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Lane-Changing Risk Analysis in Undersea Tunnels Based on Fuzzy Inference

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ABSTRACT Lane-changing in undersea tunnels has a negative impact on the normal traffic flow, and even lays hidden dangers for the occurrence of traffic accidents. Lane-changing behavior in undersea tunnels was divided into free, compulsory, and collaborative lane-changing types according to the characteristics of traffic flow to explore lane-changing risk in undersea tunnels. A fuzzy inference analysis on the three lane-changing behaviors was conducted on the basis of the behavior characteristics of fuzzy uncertainty of drivers. The most representative influencing variables, including speed difference, initial space of vehicles, traffic density, and distance for minimum lane-changing, were selected as fuzzy input variables, and lane-changing risk was used as an output variable to construct fuzzy rules for different lane-changing behavior. Risks of the three lane-changing behaviors were simulated by MATLAB/Simulink. Results demonstrated that the compulsory lane-changing in undersea tunnel was the riskiest, followed by collaborative and free lane-changing. Slope considerably influenced lane-changing risk. Specifically, the lane-changing risk at the downhill section was the highest, and the lane-changing risk at the uphill section was the lowest. The lane-changing risk at the flat section was between them.

INDEX TERMS Fuzzy inference, risk analysis, undersea tunnel, vehicle lane-changing.

I. INTRODUCTION

Undersea tunnel is a large traffic infrastructure for solving traffic interruption between the two sides of straits and bays. The traffic flow in undersea tunnel is large due to its traffic connection function. Any traffic accidents in undersea tunnel easily cause loss of local traffic functions and even traffic paralysis of the entire undersea tunnel, thereby inducing large-scaled local traffic jam. Unlike a relatively flat open traffic environment, the undersea tunnel is approximately a closed space. This undersea tunnel is a narrow longitudinal slope that can amplify the potential threats and occurrence of traffic accidents due to traffic density, vehicle speed, and lane-changing behavior of drivers. As a result, the influencing factors of traffic safety in undersea tunnels are explored, and this exploration is important in preventing traffic accidents.

Lane-changing refers to a driving behavior in which a vehicle changes from the original lane to the adjacent lane for certain reasons. Although lane-changing is a common driving behavior on a flat open highway, lane-changing behavior against regulations or random lane-changing behavior in an undersea tunnel influences the stability of tunnel traffic flow considerably and even may cause serious traffic accidents. Therefore, relevant traffic laws often forbid lane-changing in an undersea tunnel. Nevertheless, many drivers ignore relevant traffic laws and change lanes in an undersea tunnel and even overtake other cars. These driving behaviors cause great hazard and threats to the traffic environment in an undersea tunnel [1]–[3].

Lane-changing is one characteristic of traffic flow. Gipps proposed a lane-changing model that considered the influences of lane-changing risk, veering demands, and distance to barriers. Relevant rules were also designed to distinguish the influencing factors of lane-changing behaviors [4]. Tang et al. constructed a lane-changing model that

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considered lane-changing frequency based on the Gipps model and introduced random error into the model. In this model, lane-changing behavior was divided into four stages, namely, considering lane-changing, selecting the target lane, searching acceptable space, and implementing lane-changing behavior [5]. Olsen et al. divided lane-changing behavior into three types according to demands, including free, compulsory, and collaborative lane-changing [6]. Kesting *et al.* proposed the MOBIL (minimizing overall braking induced by lane change) model that considered acceleration control [7]. Xu *et al.* constructed a lane-changing model that considered the characteristics of drivers [8]. Liu and Wang investigated the application of cellular automata theory in compulsory lane-changing behavior [9]. Qiu *et al.* constructed a lane-changing model by using the Bayesian network and attempted to increase the accuracy of the lane-changing model through machine learning [10]. Talebpour *et al.* presented a lane-changing model based on a game theoretical approach that endogenously accounted for the flow of information in a connected vehicular environment [11]. Zhang *et al.* adopted a deep-learning model and long short-term memory neural network to simultaneously model car-following and lane-changing behaviors [12].

Existing studies on lane-changing behavior mainly focus on macroscopic and microscopic studies in highway or urban roads. Some research achievements on model construction have been acquired. However, only few studies on the lane-changing behavior in an undersea tunnel have been reported. For this reason, key attentions were paid to the risk characteristics of lane-changing behavior in an undersea tunnel in the present study.

