicable to other types of hazard scenarios. Other hazard scenarios will be experimentally researched and modeled in future. In addition, only vehicle speed and distance to collision were considered as impact variables in the regression model. Drivers' perception of danger may also affected by their previous experience [10]. The sample size of this study is relatively small. Therefore, the influence of other factors will be further investigated with a bigger sample size to improve the accuracy of the model in future.

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