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RESEARCH ARTICLE

Analysis and Modeling of Lane-Changing Game Strategy for Autonomous Driving Vehicles

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ABSTRACT Autonomous driving vehicles have some advantages, such as alleviating tasks of drivers and reducing carbon emissions. With the advancement of intelligent network connection technology, autonomous driving vehicles are showing a trend of practicality and popularization, so it is crucial to study the decision-making mechanism of autonomous driving vehicles. This paper focuses on the lane-changing decision-making behavior of autonomous driving vehicles. Firstly, the objective quantification of lane-changing intention is carried out to reasonably show the lane-changing intention of autonomous driving vehicles as a prerequisite for lane-changing decision-making. Besides, the lane-changing collision probability and the lane-changing dynamic risky coefficient are introduced, and explore the dynamic influencing factors of lane-changing process for autonomous driving vehicles. Based on the game theory, the decision-making behavior model of the lane-changing game for autonomous driving vehicles is established. Analyze the decision-making behavior mechanism of lane-changing, so that the autonomous driving vehicle can change lanes safely and reasonably. Finally, with SUMO software, the traditional LC2013 lane-changing model and the decision-making behavior model of the lane-changing game are used for simulation experiments and comparative analysis. The results show that under the decision-making behavior model of the lane-changing game, the average speed of vehicles increases by 3.6%, and the average number of passed vehicles increases by 10.3%, which has higher stability, safety, speed gains, and lane utilization. The modeling of lane-changing game strategy for autonomous driving vehicles comprehensively considers the dynamic factors in the traffic environment, and scientifically shows the lane-changing decision-making mechanism of autonomous driving vehicles.

INDEX TERMS Intelligent transportation, autonomous driving, lane-changing behavior, decision-making method, game strategy.

I. INTRODUCTION

With the development of advanced technologies, such as Internet of vehicles, cloud computing, and big data, the atmosphere of intelligent network connection environment is becoming stronger and stronger. For vehicles, especially autonomous driving vehicles, the introduction of intelligent network connection technology has continuously improved their functions, which not only improves the experience of users, but also alleviates some traffic problems. With the increasing number of automobile users, a series of problems such as congestion and accidents have also occurred in traffic, and the related problems are becoming more and more serious. Under these circumstances, autonomous driving technology has emerged and developed continuously. With the support of intelligent network connection technology, autonomous driving technology can reduce the driving task of drivers to a certain extent, so as to improve travel efficiency and safety. Autonomous driving vehicles are usually divided into six levels, and the higher the level of autonomous driving get, the higher the degree of intelligence and automation become [1].

Autonomous driving technology is divided into three main processes: environmental perception, decision-making

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planning, and executive control. Among them, the decision-making part directly reflects the intelligence of autonomous driving vehicles, which plays a vital role in the performance and driving safety of the whole vehicle. Generally, the richer the functions expected to be realized, the more important and difficult the autonomous driving decision-making is. Lane-changing decision-making is an extremely important part of autonomous driving decision-making. Furthermore, lane-changing behavior will increase the incidence of traffic accidents and lead to traffic congestion. At the same time, it is also one of the research hotspots in the traffic field. Therefore, this paper studies the lane-changing decision-making of autonomous driving vehicles.

II. ANALYSIS OF LANE-CHANGING BEHAVIOR

Lane-changing behavior is a basic decision-making behavior of autonomous driving vehicles, which generally needs a good driving environment. In the intelligent network connection environment, autonomous driving vehicles can accurately perceive the surrounding vehicles and environment, make the lane-changing decision-making safe and efficient, and finally improve the reliability and success rate of the lane-changing process [2].

With the application and development of autonomous driving technology, relevant researchers have carried out a series of studies on the lane-changing model of vehicles. Gipps [3] established a lane-changing decision-making model of vehicles through hierarchical decision-making, which provides ideas for the study and development of subsequent lane-changing decision-making for vehicles. Kanaris *et al.* [4] established a lane-changing model of vehicle by evaluating the lane-changing environment around the vehicle, and finally determined whether the vehicle can change lanes with a safe distance. Jula *et al.* [5] established the minimum longitudinal safety distance model to evaluate whether the lane-changing behavior of vehicles is safe. Peter [6] classified lane-changing from the perspective of reciprocity in the process of lane-changing. Langar *et al.* [7] established the lane-changing decision-making model of vehicles through game theory, and selected the deterministic strategy or mixed strategy by analyzing the gains matrix, so as to ensure the safe lane-changing of vehicles. Song [8] established the finite state machine decision-making model and Markov decision-making model respectively from the lateral and longitudinal perspectives, which makes the cooperative driving between vehicles more effective. Nie [9] established a lane-changing decision-making model of vehicles through deep learning and verified it by simulation of MATLAB software. The results show that the model makes the lane-changing of vehicles have high accuracy. Li [10] established a lane-changing decision-making model of vehicles based on fuzzy logic theory, which was verified by simulation of CarSim software. The results show that the model improves the safety of lane-changing for vehicles. Yoo *et al.* [11] developed an approach for modeling the interaction between autonomous and human-driven vehicles via game theory and analyzed the process of lane-changing. Yu *et al.* [12] presented a game theory-based lane-changing model and found the optimal timing and acceleration for changing lanes. Ali [13] developed a game theory-based mandatory lane-changing model. The model can effectively capture mandatory lane-changing decisions with a high degree of accuracy. Lopez *et al.* [14] addressed the problem of decision making for autonomous vehicles changing lanes by formulating multiple games in normal form for pairs of agents. Yao *et al.* [15] investigated the lane-changing behaviors for buses, analyzed the interactions between buses and social vehicles based on game theory, and offered the decent theoretical support for both players to make better decisions. Qu *et al.* [16] established a lane-changing model of autonomous driving vehicles based on the idea of game theory, analyzed the performance of the model with the number of vehicle accidents and other indicators, and verified that the proposed game lane-changing model has good safety and stability.

