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Optimal Parking Space Selection and Vehicle Driving Decision for Autonomous Parking System Based on Multi-Attribute Decision

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Abstract: Autonomous parking systems (APSs) can help drivers complete the task of finding a parking space and the parking operation, which improves driving comfort. Current research on APSs focus on the perception, localization, planning, and control modules, while few pay attention to the decision modules. This paper proposes a method for optimal parking space selection and vehicle driving decisions. In terms of selecting the optimal parking space, a multi-attribute decision method is designed considering the type of parking space, walking distance, and other factors. In terms of vehicle driving decisions, we first predict the behavior and trajectory of the target vehicle in a specific scenario, and then use a combination of rule-based and learning-based decision methods for safe and comfortable vehicle driving behavior decisions. Simulation results show that the proposed methods can find the optimal parking space according to the parking lot map and improve the efficiency and smoothness of vehicle driving while ensuring driving safety.

Keywords: autonomous parking system (APS); multi-attribute decision; driving behavior and trajectory; optimal parking space selection; driving decision

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1. Introduction

In the early stage of vehicle intelligence development, three technical routes have emerged for autonomous parking systems (APSs) based on the resources, costs, and other factors: vehicle-side intelligence solutions, field-side intelligence solutions, and vehicle–field collaboration solutions. An APS based on vehicle-side intelligence perceives, locates, makes decisions, plans [1], and controls [2,3] entirely through vehicle-side software and hardware technology. It can perform various driving operations without human intervention, including obstacle avoidance, scanning for empty parking spaces, and parking navigation [4–6], and is technically closer to low-speed Level-4 autonomous driving scenarios with scene migration capabilities.

While many car companies prefer vehicle-side intelligence solutions in selecting parking spaces, a lot of research prefer parking guidance systems based on smart parking lots. Young proposed a PARKSIM model to simulate the driver's behavior of finding a parking space in the parking lot where the spaces are known [7]. Idris MYI et al. designed a parking service system that uses an algorithm for selecting the shortest path to provide the user with a suitable parking location [8]. Liu et al. proposed a parking space selection model based on the main considerations such as parking difficulty and walking distance [9]. Gao proposed a method using the shortest route to choose the optimal parking space [10]. Lee et al. and Chen et al. both proposed a fuzzy multi-attribute-related method to search for the optimal parking space; while Lee et al. only considered the objective factors of the available parking space [11], Chen et al. only took the subjective factors into account [12]. Currently, the commercialized APS prefers to use a cruising method to find an available parking space with the sensing system, but this method lacks the decision of selecting an optimal parking space.

In terms of vehicle driving decisions in parking lots, many studies pay more attention to perception, localization, planning, and control. Nakrani et al. proposed a fuzzy-based obstacle avoidance controller that could perform smart parking like a person by avoiding static and moving obstacles [13]. Jiménez et al. integrated the perception, localization, decision, and maneuvering methods for the control of an autonomous vehicle to enable the vehicle to drive safely in the parking lot [14]. Although some studies have achieved many compelling results in the above part, unreasonable decision behaviors also have a certain impact on the safety and efficiency of autonomous vehicle driving. In light of these risks, autonomous vehicles need to establish a more comprehensive decision system to improve their driving safety and efficiency. However, few researchers concern and cope with the aforementioned issues. Only Bi et al. constructed a rule-based behavior tree decision model for an APS and verified its soundness and implementability [15].

Therefore, in this paper, a method for optimal parking space selection and vehicle driving decision is proposed to find the optimal parking space according to the parking lot map and to improve the efficiency and smoothness of vehicle driving in the parking lot while ensuring driving safety. The main contributions of the paper are summarized as follows:

(1) A novel method to select the optimal parking space is proposed. Different from the existing studies that only aim to find an available parking space, the proposed method uses multi-attribute decision to evaluate the candidate parking spaces in a parking lot map and select the optimal parking space by considering the driver's preference.

(2) A model to make vehicle driving decisions in the parking lot is then designed, which combines a behavior tree with a deep Q-learning network (DQN) to improve the efficiency of vehicle driving while ensuring driving safety during the parking process.

(3) A method for conflict target vehicle trajectory prediction is designed. The behavior of the target vehicle is predicted with a long and short-term memory (LSTM) model, and the trajectory of the target vehicle is predicted with a constant velocity (CV) model and a five-degree polynomial. Then the prediction results are substituted into the decision model to improve the rationality of the decision.