Fuzzy inference is a reasoning process that may draw conclusions from an inaccurate precondition set. This process can effectively describe driving behavior characteristics because it conforms to the subjective decision-making program of drivers in actual traffic environment. Fuzzy inference is widely applied in car-following and lane-changing behaviors in traffic flows due to this unique advantage. Wang *et al.* used logic method to describe the judgment process based on drivers' knowledge and experience and established a microscopic lane-changing model [13]. Mar and Lin designed a collision prevention system based on cascaded fuzzy inference system for lane-changing maneuver and car following to provide a safe, reasonable, and comfortable drive for car following and lane-changing [14]. Lin *et al.* designed compulsive and discretionary lane-changing fuzzy controllers, which were used to determine whether a vehicle will change lane with the help of the knowledge and experience of a driver [15]. Moridpour developed an exclusive fuzzy lane-changing model for heavy vehicles. The fuzzy model can increase the accuracy of simulation models in estimating the macroscopic and microscopic traffic characteristics [16]. Qiu *et al.* used fuzzy-clustering analysis method to divide variables into various fuzzy sets and established a car-following fuzzy inference system with a higher simulation accuracy of error indexes in comparison with that of the Gipps mode [17]. Li *et al.* extracted fuzzy rules of three lane-changing ways and constructed lane-changing models based on fuzzy reasoning [18].

Compared with ordinary mountain tunnels, undersea tunnels have unique characteristics. Although mountain tunnels and undersea tunnels are both closed spaces, their undersea tunnels have to extend from land to seabed and pass through below the seabed to the land again. Undersea tunnels present V-shaped structures. Several sufficiently long undersea tunnels are constructed into a U-shaped structure, which has a flat section at the valley. However, most existing undersea tunnels are V-shaped structures. In other words, undersea tunnels must have a longitudinal slope. Although numerous mountain tunnels have a longitudinal slope, they often extend toward one direction rather than V -shaped structures. Traffic flow characteristics in such V-shaped undersea tunnels may not be completely consistent with those of ordinary highways.

Lane-changing behaviors and characteristics were classified according to the characteristics of traffic flow to deeply analyze the lane-changing behaviors in an undersea tunnel. Different lane-changing behavior models in an undersea tunnel were constructed on the basis of fuzzy inference. The validity and accuracy of models were verified by a system simulation. A new method for recognizing the risk degree of lane-changing behaviors in an undersea tunnel under different slopes was provided by constructing a model based on fuzzy inference. Research conclusions lay foundations to traffic safety management in undersea tunnels.

II. TRAFFIC FLOW ANALYSIS IN AN UNDERSEA TUNNEL

A. CAR-FOLLOWING MODE ANALYSIS IN AN UNDERSEA TUNNEL

As a traffic facility that connects two sides of straits or bays, an undersea tunnel considerably promotes social economic developments in two sides. No vehicles are allowed to change lanes or overtake other cars under normal driving conditions in undersea tunnels due to their V-shaped physical structure and large traffic flow. Moreover, nearly no other lane exists in undersea tunnels, except for ordinary lanes. Therefore, traffic flow characteristics are evident in an undersea tunnel, accompanied with prominent car-following modes (Figure 1, physical images of the Jiaozhou Bay undersea tunnel in Qingdao City). Several radical drivers may change to another lane when the front vehicle is slower from the expected speed, and the adjacent lane has adequate space. Drivers in the adjacent lane do not expect such lane-changing behavior. The V-shaped structure of undersea tunnels can significantly influence vehicle speed, which is easily ignored by most drivers. In other words, lane-changing behavior in an undersea tunnel has great risks. In fact, data statistics also reflects that lane-changing behavior is the main cause of traffic accidents in an undersea tunnel.