Generally speaking, the study on lane-changing decision-making by researchers mainly focuses on considering the vehicle speed, position, and other parameters. They established the lane-changing model of vehicle based on rule or safe vehicle distance in combination with the road traffic environment. However, they lack consideration of both safety and fairness in the process of lane-changing. In addition, scholars focus on the fixed critical gap around the lane-changing vehicles and pay less attention to the dynamic factors in the lane-changing scene. In the intelligent network connection environment, while the safety of autonomous driving vehicles is met in the process of lane-changing, it should also ensure that both sides of autonomous driving vehicles in conflict have a certain fairness. Researchers have conducted a series of studies by using game theory. Under this background, this paper will quantify the lane-changing intention and establish the decision-making behavior model of the lane-changing game for autonomous driving vehicles according to the game behavior in the process of lane-changing, so as to make autonomous driving vehicles run more safely and efficiently.

The lane-changing behavior of vehicles is generally divided into discretionary lane-changing and mandatory lane-changing [17]. Mandatory lane-changing refers to the behavior that lane-changing must be carried out due to traffic rules and other conditions. Nevertheless, discretionary lane-changing has a certain degree of autonomy and non-necessity. Moreover, sometimes it will be affected by objective conditions and subjective factors to make the decision of giving up lane-changing [18]. As shown in Figure 1, in the discretionary lane-changing scene of one-way double lane, there are FV(Front vehicle) in front of the target lane, PV(Preceding vehicle) in front of the current lane, RV(Rear vehicle) in the rear of the target lane and LV(Lane-changing vehicle) in the current lane, which run along the lane centerline respectively. They are all autonomous driving vehicles, and LV is autonomous driving lane-changing vehicle. When the LV is driving on the current lane, the speed of LV is constrained

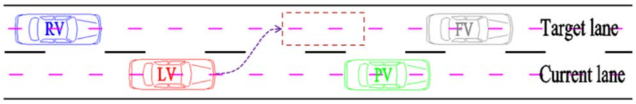


FIGURE 1. **Discretionary lane-changing scene.**

by the PV and does not reach the expected speed, resulting in the intention of lane-changing. Besides, in the process of lane-changing, LV may conflict with the RV, resulting in a collision, so the lane-changing is finally abandoned. Therefore, the lane-changing process of the above autonomous driving vehicles is discretionary lane-changing, which is unnecessary. This paper will also study the discretionary lane-changing behavior of autonomous driving vehicles.

III. GAME STRATEGY ANALYSIS OF LANE-CHANGING BEHAVIOR

For game theory, researchers generally study competitive problems based on its theories and methods. Because of its obvious characteristics of game and trade-off, it has attracted more and more attention and has been applied to many traffic scenes. Yoo and Langari *et al.* [19] considered the application of Stackelberg game theory to driver behavior modeling in highway driving. Nan *et al.* [20] discussed a game theoretic approach to model the interactive decision-making of vehicles at unsignalized intersections. Tian *et al.* [21] proposed a decision-making algorithm for autonomous vehicle control at a roundabout intersection based on a game-theoretic model. The proposed control algorithm had the feasibility. Pisarski *et al.* [22] studied the problem of optimal balancing of vehicle density in freeway traffic. The optimization problem was formulated as a non-cooperative Nash game that was solved by decomposing it into a set of two-players hierarchical and competitive games. Jing *et al.* [23] presented a cooperative multi-player game-based optimization framework and an algorithm to improve the traffic efficiency in on-ramp scenarios. Tan *et al.* [24] introduced two-player cooperation game model to solve the two-phase traffic control for single intersection, ensuring the maximization of the overall benefit of the intersection. With the development of game theory, some researchers have established lane-changing decision-making models of vehicles based on game theory. Kita [25] explored the lane-changing decision-making process of vehicles from the perspective of the game. Bell [26] coupled the idea of game theory into the lane-changing process of vehicles in the expressway scene and studied its impact on the traffic flow. Banjanovic *et al.* [27] established the cooperative lane-changing behavior strategy model based on game theory and showed the gains of participants by analyzing the behavior information of lane-changing vehicles and surrounding vehicles. Talebpour *et al.* [28] focused on the role of information in the lane-changing decision-making and used the non-cooperative game to establish lane-changing behavior model. Drivers get different gains by choosing different strategies. Liu [29] analyzed the discretionary lane-changing process of autonomous driving vehicles, considered the game behavior between vehicles changing lanes and vehicles behind the target lane, and established the static game lane-changing model under complete information. Shang *et al.* [30] introduced the dynamic game theory of incomplete information to establish the lane-changing game model. Liu *et al.* [31] described the lane-changing behavior as a dynamic game process through the framework of game theory.

A. STATIC GAME OF COMPLETE INFORMATION

According to the different nature and significance of the problem studied, different game models can be established. General game models may be different in form, but they all include three constituent elements: the participants in the game process, the strategies selected by each participant, and the gains obtained by each participant after corresponding strategy selection.

According to whether there is a specific binding agreement with cooperative relationship between game participants, the game can be divided into cooperative game and non-cooperative game [32], [33]. In addition, according to the sequence of participants' actions and the integrity of information, the non-cooperative game can be divided into four categories [34]–[37], corresponding to four equilibriums respectively. Their specific relationship is shown in Table 1.

The game object studied in this paper is the autonomous driving vehicle. The autonomous driving vehicle is regarded as the rational agent. The autonomous driving vehicle has a clear understanding of strategy and gains, so the game is a complete information game. In addition, in the process of the game, there is only one game when both sides of the game conduct autonomous driving operations at the same time, so the game is static. Based on this, this paper establishes the static game model of complete information.

B. NASH EQUILIBRIUM

Assuming that there are n participants in a game, and the strategy set of the i-th participant can be represented by S_i, the total strategy set is as follows:

$$S = \{S_1, S_2, \ldots\ldots, S_n\} \tag{1}$$

The gains matrix of two-person non-cooperative game is shown in Table 2. Suppose the strategy set of participant A is $S_a = \{\mathrm{r}_1, \mathrm{r}_2\}$ and the strategy set of participant B is $S_b = \{\mathrm{t}_1, \mathrm{t}_2\}$. The gains obtained by participants A and B when they adopt different strategies is recorded as u. For example, $\mathrm{u_a} = \{\mathrm{r}_1, \mathrm{t}_1\}$ represents the gains obtained by participant A when participant A adopts strategy r_1 and participant B adopts strategy t_1.

