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Research Article

The Design of Vehicle Profile Based on Multivehicle Collaboration for Autonomous Vehicles in Roundabouts

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The collaborative strategy of vehicle-road-environment based on intelligent and connected vehicles (ICVs) to assist in driving vehicles safely and relieve traffic congestion has become an effective solution. This paper proposed a strategy for vehicle lane change and roundabouts traffic based on vehicle profile (VP) in combination with the driving characteristics of roundabouts. Initially, in order to solve the confusion problem of multisource heterogeneous data of ICVs in roundabouts, this paper defines VP to describe and characterize the multidimensional data of ICVs, so the data in ICVs can be further applied. Furthermore, the weights of relevant parameters in the VP are updated based on the random forest algorithm. In addition, the payoff function is designed for the lane change decision at the exit of roundabouts based on the VP and dynamic weights. Finally, the performance of the proposed algorithm is compared with other algorithms through the SUMO platform and three scenarios are used in the simulation verification, including traffic congestion, normal, and sparse. The experimental results verify the optimization effect of vehicle profile on roundabout traffic strategy and also show that this algorithm can effectively improve the efficiency of vehicle traffic in roundabouts. In particular, the efficiency and comfort of vehicles in roundabouts are effectively improved in normal traffic scenarios.

1. Introduction

As a kind of traffic facility that can effectively solve the problem of urban traffic congestion, traffic roundabout has been widely used in the urban traffic system. However, the roundabout is limited by the capacity of the road, and as the volume of traffic increases, traffic congestion worsens. Ensuring the efficiency and safety of the roundabout has become an important problem in the traffic system. Traffic lights have been added to control the movement of vehicles in large roundabout areas. Although it can optimize the problem, signal lights can also cause vehicles to wait and even block [1]. With the continuous development of intelligent connected vehicles [2, 3], the application of a multivehicle coordination strategy to roundabouts has become a new solution to solve the congestion problem of roundabouts and improve traffic efficiency.

Intelligent and connected vehicles (ICVs) use the internet of vehicles communication technology [4] to introduce more data information, such as vehicle information and road condition information to form an organic whole of vehicle-road-environment and realize the coordination of the three. How to effectively use the above-mentioned multiple heterogeneous data have become the basis and key to effective vehicle-road-environmental coordination.

The key to solving the congestion and the safety of traffic around the roundabouts is to optimize the strategies of lane change and traffic order. Therefore, the coordination problem of roundabouts can be detailed as the vehicle lane change decision at the intersection. Based on the defined payoff function, Nilsson et al. [5] proposed changing lanes if the lane change time and location are appropriate. Based on reduplicated game theory, Cheng et al. [6] defined a payoff function consisting of safety, rapidity, and control indicators. Various factors related to vehicles are involved in lane change strategies, which caused the current situation of complexity when considering lane change decisions.

Combining the above-given problems, this paper researches the traffic efficiency optimization of roundabout scenes and the status quo in the multivehicle coordinated lane change, then proposes a method for cooperative control of vehicles under roundabouts based on the construction of VP. The main contributions of this paper are summarized as follows:

(1) Based on the idea of the user profile, the vehicle profile is constructed. Combining the data of vehicle, driver, and driving environment, this paper provides a basis for the further application of intelligent connected vehicle data in multivehicle cooperation problems.
(2) The dynamic weight of the vehicle lane changing payoff function is defined, which makes the weight of the function dynamically updated with the vehicle driving scene and driving state, so as to realize the scene adaptive optimization of the lane changing strategy.
(3) According to the revenue function of the vehicle profile and dynamic weight, a lane-changing decision algorithm (UPC) based on the user profile is established, and the overall traffic efficiency of the roundabout is optimized by the UPC algorithm.

2. Related Works

2.1. Vehicle Collaborative Decision Making. For collaborative decision-making of vehicles, Jin et al. proposed a lane-changing behavior decision model based on the Gaussian mixture hidden Markov model (GM-HMM) for the characteristics of drivers' lane-changing behavior [7], which can effectively simulate driving behavior. So et al. [8] proposed an emergency vehicle control strategy that achieved advantages in mobility and safety, and the advantages of the emergency vehicle control strategy can be maximized when signal preemption and autonomous driving control operate cooperatively. Bai et al. [9] established lane change models with different degrees of cooperation with the following vehicle in the target lane based on the characteristics of accelerated lane change, combined with vehicle kinematics and comfort requirements. It can achieve a safe accelerated lane change trajectory and meet the requirements of vehicle kinematics and comfort control. Ni et al. [10] established the feasibility of the cooperative lane change operation by establishing the gain function based on the excitation model. By comparing the lane change gain and lane keeping gain, we can judge whether the cooperation is feasible under the current conditions. The lane change process is divided into the lane change stage and the longitudinal vehicle distance adjustment stage.