B. LANE-CHANGING BEHAVIORAL CHARACTERISTICS

Relevant traffic laws state that vehicles are prohibited to change lanes or overtake other cars in an undersea

a) Before lane-changing behavior of the white car

b) After lane-changing behavior of the white car

FIGURE 1. Traffic flow and lane-changing behavior in an undersea tunnel.

tunnel under normal traffic conditions. Nevertheless, such dangerous driving behaviors cannot be completely eradicated in reality. When the front car is driving slowly, several drivers may opt to change to the adjacent lane to avoid car-following behavior or to realize the expected vehicle speed. Lane-changing behavior requires the speed-space comparative disadvantage and psychological conditions for safe lane-changing. Speed-space comparative disadvantage means that the expected vehicle speed cannot be realized in the current lane, but it can be achieved in the adjacent lane. The psychological conditions for safe lane-changing mean that the driver estimates that the current traffic environment supports safe lane-changing. In this process, the lane-changing behavior of the driver experiences four programs, namely, perception, impulsion, judgment, and operation [19]. The driver initially perceives surrounding traffic environments. When he/she is unsatisfied about the current lane, the driver forms impulsion for lane-changing. Then, the driver judges the surrounding traffic environment and finally operates the vehicle to the adjacent lane under the perceived safe conditions.

The preceding analysis indicates that existing lane-changing types emphasize the division of lane-changing behaviors into judgment and compulsory lane-changing from the perspective of drivers' demands. In fact, lane-changing behavior can be implemented under the collaboration of subjective intention and the driving behavior of surrounding vehicles, including avoidance, assistance, or competitive motility of following cars in the target lane. Therefore, the traditional division method often cannot accurately simulate the complicated lane-changing behaviors. On the basis of previous theoretical studies of lane-changing behaviors, lane-changing behaviors in an undersea tunnel were divided into free, collaborative, and compulsory lane-changing according to the interaction of lane-changing and following cars in the target lane.

(1) Free lane-changing refers to the state in which a vehicle changes to the target lane without influencing the front and back vehicles in the current lane and following cars in the target lane. This lane-changing state condition is the safest and most ideal.

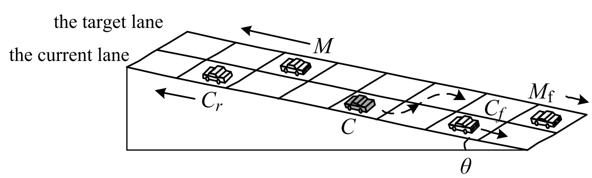
(2) Collaborative lane-changing means that a vehicle makes good interactions with surrounding vehicles in the process of lane-changing and changes to the target lane under the good assistance of following cars in the target lane. This interactive lane-changing behavior is harmonious.

(3) Compulsory lane-changing means that a vehicle coercively turns to the target lane when no sufficient condition is met for lane-changing, thereby forcing the following car in the target lane to slow down. Compulsory lane-changing is an important cause of traffic accidents in an undersea tunnel.

The risk characteristics of lane-changing behaviors in uphill, flat, and uphill sections of an undersea tunnel could be analyzed on the basis of the unique linear structure of undersea tunnels.

III. CONSTRUCTION OF A LANE-CHANGING RISK PREDICTION MODEL BASED ON FUZZEY INFERENCE

Lane-changing behavior mainly involves the current (the original lane) and target lanes. Thus, the current and target lanes were hypothesized as the environment for lane-changing behavior. The current and target lanes were also viewed as two discrete lattice diagrams composed of n cellulars. Stimulus-response theory states that vehicles in the adjacent vehicles may be stimulated by different extents and make different responses when vehicle C changes to the adjacent lane. Figure 2 shows the different stimulatory effects of lane-changing behavior of vehicle C to surrounding vehicles.



Notes: Solid lines with arrows refer to stimulus intensity and direction of lane-changing of vehicle C to surrounding vehicles.

FIGURE 2. Stimulus-response diagram of lane-changing behavior.

The desired safe space is a firm guarantee for safe lane-changing. The desired safe space is mainly determined by the initial longitudinal space and speed difference between the lane-changing vehicle and the front car in the target lane and lane-changing time. When the vehicle space is larger than the desired safe space, vehicles can safely change to adjacent lanes. This process has to meet

$$S(t) = \Delta D + \int [v_C(t) - v_M(t)]\, dt - L_C \geq 0 \tag{1}$$

where $S(t)$ is the real-time space between front and back vehicles. $v_{\mathrm{C}}(t)$ is the real-time speed of the lane-changing vehicle C. $v_{\mathrm{M}}(t)$ is the real-time speed of following car M in the target lane. ΔD refers to the initial space between front and back vehicles. L_{C} is the length of a vehicle.