When $(\mathrm{r_n},\mathrm{t_n})$ satisfies the following formula, $(\mathrm{r_n},\mathrm{t_n})$ is called Nash equilibrium under pure strategy [38].

$$\begin{cases} u_a\left(r_n, t_n\right) \geq u_a\left(r, t_n\right), & \forall r \in S_a \\ u_b\left(r_n, t_n\right) \geq u_b\left(r_n, t\right), & \forall t \in S_b \end{cases} \tag{2}$$

In a given two-person game, there may be pure strategy Nash equilibrium or mixed strategy Nash equilibrium in a

TABLE 1. Division of game types and corresponding equilibrium under non-cooperative game.

Sequence of actions Information	Static	Dynamic
Complete information	Static game of complete information (Nash equilibrium)	Dynamic game of complete information (Sub-game perfect Nash equilibrium)
Incomplete information	Static game of incomplete information (Bayesian Nash equilibrium)	Dynamic game of incomplete information (Perfect Bayesian Nash equilibrium)

TABLE 2. Gains matrix of two-person non-cooperative game.

Participants and their strategies		Participant *B*	
		t_1	t_2
Participant *A*	r_1	$u_a(r_1,t_1)$, $u_b(r_1,t_1)$	$u_a(r_1,t_2)$, $u_b(r_1,t_2)$
	r_2	$u_a(r_2,t_1)$, $u_b(r_2,t_1)$	$u_a(r_2,t_2)$, $u_b(r_2,t_2)$

TABLE 3. Gains matrix of two-person non-cooperative mixed strategy game.

Participants and their strategies		Participant *B*		
		d_1	d_2	
Participant *A*	c_1	$u_{a'}(c_1,d_1)$, $u_{b'}(c_1,d_1)$	$u_{a'}(c_1,d_2)$, $u_{b'}(c_1,d_2)$	p
	c_2	$u_{a'}(c_2,d_1)$, $u_{b'}(c_2,d_1)$	$u_{a'}(c_2,d_2)$, $u_{b'}(c_2,d_2)$	$1-p$
		q	$1-q$	

non-cooperative game. The mixed strategy describes the situation where participants randomly choose different strategies with a certain probability under given information. The gains matrix of two-person non-cooperative mixed strategy game is shown in Table 3.

Based on the gains of strategy game in the above gains matrix, the gains of participant *A* and participant *B* can be expressed as follows, (3), as shown at the bottom of the next page.

The probability q can be obtained by differentiating the gains $\varphi_{a'}$ of participant *A* with respect to p and making the derivative 0. The outcome of the solved probability q is as follows:

$$q = \frac{u_{a'}(c_2, d_2) - u_{a'}(c_1, d_2)}{u_{a'}(c_1, d_1) - u_{a'}(c_1, d_2) - u_{a'}(c_2, d_1) + u_{a'}(c_2, d_2)} \tag{4}$$

The probability p can be obtained by differentiating the gains $\varphi_{b'}$ of participant *B* with respect to q and making the derivative 0. The outcome of the solved probability p is as follows:

$$p = \frac{u_{b'}(c_2, d_2) - u_{b'}(c_2, d_1)}{u_{b'}(c_1, d_1) - u_{b'}(c_1, d_2) - u_{b'}(c_2, d_1) + u_{b'}(c_2, d_2)} \tag{5}$$

To sum up, when the pure strategy Nash equilibrium does not exist in the non-cooperative game, participant *A* and participant *B* should make random probabilistic strategy selections respectively, so as to obtain the Nash equilibrium under the mixed strategy.

IV. ESTABLISHMENT OF DECISION-MAKING BEHAVIOR MODEL OF THE LANE-CHANGING GAME

Autonomous driving vehicles can exchange information through perception technology in the process of lane-changing, so the lane-changing behavior process of autonomous driving vehicles is modeled based on game theory. In order to better model the lane-changing of autonomous driving vehicles, the following assumptions are made:

1. Autonomous driving vehicles have a high level of automation, and they can complete the driving operation by themselves.
2. Autonomous driving vehicles can obtain the position, speed, acceleration, and other information of themselves and surrounding vehicles, and speed gains can be obtained in time through speed information.
3. Autonomous driving vehicles are unified standard cars.

A. GENERATION OF LANE-CHANGING INTENTION

The speed of the vehicle in front of the target lane and the speed of the vehicle in front of the current lane play an extremely important role in the generation of lane-changing intention [39]. Consequently, objectively quantify the lane-changing intention of autonomous driving vehicles based on the speed information of surrounding vehicles:

$$k = \frac{v_f}{v_p} \tag{6}$$

In the above formula, k is the lane-changing intention of LV; v_f is the speed of FV; v_p is the speed of PV.

The lane-changing intention of autonomous driving vehicles is determined by the ratio of the speed of the vehicle in front of the target lane to the speed of the vehicle in front of the current lane. Whether the lane-changing intention is generated or not is reflected by the k value. When $k > 1$, the speed condition of the target lane is better, and then the intention of lane-changing is generated. Furthermore, autonomous driving vehicles can reap the speed gains by lane-changing. When $k < 1$, the speed condition of the current lane is still good, so there is no intention to change lanes, and the vehicle keeps following.

B. MODEL OF LANE-CHANGING GAME

After the lane-changing intention is generated, the autonomous driving vehicle also needs to make the lane-changing decision-making [40]. If the lane-changing conditions are not met, the vehicle can only give up lane-changing and continue to follow in the current lane. The lane-changing of the vehicle is regarded as the dynamic and changeable behavior on the two-dimensional plane, and the moving vehicle is regarded as a particle. In terms of safety, it is considered that there will be no collision accident during the lane-changing. In addition, the distance between vehicles affects the safety of vehicles. Therefore, the lane-changing collision probability is introduced:

$$\begin{cases} p(x,y) = \exp[-\frac{1}{2\sigma_g^2}(x^2 + \mu y^2 \sin^2\theta)] \\ \sigma_g = e\left(m\sqrt{v^2+a^2}+\varepsilon\right) \end{cases} \tag{7}$$

In the above formula, θ indicates the maximum steering angle of the vehicle; μ is the lateral stability coefficient; σ_g represents the distribution factor in the speed direction when the vehicle is running; e and ε represent non-zero constants; v and a represent the speed and acceleration of the vehicle respectively; m represents the mass of the vehicle. The specific lane-changing collision probability is shown in Figure 2.