Song et al. analyzed the game characteristics and game models existing in traffic signal control at intersections [11], analyzed the game characteristics in multiphase signal control at single intersections in detail, studied the multiperson cooperative game method in multiphase signal control at single intersections, and established the corresponding game model and solved it. Dewangan and Sahu [12] designed finite state machine models for straight and turning intersections, combined with safety judgment rules, and realized the safe passage of intelligent vehicles at intersections. Guo et al. combined with trajectory prediction [13], proposed a decision-making process (model) and multifactor driving behavior selection method for intelligent driving vehicles based on conflict resolution. Ali et al. developed a forced lane change model based on game theory (AZHW model) that can effectively capture forced lane change decisions with high accuracy [14]. The game-based lane change behavior modeling under incomplete information proposed by Yu et al. [15], whose model parameters can be learned and updated during the lane change. Leon Calvo and Mathar designed a cooperative formation scheme using the joint paradigm to increase traffic flow and stability [16], in which platoon formation is based on the method of alliance game theory. Jing et al. formulated the lane-changing problem as a Markov game between active and passive vehicles [17]. Ding derived the global optimal merging model based on a cooperative game to minimize the global revenue and achieve the optimal MS and trajectory. The fuel consumption, passenger comfort, and travel time in the merged control area were used as the revenue conditions [18].

2.2. Collaborative Decision-Making in Roundabouts. Since the appearance of roundabouts in the 1960s, researchers from many countries have tried to study and optimize the capacity of the roundabout [19]. Due to the right-of-way problem of vehicles and insufficient data [20], the efficiency of the roundabout will decrease with the increase in traffic volume [21] and other problems. Therefore, it has not been able to play its capacity advantage in the actual scene of high traffic flow [22]. But the further development of technologies such as the Internet of vehicles now offers a great opportunity to improve transportation efficiency.

Since deceleration, lane merging and lane changing at roundabouts are the main causes of congestion, the current research mainly focuses on route planning inside the roundabout and lane merging at the junction. And, they achieve this by controlling vehicle speed, traffic flow, etc. Silva and Grassi [23] make path planning by clothoid, circular arcs, and straight lines, whose curvature is piecewise linear and continuous as well. A continuous and smooth driving line is planned based on the linear variation of curvature relative to distance. Hidalgo et al. [24] proposed a method to solve the roundabout merging considering a nominal trajectory generated through Bézier curves combined with a model predictive control (MPC) to assure a safe future state.

For coordinated decision-making at the intersection, Hang et al. [25] designed and optimized a motion prediction module through model predictive control (MPC), and the payoff function of decision-making was defined with the consideration of vehicle safety, ride comfort, and travel efficiency. Stackelberg game and grand coalition game approaches are adopted to address the decision-making of CAVs at an unsignalized roundabout. Tian et al. [26] proposed an algorithm based on a game-theoretic model; the algorithm shows the interactions between the ego vehicle and an opponent vehicle and adapts to an online estimated driver type of the opponent vehicle. Similar to the problems of Nilsson et al. [5] and Cheng et al. [6], their construction of the payoff function lacks the definition of the weights of the relevant factors, which makes the constructed payoff function not accurately characterize the vehicle payoff.

At the same time, Ye et al. explored the influence of different parameter values on high-precisiondecision-making in complex scenes [27], and Yu et al. [15] and Xu et al. [28] also verified that model parameters can be learned and updated in the process of lane change to bring better decision-making effects, and the decision optimization effect combined with different road weights in different road scenarios [29]. Therefore, in order to better characterize the vehicle state and optimize the decision-making performance, it is necessary to update the weight of the payoff function.

3. System Model and Problem Formulation

3.1. Vehicle Profile. In this paper, the method of the vehicle profile (VP) is used to construct (design) vehicle tags from five aspects, including driver information, vehicle information, vehicle driving status, driving behavior, and external environment, as shown in Figure 1. And, the VP is used to characterize the vehicle status, the feature types are shown in Table 1.

Based on the environment of Intelligent and connected vehicles (ICVs) built by roadside unit (RSU), this paper builds a vehicle profile. A roadside unit (RSU) is set in the roundabout where vehicles can obtain traffic information about themselves and surrounding vehicles and sets the data transfer to the ideal case: no delay no packet loss. When the vehicle enters the communication range, the vehicle immediately connects with the roadside unit and accesses the network. Data in vehicle driving are gathered and managed by the roadside unit, then the vehicle completes the construction of its vehicle profile by the data; in addition, the VP is used for the problems of collaborative decision-making or others, as shown in Figure 2.