A. BASIC PRINCIPLE OF FUZZY INFERENCE

Fuzzy system is based on the natural language that conforms to the thinking habit of a human; thus, convenient and fast prediction and control over uncertain inference can be achieved. Fuzzy inference is a process of mapping certain inputs to outputs according to the logic rules of a fuzzy system. This process is widely applied in the decision-making modeling of human and can describe the characteristics of driving behaviors that cannot be accurately expressed in a mathematical model. In the research field of driving behaviors, traffic experts often control or solve the complicated nonlinear problem in car-following and lane-changing behaviors by using the fuzzy technology. Fuzzy inference generally covers the following steps [20], [21]:

(1) Fuzzification of input variables: This step transforms certain inputs into a fuzzy set described by a membership function.

(2) Applying a fuzzy operator (and-or-not) to the antecedent part of fuzzy rules

(3) Inferring conclusions from antecedent parts according to the fuzzy implication rule

(4) Synthesizing the conclusion of each rule and finally obtaining the overall conclusion

(5) Anti-fuzzification: This step transforms fuzzy variables into certain outputs

In the fuzzification process, the input value has to be transformed into a numerical value of domain of discourse at an appropriate proportion. Physical variables were described and measured by colloquial variables, and then the relative degree of membership of the numerical value was calculated according to an appropriate language value. Common centralized membership functions include Gaussian, generalized bell-shaped, S-shaped, trapezoid, and triangular membership functions. In this study, the triangular membership function was applied as the main proportional transformation mode according to the characteristics of lane-changing behavior supplemented by the trapezoid membership function to process two ends of the domain of discourse. In the triangular membership function, fuzzy samples $\{x_j\}_{j=1}^{n}$ and a domain of discourse of U exist. The first-order partition of U $\{P_i\}_{i=1}^{r}$ is performed, and the corresponding language variable is $\{L_i\}_{i=1}^{r}$. m_i is the intermediate value of the partition set p_i, and x_j is between m_i and m_{i+1}. The membership of the language variable L_i is $\frac{m_{i+1}-x_j}{m_{i+1}-m_i}$, and the membership of the language variable L_{i+1} is $\frac{x_j-m_i}{m_{i+1}-m_i}$. The transformation based on the trapezoid membership function was not introduced in this study, because it is similar to that of the triangular membership function. The risk prediction models of three lane-changing behaviors were constructed by using the fuzzy control method in the following text.

B. FUZZY INFERENCE MODEL OF FREE LANE-CHANGING BEHAVIOR

1) DETERMINING THE FUZZY SET OF FREE LANE-CHANGING BEHAVIOR

Under free lane-changing state, vehicle C will not influence the following car (C_r) and front car (C_f) of the current lane and the vehicle (M_f) in the target lane due to small traffic density and large space between vehicles, or such influence can be neglected. The running state of vehicle C may not disturb the overall dynamic situation of the traffic flow in lanes, or the disturbance could be ignored. In this case, speed difference ($\Delta v_{\mathrm{CM}} = v_{\mathrm{C}}(t) - v_{\mathrm{M}}(t)$) and initial space of vehicles (ΔD) between vehicles C and M in the target lane are primary factors that influence lane-changing safety. Thus, Δv_{CM} and ΔD were selected as the input variable of the fuzzy inference model of free lane-changing. In this fuzzy inference model, the fuzzy subset of Δv_{CM} is {large negative, small negative, zero, small positive, large positive}. The discrete domain of discourse of Δv_{CM} is selected as $\Delta v_{\mathrm{CM}} = \{-4, -2, 0, 3, 5\}$ (units: cellular, hereinafter the same). The fuzzy subset of the initial space of vehicles (L_0) is {very near, near, moderate, far, very far}, and the discrete domain of discourse of ΔD is selected as $\Delta D = \{1, 3, 4, 5, 7\}$. Figure 3 shows the membership functions of two input variables.

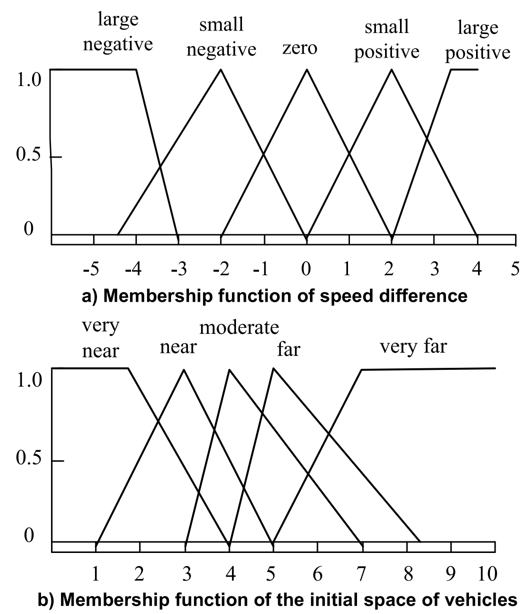


FIGURE 3. Membership functions of variables in the fuzzy inference model of free lane-changing.