Based on the lane-changing collision probability, the lane-changing dynamic risky coefficient is further introduced as the condition to judge whether to change lanes, so as to form the lane-changing decision-making mechanism of autonomous driving vehicles:

$$\begin{cases} \xi = \alpha p(x,y)G\sqrt{1+j^2} \\ j = \frac{d^2v(t)}{d^2t} = \frac{da(t)}{dt} \end{cases} \tag{8}$$

In the above formula, α represents a constant; G is the vehicle size coefficient; j represents the jerk when the vehicle is running. When $\xi \leq 1$, the vehicle can change lanes. The lane-changing dynamic risky coefficient is shown in Figure 3. Let the vehicle move in a straight line at a uniform speed, so the acceleration a and the jerk j are both 0, and the speed follows the positive direction of x. As can be seen from the Figure 3, the dynamic risky coefficient ξ at (0,0) position has maximum, and its value decreases with the increase of distance, so that it is close to zero. This is also consistent with the actual situation.

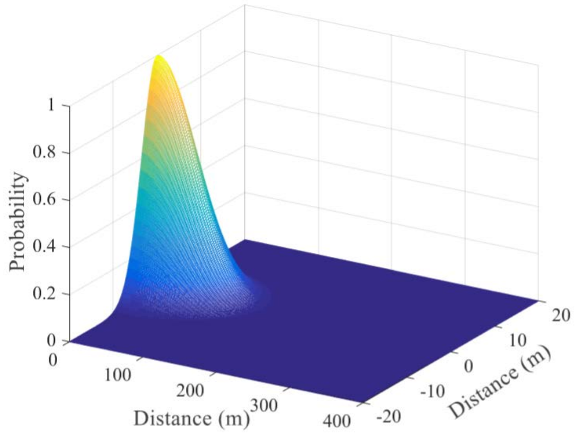


FIGURE 2. Lane-changing collision probability.

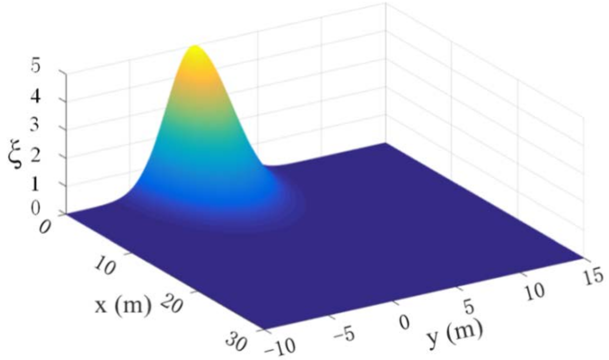


FIGURE 3. Lane-changing dynamic risky coefficient.

In the intelligent network connection environment, information can be exchanged between autonomous driving vehicles [41]. Therefore, the idea of game theory is introduced to establish the model. After generating the intention of lane-changing, the autonomous driving vehicle obtains the relevant information of the surrounding vehicles, forms a game system after clarifying the game object, and takes the speed gains as the game gains, so as to obtain the Nash equilibrium under the mixed strategy of the game. Finally, the autonomous driving vehicle can change lanes safely and efficiently [42]. The specific decision-making process of game lane-changing for autonomous driving vehicles is shown in Figure 4.

$$\begin{cases} \varphi_{a'} = u_{a'}(c_1,d_1)pq + u_{a'}(c_1,d_2)p(1-q) + u_{a'}(c_2,d_1)(1-p)q + u_{a'}(c_2,d_2)(1-p)(1-q) \\ \varphi_{b'} = u_{b'}(c_1,d_1)pq + u_{b'}(c_1,d_2)p(1-q) + u_{b'}(c_2,d_1)(1-p)q + u_{b'}(c_2,d_2)(1-p)(1-q) \end{cases} \tag{3}$$

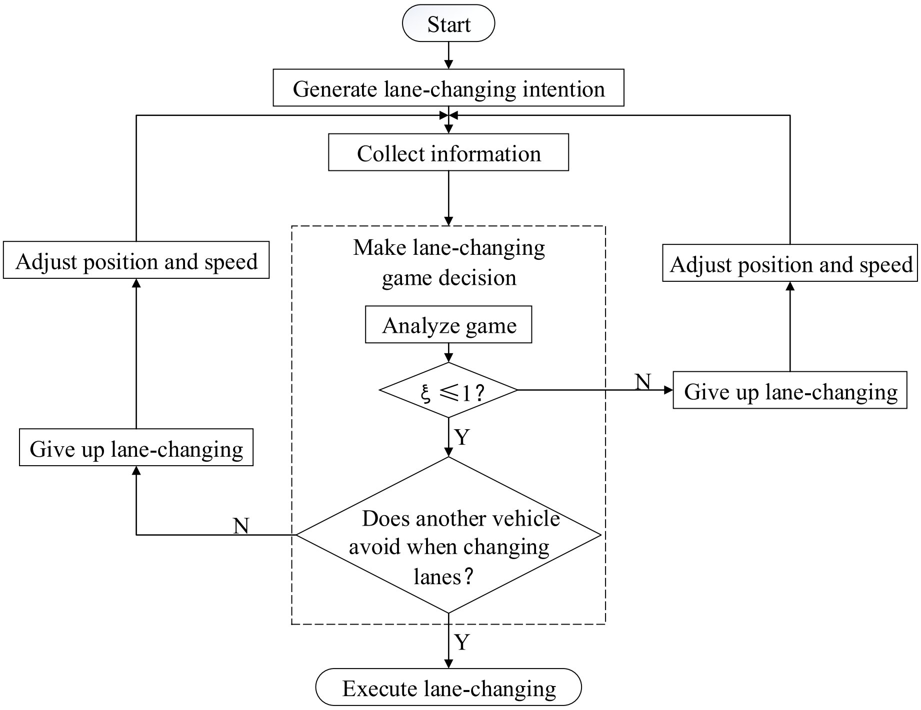


FIGURE 4. Lane-changing game decision-making process.