Autopilot mentioned in the paper intelligent snatched automotive vehicle data not only included in the basic data, including infrastructure, environment, traffic data, road lane around size, location of the vehicle, road and the direction of motion, weather conditions, traffic intensity), the identity of the owner (driving experience, age), the state data (gestures, Eye position changes, etc.), and behavioral data (abnormal lane change frequency, driving style, etc.). The driver information and vehicle information are inherent information, and the external environmental data are collected by RSU and distributed to each node. The driving behavior can be obtained by visual collaborative analysis and other methods, and the vehicle running state can be obtained by onboard sensors and dynamically divided by combining the definition of safe driving in different scenarios in relevant laws and regulations.

Except for driving behavior, the data used for VP are all inherent factors related to the vehicle, and all information can be obtained directly through RSU. As for the representation of driving behavior, Murphey et al. [30] proposed the driver style identification coefficient Rdriver by taking advantage of vehicle acceleration and its standard deviation and proved that the proposed style coefficient could accurately describe the driver's driving style through experimental verification.

Based on this idea and the timeliness of the VP, this paper presents a simple representation of driving behavior style through vehicle spacing.

Definition 1. Driving behavior identification parameters:

$$U_{\mathrm{sp}} = \begin{cases} 1, & x \geq x_{\mathrm{safe}}, \\ \dfrac{x}{x_{\mathrm{safe}}}, & x < x_{\mathrm{safe}}, \end{cases} \tag{1}$$

where x is the vertical distance between two cars, x_{safe} is the safe distance between two cars at the current speed.

The construction of the VP provides a unified basis for the consideration of the relevant factors in the multivehicle cooperation problems so that the research on multivehicle cooperation problems can be taken and used on demand.

3.2. Label Weight Calculation. Breiman [31] proposed the random forest algorithm based on combining the Bagging method with the random subspace method. Random forest algorithm is an algorithm for classification and prediction, which uses the bootstrap resampling method to draw multiple samples from the original sample model decision trees for each bootstrap sample and then combine the predictions of multiple decision trees to arrive at the final prediction result by voting and has high prediction accuracy, good tolerance for outliers and noise, and is not prone to overfitting [32]. Applications of random forest in the field of assisted driving include the detection of trains ahead to avoid collisions [33] and the monitoring of driver emotions [34]. Considering that the process of random forest algorithm implementation is to set up different weights for different decision trees to complete the voting to arrive at the final result. Random forest can be used for the calculation and selection of feature weights for the dataset, although the random forest algorithm appears to classify and predict the data.

The common decision trees are divided into ID3, C4.5, and CART. ID3 divides attributes by information gain (IG) and recursively constructs decision trees, C4.5 constructs decision trees by gain rate, and CART constructs decision trees by Gini coefficient as a criterion. In this paper, the calculation of different label weights in the vehicle profile is completed by the random forest algorithm constructed with IG. Information gain is a feature selection method based on the information theory proposed by Harrington [35]; in other words, information gain is the change resulting from

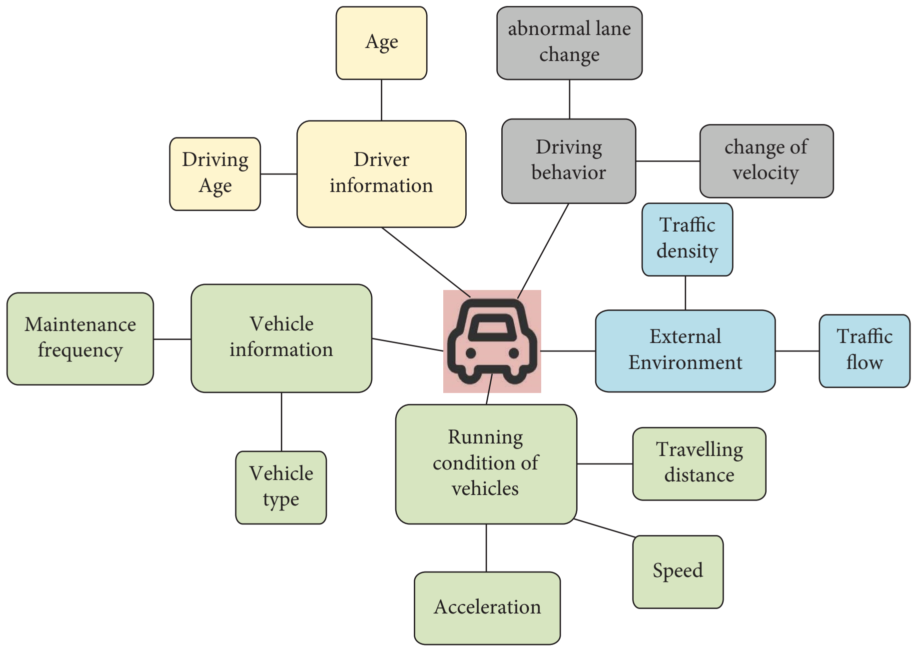

Figure 1: The label of vehicles.