2) FUZZY EVALUATION OF FREE LANE-CHANGING RISKS

If the output is lane-changing risk degree RD, then the fuzzy subset is safe, generally safe, risky, very risky, accident, and the domain of discourse is $RD = \{\mathrm{S, M, L, XL, XXL}\}$.

TABLE 1. Fuzzy rule of risks in the fuzzy inference model of free lane-changing behavior.

Lane-changing risk degree (*RD*)		Speed difference Δv_{CM}				
		Large negative	Small negative	Zero	Small positive	Large positive
Initial space of vehicles ΔD	Very near	XXL*	XXL*	XL*	L*	M*
	Near	XXL*	XL*	XL*	L*	M*
	Moderate	XL	XL	L	L	S
	Far	XL	L	M	M	S
	Very far	L	M	M	S	S

* reflects small possibility of the situation.

Here, S stands for safety, M stands for general safety, L stands for risky, XL stands for very risky and XXL stands for accident. The fuzzy rule of free lane-changing risk was constructed (Table 1).

C. FUZZY INFERENCE MODEL OF COMPULSORY LANE-CHANGEING BEHAVIOR

1) DETERMINING THE FUZZY SET OF COMPULSORY LANE-CHANGING BEHAVIOR

The compulsory lane-changing behavior can be divided into positive and coercive types. The former one is mainly attributed to the strong radicalism of the driver. The driver opts for the adjacent lane when the driving speed of the front car cannot meet his/her expectation. The latter mainly refers to the lane-changing behaviors due to front barriers or traffic limitations and the delayed action of lane-changing behavior. The distance for the minimum lane-changing can influence the occurrence of the compulsory lane-changing behavior. According to Reference [22], the lane-changing pressure (ψ) refers to the degree of passive impacts in lane-changing behavior, and it is sensitive to the distance for the minimum lane-changing (l). Radicalism of driver is an abstract summary of driver types (conservative and radicalism types). The radicalism coefficient (ζ) can reflect the positive factors of drivers' compulsory lane-changing behavior. Given the same vehicle space, radical drivers are more confident on lane-changing behavior and acts more frequently than conservative drivers. As a result, expression of radicalism is mainly determined by ΔD (or traffic density (ρ)). The higher ΔD is, the higher ζ and the possibility of drivers' compulsory lane-changing behavior will be.

$$\psi = \frac{50 - l}{50}, \quad 0 \leq l \leq 50 \tag{2}$$

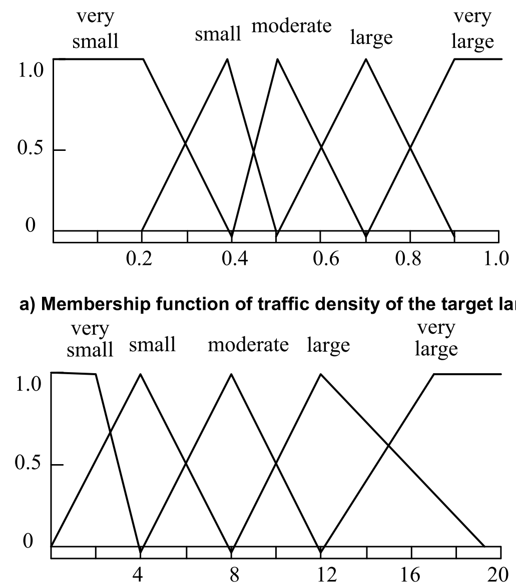
where ψ is the lane-changing pressure, and l is the distance for the minimum lane-changing.

Therefore, the feasibility for compulsory lane-changing behavior of the driver can be calculated as

$$\gamma = \lambda/(\psi\zeta) \tag{3}$$

where γ is the feasibility of lane-changing behavior, and λ is a coefficient.