Under the decision-making behavior model of the lane-changing game, the strategy set of LV is expressed as {lane-changing, no lane-changing}, and the probability of selecting the "lane-changing" strategy is p. The strategy set of RV is expressed as {avoidance, no avoidance}, and the probability of selecting "avoidance" strategy is q. In addition, take the speed gains as the game gains. The specific game gains matrix is shown in Table 4.

The autonomous driving lane-changing vehicle will obtain different gains when choosing different strategies. From the game gains matrix of the model, it can be seen that the LV has four different gains, such as $u_L(c_1,d_1)$, $u_L(c_1,d_2)$, $u_L(c_2,d_1)$ and $u_L(c_2,d_2)$. And the total gains will change with the change of probability. Figure 5 shows that in a game, the speed gains of the autonomous driving lane-changing vehicle changes with the change of probability p and probability q.

When the LV has the intention to change lanes at time t_0 and selects the "lane-changing" strategy, and the RV selects the "avoidance" strategy, the two sides of the game can change lanes by exchanging information. LV makes uniform acceleration linear motion, while RV makes deceleration motion to avoid, so as to provide appropriate lane-changing space for LV [43]. When changing lanes in the game, we first consider security, but not only security. For safety, the lane-changing dynamic risky coefficient $\xi = 1$ is the critical value, and lane-changing can be carried out when $\xi \leq 1$. Considering the game gains, lane utilization and other factors, lane-changing can be allowed when the lane-changing dynamic risky coefficient $\xi = 1$. When the distance between LV and PV meets the lane-changing dynamic risky coefficient $\xi = 1$, the time Δt can be calculated according to the function of the autonomous driving vehicle and the above formula. Based on the idea of maximizing the gains of lane-changing game, the loss of speed should be reduced as much as possible. Therefore, after the lapse of the time Δt, the distance between LV and RV should meet the lane-changing dynamic risky coefficient $\xi = 1$. Finally, after the lane-changing, the acceleration, the speed and the speed gains of the autonomous driving vehicles can be obtained.

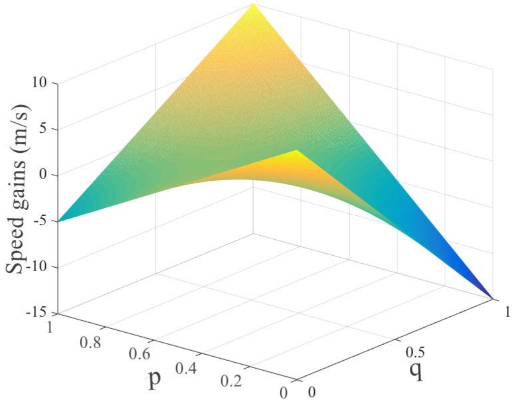


FIGURE 5. Changes of speed gains.

In the lane-changing game process, there are corresponding changes in the distribution range of the dynamic risky coefficient for autonomous driving vehicles. And the specific

TABLE 4. Gains matrix of two-person non-cooperative mixed strategy game.

Game objects and their strategies		RV		
		d_1(avoidance)	d_2(no avoidance)	
LV	c_1(lane-changing)	$u_L(c_1,d_1)$, $u_R(c_1,d_1)$	$u_L(c_1,d_2)$, $u_R(c_1,d_2)$	p
	c_2(no lane-changing)	$u_L(c_2,d_1)$, $u_R(c_2,d_1)$	$u_L(c_2,d_2)$, $u_R(c_2,d_2)$	$1-p$
		q	$1-q$	

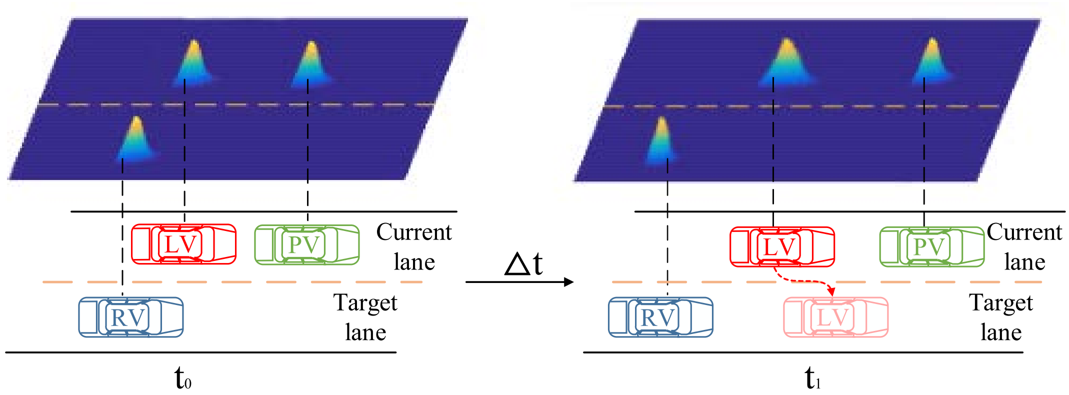


FIGURE 6. Game lane-changing dynamic risky diagram.

changes are shown in Figure 6. The distribution range of the risky coefficient for LV increases due to the increase of the speed, and the distribution range of the risky coefficient for RV decreases due to the decrease of the speed.

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. PLATFORM AND ENVIRONMENT OF SIMULATION

In this paper, SUMO simulation software is used to verify the performance of the above decision-making behavior model of the lane-changing game. SUMO is an open-source micro continuous traffic flow simulation software. And its rich functions have attracted the use of some traffic researchers. SUMO contains the traffic simulation road network editor, which can add roads, edit the connection relationship of lanes, etc. At the same time, SUMO can also define departure and arrival attributes, such as lane, speed, or location. Through the TraCI (Traffic Control Interface) of SUMO, the vehicle can be tracked to obtain information. With the advancing development of intelligent network connection environment, SUMO begins to simulate autonomous driving gradually, and also provided a diversified dynamic environment for autonomous driving models.