Table 1: Feature type of vehicle profile.

Feature	Feature type
Traffic flow (A)	(1) Fewer vehicles (2) More vehicles (3) Traffic congestion
Light conditions (B)	(1) Morning (2) Daytime (3) Nighttime
Traffic control (D)	(1) No signal light (2) Signal light (3) Signal light damage
Driving distance (E)	(1) Close (2) Moderation (3) Far away
Change of driving angle (F)	(1) Little (2) Moderation (3) Large
...	...
Changes in acceleration (G)	(1) Gentle (2) Normal (3) Great
Speed (H)	(1) Slow (2) Normal (3) Fast
Space headway (J)	(1) Little (2) Moderation (3) Large
Age of driver (K)	(1) Young (2) Middle-aged (3) Old
Driving style (L)	(1) Gentle (2) Normal (3) Radical
...	...

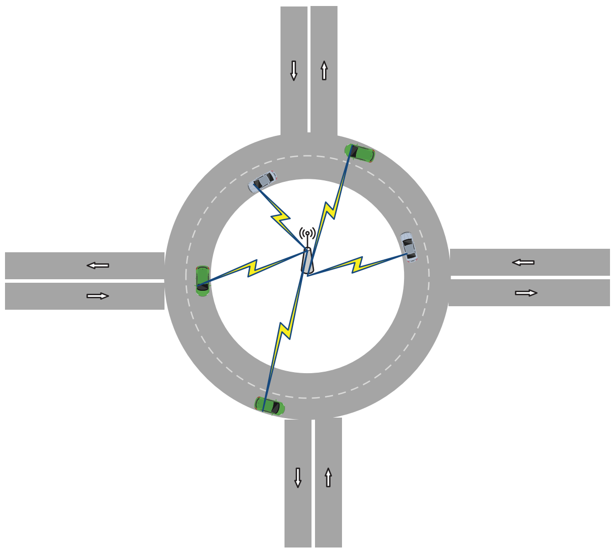

Figure 2: The roundabout scene.

the regularization of a data set. IG is calculated via entropy, which is the expectation of information. Then, the empirical entropy for the traffic dataset T is

$$H(T) = -\sum_{k=1}^{k} \frac{|c_k|}{|T|} \log_2 \frac{|c_k|}{|T|}. \tag{2}$$

The data types of dataset T are C_k, and the total number of datatypes is k. The subsets $(\{T_1, T_2, T_3, \ldots, T_i\})$ can be divided from the traffic dataset T based on feature A. Then, the empirical conditional entropy of A is

$$\begin{aligned} H(T|A) &= \sum_{i=1}^{n} \frac{|T_i|}{T}, \\ H(T_i) &= -\sum_{i=1}^{n} \frac{|T_i|}{T} \sum_{k=1}^{k} \frac{|T_{\mathrm{ik}}|}{|T_i|} \log_2 \frac{|T_{\mathrm{ik}}|}{|T_i|}. \end{aligned} \tag{3}$$

The information gain of A is

$$\mathrm{IG}(T, A) = H(T) - H(T|A). \tag{4}$$

Traditional user profiles generally complete personalized recommendations through user profile tag data, the correlation between tags, and the tag weight value. This paper mainly defines the weight of each component in the payoff function through the label weight value of the VP. That means we get the weight from the calculation of information gain.

If three factors that speed, acceleration, and travel time in the vehicle profile need to be taken into the construction of the payoff function, the weights of speed, acceleration, and travel time in the payoff function are

$$\begin{aligned} P_v &= \frac{\mathrm{IG}(T, v_{sv})}{\mathrm{IG}(T, a_{\mathrm{sv}}) + \mathrm{IG}(T, v_{\mathrm{sv}}) + \mathrm{IG}(T, \mathrm{time}_{\mathrm{sv}})}, \\ P_{\mathrm{acc}} &= \frac{\mathrm{IG}(T, a_{\mathrm{sv}})}{\mathrm{IG}(T, a_{\mathrm{sv}}) + \mathrm{IG}(T, v_{\mathrm{sv}}) + \mathrm{IG}(T, \mathrm{time}_{\mathrm{sv}})}, \\ P_{\mathrm{time}} &= \frac{\mathrm{IG}(T, \mathrm{time}_{\mathrm{sv}})}{\mathrm{IG}(T, a_{sv}) + \mathrm{IG}(T, v_{\mathrm{sv}}) + \mathrm{IG}(T, \mathrm{time}_{\mathrm{sv}})}. \end{aligned} \tag{5}$$

The weight of each part of the payoff function involved in the game of multivehicle coordination is usually used as a parameter in the construction process, then constantly adjusting the parameter to optimize the experimental results. However, in the process of continuous debugging, the importance degree of each part reflected by the weight value proportion is not accurate enough, and the importance degree of all kinds of income of the vehicle in its running process should be constantly changing.