On the basis of the preceding analysis, the traffic density (ρ) and distance for the minimum lane-changing (l) are selected as the input variable of the fuzzy inference model of compulsory lane-changing behavior. The fuzzy subset of traffic density is {very small, small, moderate, large, very large}, and its domain of discourse is $\rho = \{0.2, 0.4, 0.5, 0.7, 0.9\}$. The fuzzy subset of distance for the minimum lane-changing is {very small, small, moderate, large, very large}, and its domain of discourse is $l = \{2, 4, 8, 12, 17\}$. The membership functions of two input variables are shown in Figure 4.



a) Membership function of traffic density of the target lane

b) Membership function of distance for the minimum lane-changing

FIGURE 4. Membership function of variables in fuzzy inference model of compulsory lane-changing behavior.

TABLE 2. Fuzzy rule of risks in the fuzzy inference model of compulsory lane-changing behavior.

RD		Traffic density ρ				
		Very small	Small	Moderate	Large	Very large
Distance for the minimum lane-changing l	Very small	XL	XL	XL	XXL	XXL
	Small	L	L	XL	XXL	XXL
	Moderate	M	L	XL	XXL	XXL
	Large	S	M	L	XL	XXL
	Very large	S	S	M	XL	XL

2) FUZZY EVALUATION OF COMPULSORY LANE-CHANGING RISK

The fuzzy rule of compulsory lane-changing risk was constructed (Table 2).

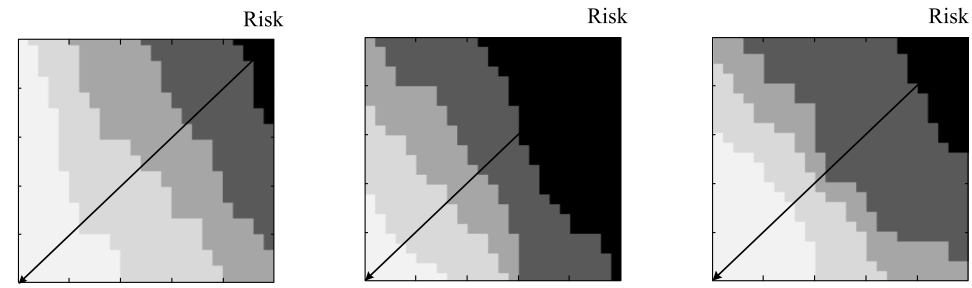


FIGURE 5. Color gradation of RD of three lane-changing behaviors.

D. FUZZY INFERENCE MODEL OF COLLABORATIVE LANE-CHANGING BEHAVIOR

1) DETERMINING THE FUZZY SET OF COLLABORATIVE LANE-CHANGING BEHAVIOR

Collaborative lane-changing is a near-distance lane-changing behavior based on mutual communication and cooperation. Whether vehicle C can conduct lane-changing behavior smoothly is determined through the judgment and decision of following car M in the target lane. If vehicle M opts to actively cooperate and slow down when it sees the lane-changing signal of vehicle C, then the lane-changing conditions are met. On contrary, if vehicle M rejects the lane-changing request of vehicle C and keeps driving at a constant speed or accelerated speed, then vehicle C cannot conduct lane-changing behavior. However, vehicle C's decision on speed changing is mainly reflected by the type of drivers, that is, the radicalism coefficient ζ. Deceleration of vehicle M is also determined by traffic density of the target lane. When ρ is large, the space between vehicle M and the following car is small. With considerations to safety, vehicle M will not cooperate with vehicle C in lane-changing behavior. From the preceding analysis, ΔD and ρ were selected as fuzzy set of the compulsory lane-changing behavior. Fuzzy subsets of ΔD and ρ are the same as mentioned previously.

2) FUZZY EVALUATION OF COLLABORATIVE LAND-CHANGING RISK

The fuzzy rule of collaborative lane-changing risk was constructed (Table 3).

TABLE 3. Fuzzy rule of risks in the fuzzy inference model of collaborative lane-changing behavior.

RD		Traffic density ρ: Very small	Small	Moderate	Large	Very large
Initial space L_0	Very near	L	XL	XL	XL	XXL
	Near	L	L	XL	XL	XXL
	Moderate	S	M	XL	XL	XL
	Far	S*	S*	M*	XL*	XL*
	Very far	S*	S*	M*	L*	L*

* reflects small possibility of the situation.