Compared to references [11,12], reference [11] primarily considered objective factors in selecting parking spaces, while reference [12] focused on subjective factors. This bias makes both studies somewhat one-sided. In contrast, this paper adopts a method that integrates both subjective and objective factors, considering not only the decision maker's subjective preferences but also the objective attributes of each alternative, thereby making the decision-making process more comprehensive and reasonable. Furthermore, compared to reference [15], which only established a simple behavior tree decision model with insufficient consideration of scenarios, in this paper, a more complex behavior tree decision model is developed, and DQN technology is combined, which can not only make more reasonable decisions about the behavior of vehicles, but also reasonably determine the driving speed of vehicles and significantly improve the applicability and efficiency of the model.

The remainder of the paper is organized as follows. Section 2 proposes the model about selecting the optimal parking space decision and vehicle driving decision; Section 3 presents the simulation validation; and Section 4 concludes the paper.

2. Materials and Methods

2.1. System Overview

Two types of autonomous vehicle decision-making behavior in the parking lot are considered, namely the decision to select the optimal parking space and the behavioral decision during autonomous vehicle driving. The overall structure is shown in Figure 1. In the optimal parking space decision, the study uses multi-attribute decision to select the optimal parking space [12]. In autonomous vehicle driving behavioral decisions, the study uses a combination of the behavior tree and DQN to make decisions about the behavior of autonomous vehicles and incorporates the predictive trajectory method from other vehicles in some specific scenarios.

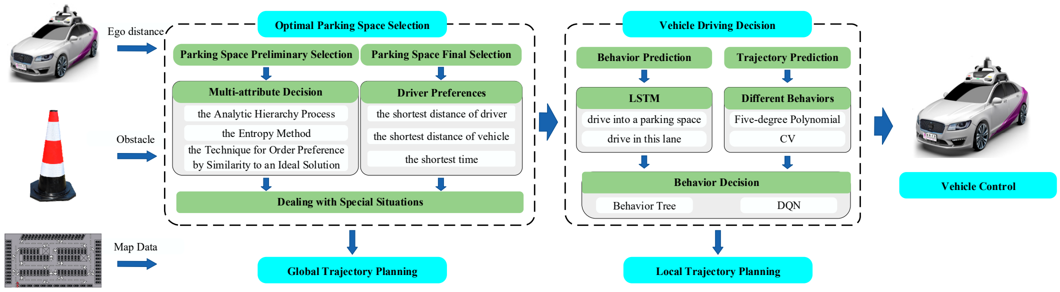


Figure 1. Overall structural framework.

2.2. *Optimal Parking Space Selection*

The decision framework for selecting the optimal parking space is shown in Figure 2. The decision method is divided into two main parking scenarios: at the entrance of the parking lot and during the driving in the parking lot.

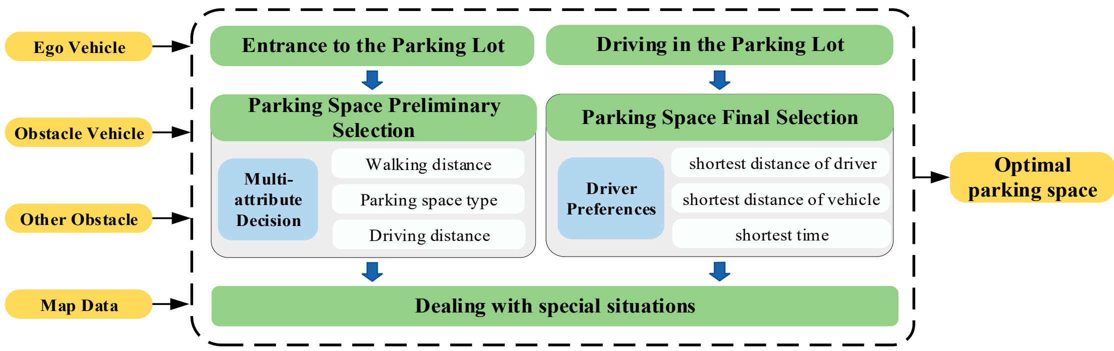


Figure 2. The optimal parking space selection framework.

2.2.1. Parking Space Preliminary Selection Model

When the autonomous vehicle arrives at the entrance of the parking lot, an optimal parking space needs to be preliminarily determined as the driving destination. In order to improve the calculation efficiency, we first select a few high-quality parking spaces from a large number of parking spaces by preliminary selection. Our goal is to filter the parking spaces around each pedestrian exit to find a better parking space and then determine an optimal parking space as the vehicle's driving destination. The method first needs to determine the factors that affect the choice of parking space.

Factors influencing the selection of parking spaces include walking distance, vehicle driving distance, and the type of parking space, etc. [16]. As the distance difference between the parking spaces around each pedestrian exit and the entrance of the parking lot is small, we only consider two influencing factors: the walking distance and the type of parking space in the initial selection of parking spaces.