Therefore, on the basis of constructing the vehicle profile, this paper introduces the weight value of each label into the construction process of the payoff function, so that the weight value of the payoff function can change dynamically during the driving process and describe the vehicle driving state more accurately. In this case, the weight in the payoff function is no longer a customizable parameter but participates as a variable calculated from the vehicle data.

3.3. Lane Change Scenarios. The vehicle lane change decision in the roundabouts is similar to the vehicle lane change decision at the highway intersection, in that they both have fixed exits, and the vehicle must complete its lane change action before the fixed exit. In general, the lane-changing behavior of vehicles is only related to the changing vehicle and its surrounding vehicles. However, the VP also has the problem of a cold start caused by insufficient behavioral data at the early stage of construction like traditional user profiles, making it difficult to accurately portray user characteristics. In the new scenario, the data before the vehicle enters the new decision point is processed and divided according to relevant standards, which serves as the basis for constructing the initial VP. The decision module can obtain the information of the VP label only after the VP is built. VP is constantly improved in the process of driving in new road conditions, including the update of weights. As shown in Figure 3, the dynamic update of the vehicle profile starts from the vehicle distance X from the start of the intersection and provides decision help for an intersection lane change.

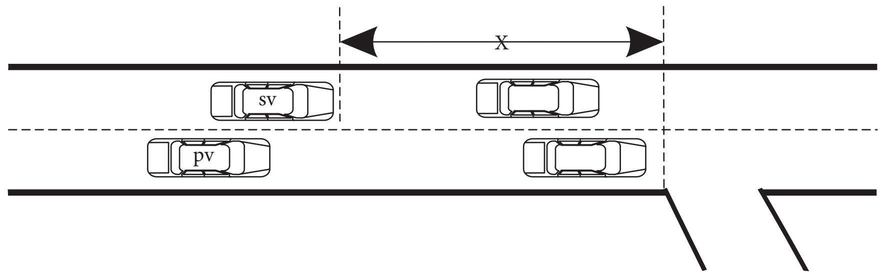

Figure 3: The traffic scene.

4. Lane Change Strategy Based on Vehicle Profile

4.1. Vehicle Payoff Function. In this paper, the payoff functions for the lane change vehicle SV and the yield vehicle SRV are defined as follows:

$$\begin{aligned} C_{\mathrm{sv}} &= P_v U_v(k) + P_{\mathrm{acc(sv)}} U_{\mathrm{acc(sv)}}(k) + P_x x(k), \\ C_{\mathrm{srv}} &= \alpha\left(P_x U_{\mathrm{sp}}(k)\right) + P_v U_v(k) + P_{\mathrm{acc}} U_{\mathrm{acc(srv)}}(k), \end{aligned} \tag{6}$$

subject to:

$$U_{\mathrm{acc(sv)}}(k) = \beta \frac{\left|a_{\mathrm{sv}}(k) - a_{\max}\right|}{a_{\max}}, \tag{7}$$

$$U_{\mathrm{acc(srv)}}(k) = \beta \frac{\left|a_{\mathrm{srv}}(k) - a_{\max}\right|}{a_{\max}}, \tag{8}$$

$$U_v(k) = \frac{\left|\left(v_{\mathrm{srv}}(k) - v_{\mathrm{sv}}(k)\right)\right|}{v_{\max}}, \tag{9}$$

$$\begin{aligned} &0 < k \leq N \\ &N = \frac{x_{\mathrm{des}} - x_{\mathrm{pos}}}{v_{\mathrm{pos}}}, \end{aligned} \tag{10}$$

where x_{des} is the location of vehicle target intersections, x_{pos} is the current position of the vehicle, and the expected vehicle travel period N is obtained from the distance and the current speed.