IV. MODEL SIMULATION AND RESULT ANALYSIS

Three lane-changing behaviors were fitted by the MATLAB/Simulink simulation environment on the basis of the constructed fuzzy inference models and fuzzy rules of *RD*. In simulation models, fuzzy control applies the fuzzy controller component provided by the Simulink environment, and the fuzzy control database is edited by Fuzzy of MATLAB. Influences of input variables on *RD* are manifested by a color gradient diagram (Figure 5). *RD* is reflected by different colors. The darker color refers to higher risk for lane-changing behavior under this circumstance, whereas lighter color implies the higher safety for lane-changing behavior.

The color gradient diagram of simulation analysis shows that the compulsory lane-changing behavior in an undersea tunnel has the highest risk, followed by collaborative and free lane-changing behaviors. In other words, free lane-changing is safer than collaborative lane-changing, and collaborative lane-changing is safer than compulsory lane-changing. The simulation results conform to actual traffic flow in an undersea tunnel.

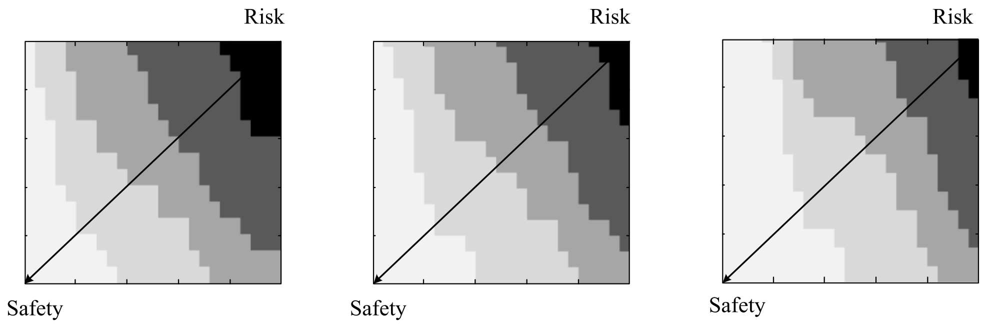
Risk characteristics of lane-changing behavior at downhill, flat, and uphill sections of a V-shaped undersea tunnel were analyzed by introducing a slope influence coefficient. The Jiaozhou Bay undersea tunnel in Qingdao City was used as the research object in this study. The length of the undersea tunnel is 7797 meters, with a maximum downhill of - 3.54% and a maximum uphill of 3.90%. The basic relationship between slope and slope length is shown in Table 4.

Taking the basic slope and slope length of Jiaozhou Bay undersea tunnel as parameters, the simulation was carried out, and *RD* changes of three lane-changing behaviors with slope were disclosed (Figures 6-8).

A comparison of Figs. 6-8 implies that lane-changing risk is highly sensitive to slope. Lane-changing risk reaches the peak at the downhill section and the valley at the uphill section. The lane-changing risk at flat section is found between them. When vehicle C sends request of lane-changing at the downhill section, vehicle M slows down to some extent under the premise of tailgating of back vehicles. However, such deceleration act is mainly based on vehicle perception on open horizontal roads, whereas the acceleration by slope of road is often ignored, thereby causing accidents. Moreover, the compulsory lane-changing behavior of the front car will cause the back car to make delayed response and thereby increase the risk, because lane-changing

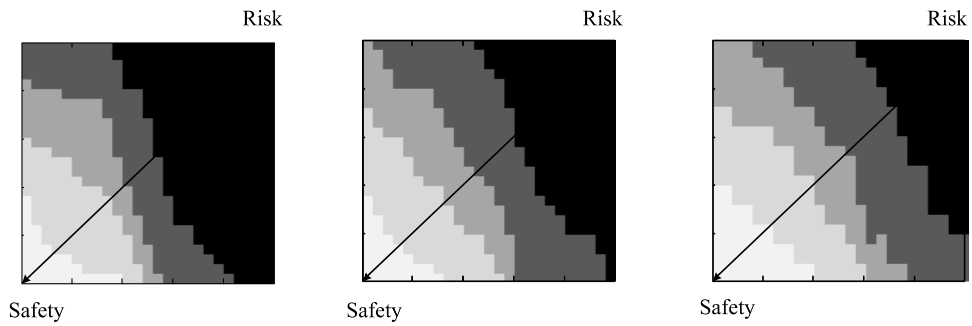
TABLE 4. The basic relationship between slope and slope length about Jiaozhou Bay undersea tunnel.