B. ANALYSIS OF SIMULATION RESULTS

In order to simplify the model problem, the simulation scene is set as a one-way two lane with a length of 3000 m and a speed limit of 120 km/h. The experiment is divided into group A and group B, in which the lane-changing model adopted by group A is the LC2013 lane-changing model in SUMO software, and the lane-changing model adopted by group B is the decision-making behavior model of the lane-changing game proposed above. The LC2013 lane-changing model is an instantaneous lane-changing model, and its lane-changing selection is completed through the calculation of effective path in the road network. In addition, the LC2013 lane-changing model distinguishes the lane-changing motivation, and the vehicle will perform the lane-changing steps in sequence under the model. The relevant characteristic parameters of the two groups of experimental lane-changing models are shown in Table 5.

In the two groups of experiments, blue and red traffic flow are used to simulate respectively. When the vehicle is driving in the current lane, it will turn on the turn signal light to prepare for lane-changing after it has the intention of lane-changing and makes the lane-changing decision. Figure 7 shows the lane-changing simulation interface of the two groups of experiments.

In the simulation process of the SUMO platform, the relevant information of lane-changing vehicles can be obtained by using the TraCI. Some relevant data are shown in Figure 8. Among them, figure (a) and figure (d) can clearly show the lane-changing state of vehicles. When the vehicle changes lanes, its lateral speed will first increase and then decrease, and will decrease to zero when reaching the center of the target lane. At the same time, the offset of the right side of the vehicle relative to the right side of the road will also change during lane-changing, and the final change is the width of a single lane.

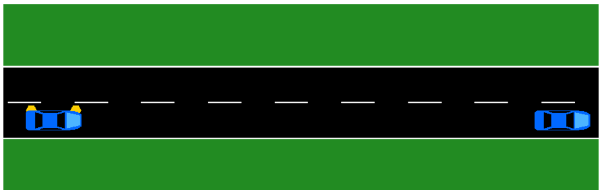
Firstly, the dynamic risky coefficient ξ and collision probability p(x,y) of autonomous driving vehicles in the

TABLE 5. Relevant characteristic parameters of the lane-changing model.

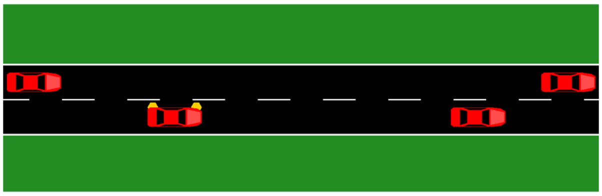
	LC2013 lane-changing model	Decision-making behavior model of the lane-changing game
Vehicle length (m)	4.8	4.8
Vehicle width (m)	1.8	1.8
Vehicle color	blue	red
Maximum speed (m/s)	33.33	33.33
Maximum acceleration (m/s^2)	2.61	2.61

TABLE 6. Number of vehicle accidents under different traffic flow densities.

Traffic flow densities (veh/km)	LC2013 lane-changing model	Decision-making behavior model of the lane-changing game
10	0	0
20	0	0
30	0	0
40	0	0
50	1	0
60	1	0
70	2	0
80	3	0
90	2	0
100	1	0



(a) Traffic flow of LC2013 lane-changing model



(b) Traffic flow of decision-making behavior model of the lane-changing game

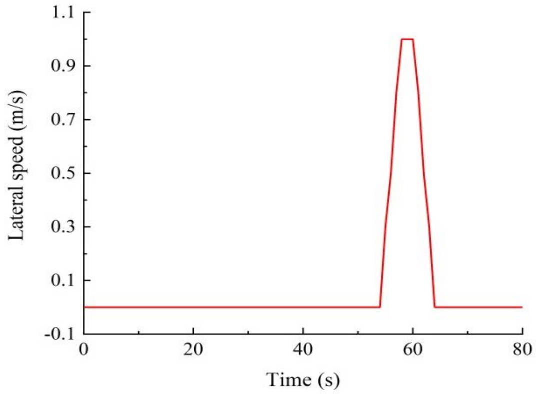
FIGURE 7. Lane-changing simulation interface.

experimental group of the decision-making behavior model of the lane-changing game are analyzed. The specific results are shown in Figure 9. According to the analysis, we can know that the dynamic risky coefficient fluctuates in the range of 0.5-1.5, and the collision probability fluctuates around 0.5, indicating that the decision-making behavior model of the lane-changing game has good stability.

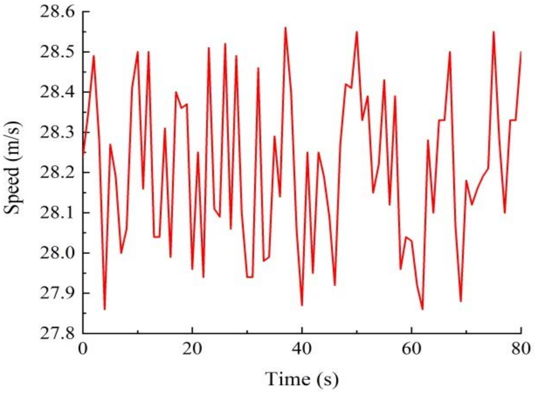
Furthermore, in the two groups of experiments, the average speed of vehicles, the number of passed vehicles within 360 s, the number of vehicle accidents, and the perturbation of lane-changing vehicle are used to compare and analyze the performance of the model.

As shown in Figure 10, analyze the performance of the model from the perspective of average vehicle speed under different traffic flow densities. Figure 10 (a) shows that when the traffic flow density is less than 70 veh/km, the average vehicle speed of the experimental group of the decision-making behavior model of the lane-changing game is significantly higher than that of the traditional LC2013 lane-changing model. With the continuous increase of the traffic flow density, the lane-changing opportunities gradually decrease. Therefore, the average vehicle speed difference between the two models shows a decreasing trend, but the average vehicle speed of the experimental group of the decision-making behavior model of the lane-changing game is still higher than that of the traditional LC2013 lane-changing model. Figure 10 (b) further shows the increase in the average speed. The average speed data under the two groups of models are evenly distributed without abnormal values. The three data around the box are the maximum, average, and minimum values of speed from top to bottom. Compared with LC2013 lane-changing model, the vehicle running speed under the decision-making behavior model of the lane-changing game has increased by an average of 3.6%, with higher speed gains. In general, the vehicles under the decision-making behavior model of the lane-changing game proposed in this paper have better operation efficiency, so as to ensure that autonomous driving vehicles can implement lane-changing more efficiently.