The payoff function includes three parts. The first part (9) describes the benefits of security. When the speed difference between the two vehicles is larger, the safety benefit is higher. The second parts (8) and (10) describe the benefits of comfort when the acceleration of the vehicle is less, that is the difference between the vehicle acceleration ($a_{\mathrm{srv}}(k)$, $a_{\mathrm{sv}}(k)$) and the upper limit of the road acceleration ($a_{\max}$) tends to level off, the benefits of comfort are higher. For the lane change vehicle SV, the third part is the benefits of efficiency. The smaller the vehicle distance ($x(k)$) from the exit, the lower the probability that the vehicle will successfully change lanes, and the lower the benefit it will bring. And, for the yield vehicle SRV, the third part is the benefits of aggressive ($U_{\mathrm{sp}}(k)$). When the distance between two vehicles is greater than the safe distance, the greater the willingness of SRV vehicles to give way, and when the vehicle distance is smaller, the lower the willingness of vehicles to give way. α, β are all set to 1. And, variables such as $P_v, P_{\mathrm{acc(sv)}}, P_x$ are all obtained by calculating the weights in formula (5).

4.2. The UPC Algorithm. In the previous subsection, the payoff function of the vehicle was defined. Therefore, the multivehicle cooperation algorithm based on vehicle profile is shown in Algorithm 1.

For the inner lane vehicles exiting the roundabout, this algorithm obtains the weight coefficients of each part of the vehicle payoff function based on the vehicle profile and builds the vehicle payoff function based on this. The estimated vehicle payoff function value is obtained by the vehicle driving state, and the threshold value is set as its average value. For the inner lane vehicles whose payoff function value exceeds the threshold, it is forced to change lanes to the outer lane of the roundabout at the driving position beyond the threshold. The vehicles, namely, the inner lane vehicles, change lanes at the position where the impact on the surrounding vehicles is low and the revenue is high, so as to improve the lane-changing efficiency and exit efficiency of the vehicles at the exit of the roundabout, so as to improve the overall operational efficiency of the roundabout.

The state machine of the algorithm in this paper is shown in Figure 4, and the corresponding execution process is as follows:

S1: complete the initialization work, and collect vehicle data, when the vehicle reaches the critical position ($x == 50$), enter S2, if S5 exists, transmit vehicle data to S5.

S2: normalize the vehicle data set, and start the vehicle user profile update work after completion (enter S3).

S3: select the desired vehicle user portrait label, and enter S4.

S4: calculate the weight of the selected label, and enter S5.

S5: construct the vehicle income function and calculate the income value based on the vehicle data (S1) and the label weight (S4), enter S6.

S6: it is judged whether the income value satisfies the lane-changing condition. If the condition is met, the lane change is performed, and enter S2 to make the lane change decision of the next vehicle. If the condition is

Input: The data of vehicles
Output: The lane-changing position of the vehicle
Initializing data;
VP (data);
WHILE (TRUE):
  IF ($0 < X < 50$)
    P = CalculateWeight();
    Payoff (k) = GetPayoff (P, VP (data));
    IF (Payoff (k)>Payoff)
      ChangeLane (position);
    ELSE
    Payoff ($k+1$) = GetPayoff (P, VP (data));
      IF (Payoff ($k+1$) > Payoff)
        ChangeLane (position);
      END
END

Algorithm 1: (UPC).

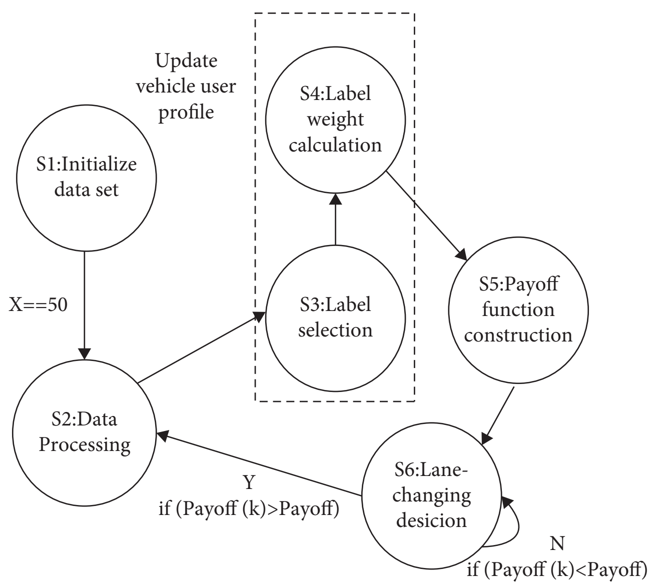

Figure 4: Finite state machine.

not met, enter S6 to make a decision at the next moment.

5. Evaluation

5.1. Experiment Setup. In this paper, we use SUMO as the simulation platform to simulate and compare the method proposed. The simulation scene is shown in Figure 5, and the data related to the scenario are shown in Table 2.