Slope (%)	-3.54	-2.15	-0.30	-3.50	-2.23	0.00	2.88	3.90	2.47	3.90
Slope length (m)	314	750	895	815	1488	865	765	750	365	790



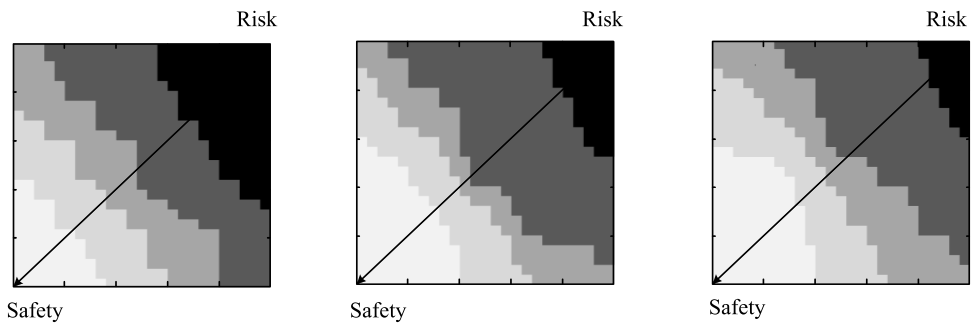
a) Downhill section b) Flat section c) Uphill section

FIGURE 6. ***RD*** **analysis of free lane-changing under different slope environments.**



a) Downhill section b) Flat section c) Uphill section

FIGURE 7. ***RD*** **analysis of compulsory lane-changing under different slope environments.**



a) Downhill section b) Flat section c) Uphill section

FIGURE 8. ***RD*** **analysis of collaborative lane-changing under different slope environments.**

in tunnels is generally forbidden. The simulation results conform to the actual situation.

V. DISCUSSIONS

The characteristics of a V-shaped undersea tunnel are different from those of ordinary mountain tunnels. The lane-changing behavior in a V-shaped undersea tunnel not only has complexity of operation but also has evident risks. Although the lane-changing of vehicles in an undersea tunnel is forbidden, it cannot be completely eradicated in practice. In this study, the lane-changing behavior in an undersea tunnel is divided into free, collaborative, and compulsory lane-changing. The risks of the three lane-changing behaviors are evaluated by fuzzy inference. The triangle membership function is selected from the perspective of qualitative analysis, assisted by trapezoid membership function. However, multiple membership functions, such as Gaussian, generalized bell-shaped, and S-shaped membership functions, exist.

In this study, not all membership functions are evaluated individually. Finally, different membership functions might cause various analysis outcomes.

VI. CONCLUSION

Free, compulsory, and collaborative lane-changing behaviors in an undersea tunnel are analyzed. Lane-changing risk of an undersea tunnel is analyzed on the basis of fuzzy inference. Several conclusions could be drawn.

(1) Fuzzy inference models of three lane-changing behaviors (free, compulsory, and collaborative lane-changing) and fuzzy rules of relevant risk degree in an undersea tunnel are concluded.

(2) The simulation results show that compulsory lane-changing risk in an undersea tunnel is the highest, whereas the free lane-changing risk is the lowest. Collaborative lane-changing risk is between the aforementioned risks. In other words, the free lane-changing behavior is safer than the collaborative lane-changing behavior, and the collaborative lane-changing is safer than the compulsory lane-changing behavior.

(3) The simulation results also indicate that slope can considerably influence lane-changing risk. Lane-changing risk reaches the maximum at downhill section and the minimum at the uphill section. The lane-changing risk at the flat section is between those of downhill and uphill sections.

Conclusions (2) and (3) indicate that the compulsory lane-changing risk at the downhill section of an undersea tunnel is extremely high and might cause traffic accidents. Therefore, such lane-changing behavior shall be strictly prohibited.

To sum up, fuzzy inference models of lane-changing behavior and fuzzy rules of risk degree in an undersea tunnel can provide reference for traffic safety management and risk control and provide suggestions for drivers to drive safely in an undersea tunnel.

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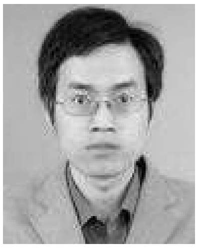

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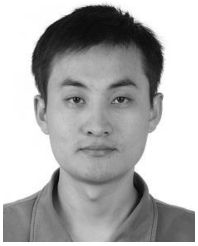

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