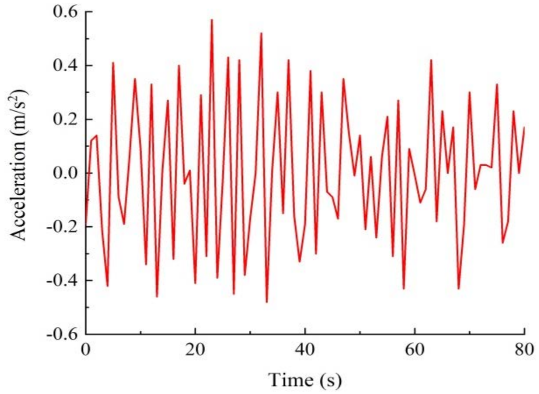
As shown in Figure 11, the performance of the model is analyzed from the number of passed vehicles within 360 s under different traffic flow densities. Figure 11 (a) shows that the number of passed vehicles of the experimental group of the decision-making behavior model of the lane-changing game is always higher than that of the traditional LC2013 lane-changing model. When the traffic flow density is greater



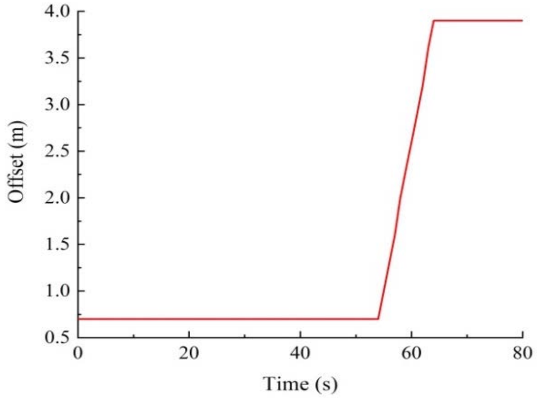
(a) Lateral speed



(b) Speed

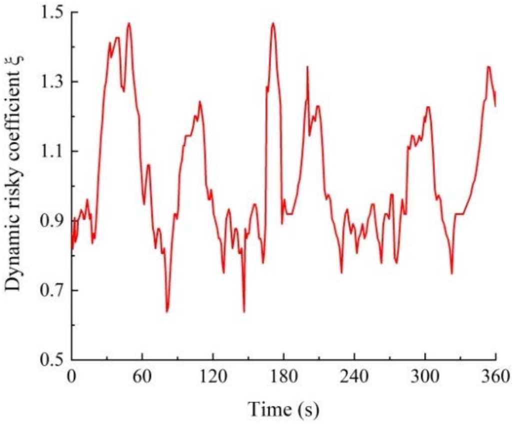


(c) Acceleration

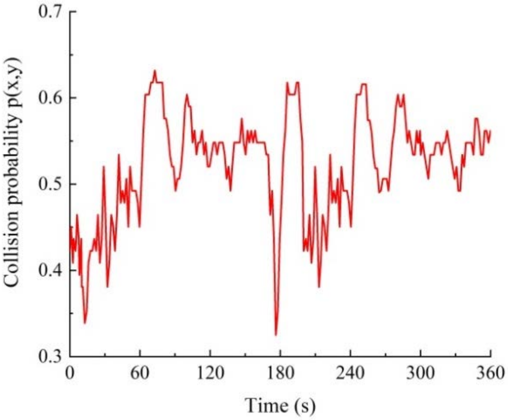


(d) Offset

FIGURE 8. **Information about lane-changing vehicle.**



(a) Dynamic risky coefficient

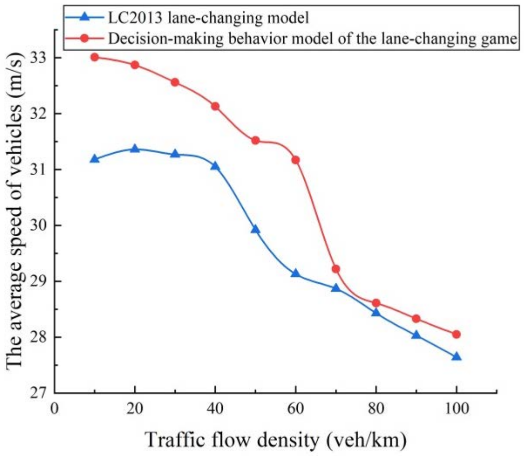


(b) Collision probability

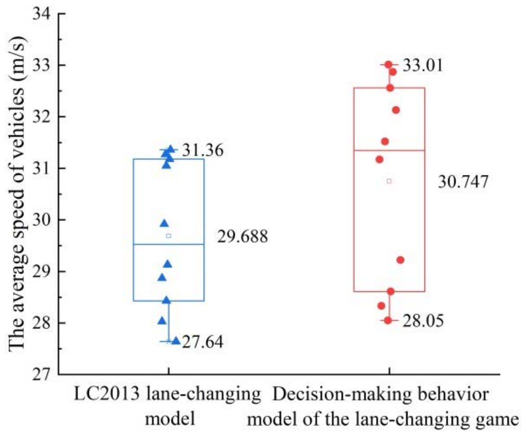
FIGURE 9. **Diagram of dynamic risky coefficient and collision probability.**

than 50 veh/km, the advantage of the decision-making behavior model of the lane-changing game in the number of passed vehicles is further obvious. Figure 11 (b) shows that the number of passed vehicles under the two groups of models is evenly distributed without abnormal values. In addition, compared with LC2013 lane-changing model, the average number of passed vehicles under the decision-making behavior model of the lane-changing game increased by 10.3%. Therefore, according to the above analysis, the decision-making behavior model of the lane-changing game has better road utilization and efficiency. With the continuous increase of car ownership, the demand for road utilization and efficiency of autonomous driving vehicles is also increasing day by day. Therefore, the decision-making behavior model of the lane-changing game also has certain adaptability and practical application to the changing and developing traffic environment.