According to the vehicle generation probability of SUMO, this section is divided into three roundabout traffic scenarios. According to the provisions of the old and new traffic laws on the safe driving distance, when the vehicle generation probability of SUMO is 0.05 (maximum 5 vehicles per 100 meters) [36], the safe driving distance limit has been reached. Considering the safe driving distance, lane change has little impact on surrounding vehicles. Therefore, this paper divides SUMO vehicle generation probability into three round-island traffic scenarios based on vehicle driving safety spacing. They are a congestion scenario with a generation probability of 0.1 (up to 10 cars per 100 meters), a normal scenario with a generation probability of 0.08 (up to 8 cars per 100 meters), and a sparse scenario with a generation probability of 0.05 (up to 5 cars per 100 meters).

To compare the performance analysis, in addition to the UPC algorithm proposed in this paper, three algorithms are also introduced: (1) the built-in algorithm of the SUMO platform, (2) the lane-changing algorithm with the uniform weight of the revenue function (UW) [37], (3) the algorithm that focuses on driving comfort (HA), which is mainly based on the acceleration parameters to construct the vehicle payoff function [38], and (4) the algorithm (CRP) that

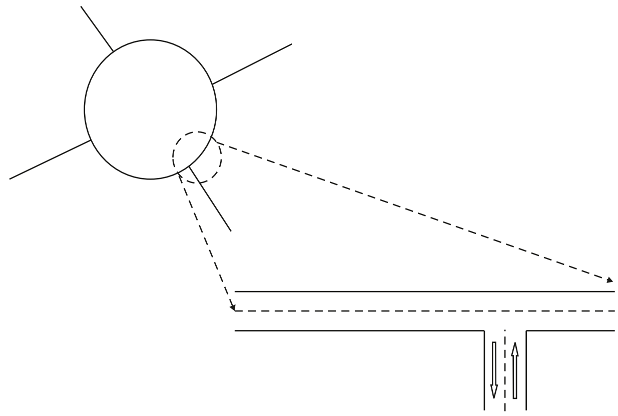

Figure 5: The simulation scene.

Table 2: Explanation of experimental parameters.

Parameter	Value
Accel (maximum acceleration: m/s^2)	2.5
Decel (maximum deceleration: m/s^2)	2.5
X (vehicle distance from intersection: m)	50
Speed (maximum speed: m/s)	13.89
Radius (m)	200

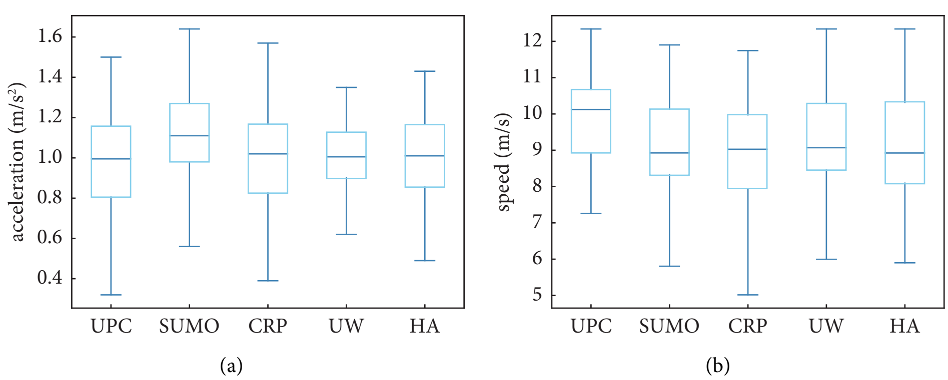

Figure 6: Main parameter analysis in normal scenarios. (a) Trend of acceleration. (b) Velocity distribution.

optimizes the overall revenue of multiple vehicles on the basis of the cooperative game [39].

5.2. Results Analysis in Normal Traffic Scenarios. Figures 6(a) and 6(b) and Figures 7(a) and 7(b) are the acceleration distribution diagram, the vehicle speed distribution diagram, and the vehicle traveling time distribution diagram of some selected vehicles, respectively. It can be seen from Figures 6(a) and 6(b) and Figures 7(a) and 7(b) that the lower and upper quartiles of the UPC algorithm are lower than those of the SUMO algorithm, and the acceleration distribution interval of the UPC algorithm is smaller in normal traffic scenarios. That means the vehicle driving stability of the UPC algorithm is better.

The lower quartile and the minimum and median values of the velocity distribution of the UPC algorithm in Figure 6(b) are also higher than those of the SUMO algorithm. In Figure 7(a), the vehicle travel time of the UPC algorithm is less than that of other algorithms. And, the vehicle speed of the UPC algorithm in Figure 7(b) is mostly distributed in the high range. Therefore, the vehicle traffic efficiency of the UPC algorithm is higher than that of the SUMO algorithm.

And, the distribution of acceleration, speed, and vehicle travel time of the UPC algorithm all show that the vehicle driving stability and vehicle traffic efficiency of the UPC algorithm are better than the CRP algorithm, the UW algorithm, and the HA algorithm.

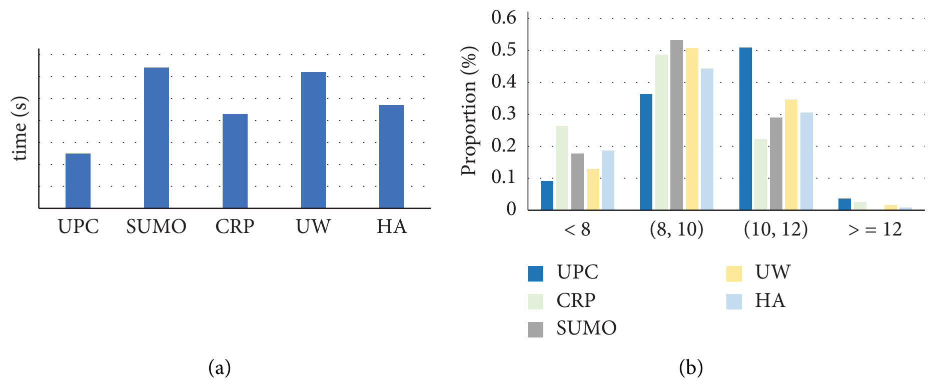

Figure 7: The results in normal scenarios. (a) Vehicles' travel time. (b) Velocity distribution interval.

Table 3: The results in different situations.

Parameters	Scene		
	Sparse scene	Normal scene	Congestion scene
Average speed (m/s)	10.6813	9.5963	8.5698
Travel time (s)	4334	7578	10051

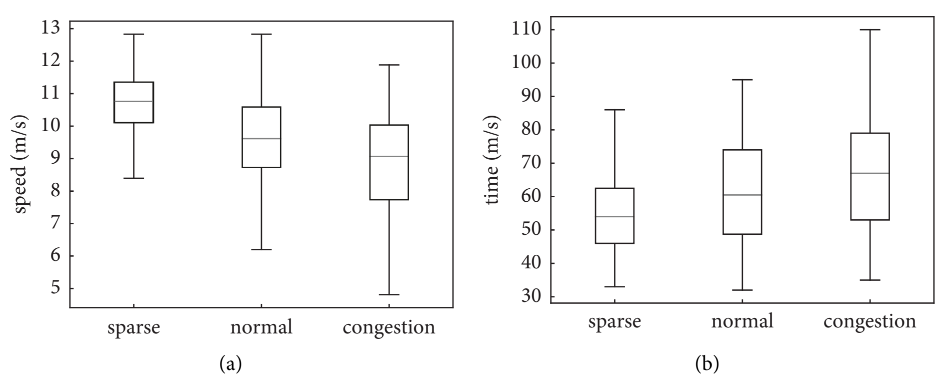

Figure 8: The results in different scenarios. (a) Velocity distribution. (b) Vehicles' travel time.

5.3. Results Analysis in Different Traffic Scenarios. The vehicle traffic efficiency optimization ability of the UPC algorithm proposed in this paper has been verified in the normal traffic situation of the roundabout. Therefore, we verify the difference in the traffic efficiency optimization ability of the UPC algorithm in different scenarios by changing the vehicle generation probability as shown in Table 3.

Figures 8(a) and 8(b) show the UPC algorithm's ability to optimize vehicle traffic efficiency in three different scenarios. Due to the difference in vehicle generation probability, the number of final vehicles is proportional to the generation probability, and the speed and travel time are inversely proportional to the generation probability.

6. Conclusion

For the problem of vehicle cooperation at the exit of roundabouts, this paper constructs the vehicle profile based on the idea of a user profile and designs the vehicle payoff function according to the characteristics of roundabout traffic scenarios and establishes the vehicle lane-changing cooperative strategy model. SUMO software is used to simulate the model, and the main conclusions of this paper are as follows.

The vehicle profile (VP) can objectively describe the driving state of the vehicle, and the label weight of the VP obtained by the random forest algorithm can solve the problem of manual debugging of the weight in the payoff function, making the weight as a variable rather than a parameter.

The vehicle payoff function is constructed based on the dynamic weight, and the UPC algorithm designed can effectively improve the traffic efficiency of vehicles in the roundabout scene.

However, the experimental scenario in this paper assumes that there is no delay and no packet loss and does not consider the problems that may exist in real-time communication limitation and data packet loss in practical applications. Therefore, the actual situation of communication limitations and so on should be considered in subsequent studies.

Data Availability

The data used to support the findings of this study have not been made available because the data are relevant for followup studies.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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