As shown in Table 6, the performance of the model is analyzed in terms of the number of vehicle accidents. There are no accidents in LC2013 lane-changing model and decision-making behavior model of the lane-changing game under the condition of small traffic flow. However, with the continuous

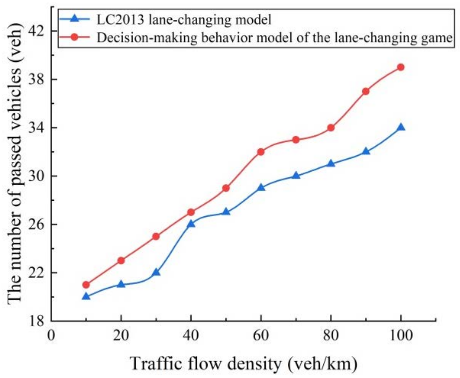


(a) Qualitative diagram of vehicle speed

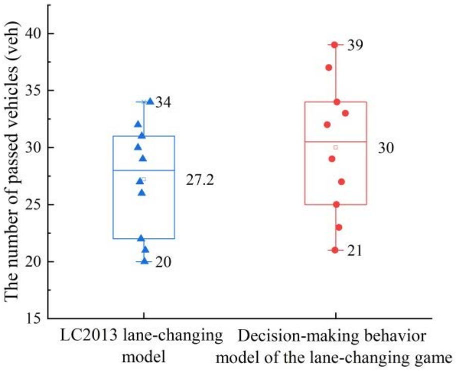


(b) Quantitative diagram of vehicle speed

FIGURE 10. Average speed of vehicles under different traffic flow densities.

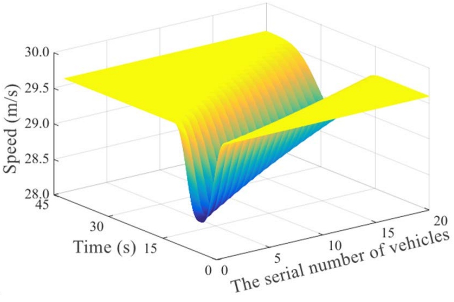


(a) Qualitative diagram for the number of passed vehicles

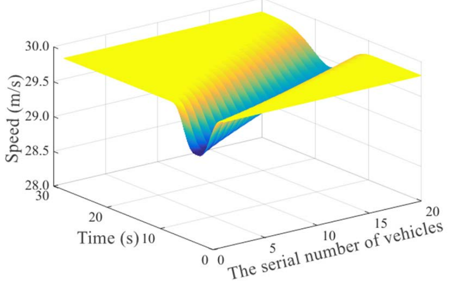


(b) Quantitative diagram for the number of passed vehicles

FIGURE 11. Number of passed vehicles under different traffic flow densities.



(a) Perturbation under LC2013 lane-changing model



(b) Perturbation under decision-making behavior model of the lane-changing game

FIGURE 12. Perturbation of the lane-changing vehicle under different models.

increase of traffic flow density, especially after the traffic flow density of 40 veh/km, the number of vehicle accidents in LC2013 lane-changing model shows an increasing trend, while the vehicles under the decision-making behavior model of the lane-changing game have no accidents, which makes the traffic flow run smoothly. In general, the decision-making behavior model of the lane-changing game has good reliability and security.

For the traffic flow running in the target lane, the entry of lane-changing vehicles will cause a certain perturbation. The smaller the impact of perturbation, the more conducive to the efficient operation of vehicle flow in the target lane. Based on this, the performance of the model is analyzed from the perturbation of the lane-changing vehicle to the traffic flow. A fleet of 20 vehicles is set in the rear of the target lane, and the operation of vehicles follows certain rules. The lane-changing vehicle running in the current lane looks for opportunities to change lanes under the lane-changing rules of LC2013 lane-changing model and decision-making behavior model of the lane-changing game. As shown in Figure 12, after the vehicles in the fleet are disturbed by the lane-changing vehicle, the speed fluctuation gradually propagates backward and the intensity gradually decreases, which is also in line with the actual situation. However, the perturbation of lane-changing vehicle to the target traffic flow after successful lane-changing is different between the two lane-changing models. Compared with LC2013 lane-changing model, the lane-changing vehicle under the decision-making behavior model of the lane-changing game has less perturbation to the traffic flow of target lane. After the traffic flow of target lane is disturbed by the lane-changing vehicle under the decision-making behavior model of the lane-changing game, it can return to the previous driving state in a short time, and the overall speed fluctuation is also small, which makes the traffic flow run in a more efficient and stable state.

In general, the decision-making behavior model of the lane-changing game has good stability and efficiency. The lane-changing vehicle under the decision-making behavior model of the lane-changing game is good at choosing the lane-changing time and making friendly lane-changing, which has less perturbation to the traffic flow of target lane. It will also alleviate the problem of traffic congestion to a certain extent.

VI. CONCLUSION

Compared with the previous research work, this paper objectively quantifies the lane-changing intention, reasonably shows the lane-changing intention of autonomous driving vehicles, and takes it as the initial condition of lane-changing decision-making. Different from the traditional lane-changing decision-making mechanism focusing on fixed critical gap, this paper comprehensively considers the dynamic factors in the traffic environment and scientifically shows the lane-changing decision-making mechanism of autonomous driving vehicles. Through relevant theoretical analysis and simulation experiments, the following conclusions and prospects are obtained.

(1) Autonomous driving vehicles can exchange information in the process of lane-changing, and their micro lane-changing behavior can be reasonably displayed by using the idea of game theory. Based on the objective quantification of lane-changing intention, the lane-changing collision probability and lane-changing dynamic risky coefficient are introduced to ensure the safety and fairness of lane-changing decision-making, and the decision-making behavior model of the lane-changing game is established. The experimental results show that, compared with the traditional lane-changing model, the average speed of vehicles under the decision-making behavior model of the lane-changing game is increased by 3.6%, and the average number of passed vehicles is increased by 10.3%. There is no vehicle accident, and the perturbation of lane-changing vehicle to the traffic flow of target lane is small. Therefore, the decision-making behavior model of the lane-changing game has good security, stability, and efficiency. At the same time, this study can provide the theoretical basis and technical support for the lane-changing research of autonomous driving vehicles to a certain extent.

(2) In the future, we will further study the lane-changing game decision-making behavior of autonomous driving vehicles, and consider diversified lane-changing influencing factors and complex traffic environments, so as to make the game lane-changing behavior more reasonable. Besides, we improve the decision-making behavior model of the lane-changing game, so as to promote the development of autonomous driving technology.

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