The walking distance refers to the distance between the parking space and the pedestrian exit. Drivers usually prefer a shorter distance due to human initiative. The walking distance can be calculated using the Euclidean distance [16]:

$$d_{i\_j} = \sqrt{\left(x_i - x_{i\_j}\right)^2 + \left(y_i - y_{i\_j}\right)^2} \tag{1}$$

where (x_i, y_i) represents the coordinates of the pedestrian exit and (x_{i_j}, y_{i_j}) represents the coordinates of the center of the parking space.

There are three types of parking spaces, namely the T shape parking space, the line shape parking space, and the bias shape parking space, as shown in Figure 3. We use $t_f, t_y,$ andt_x to represent the parking difficulty of three types of parking spaces, with the value relationship $t_y > t_f > t_x$ [9].

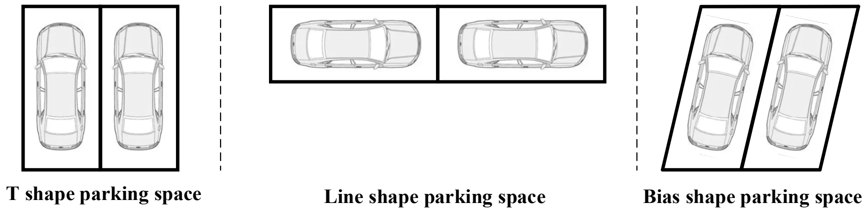


Figure 3. Three types of parking spaces.

Considering that different drivers evaluate the importance of the influencing factors differently, we use a multi-attribute decision model with a combination of subjective and objective weighting methods. The subjective factors are analyzed using the analytic hierarchy process (AHP) [17] and the objective factors are evaluated using the entropy method [18]. The final solution to the multi-attribute decision problem is obtained by using the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) [19].

The calculation process of AHP is shown below. Firstly, the hierarchical structure model is established as shown in Figure 4. The goal layer is the optimal parking space, the criterion layer is the walking distance and the type of parking space, and the scheme layer is the alternative parking space.

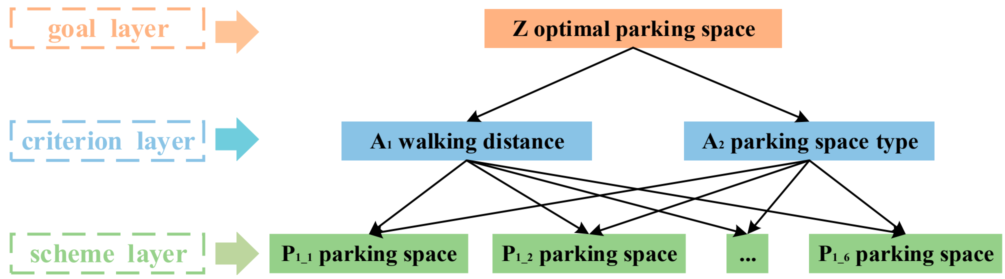


Figure 4. Hierarchical structure of the hierarchical analysis method.

The judgment matrix $W_{2\times2}$ is constructed according to the relative importance of the two influencing factors, where w_1/w_2 indicates the importance of influence factor w_1 relative to influence factor w_2. The method takes values from 1 to 9 depending on the level of importance, where 1/1 indicates equal importance while 9/1 indicates extreme or absolute importance. In addition, the elements on the main diagonal of the matrix are set to 1.

$$W_{2\times2} = \begin{bmatrix} 1 & w_1/w_2 \\ w_2/w_1 & 1 \end{bmatrix}. \tag{2}$$

The maximum eigenvalue λ_{max} of this matrix and its corresponding eigenvector $a = (a_1', a_2')$ are solved for the consistency test. If the test is passed, the eigenvector a is regularized $(a_1 + a_2 = 1)$, where a_1 and a_2 are the subjective weights of the corresponding influencing factors, otherwise, the judgement matrix is adjusted.

The stochastic consistency ratio of the judgment matrix is

$$CR = \frac{CI}{RI(n)}, \tag{3}$$

where the consistency indicator of the judgment matrix is CI, which can be calculated as

$$CI = \frac{\lambda_{max} - n}{n - 1}, \tag{4}$$

where $RI(n)$ is the average random consistency index of the judgment matrix, and the values of $RI(n)$ can be found in Table 1.

Table 1. Average random consistency indicators.

n	1	2	3	4	5
RI	0	0	0.58	0.90	1.12

When $CR < 0.1$, the judgment matrix is considered to have better consistency; otherwise, the consistency test of the judgment matrix fails.

The calculation process of entropy method is shown as follows: Let $E = \{e_i | i = 1, 2, \cdots, n\}$ be the set of alternative parking spaces and $F = \{f_j | j = 1, 2\}$ be the set of influence factor values of each alternative parking space. The obtained original data matrix is $A = (a_{ij})_{n \times 2}$ and the walking distance and parking difficulty are both negative indicators; therefore, the evaluation matrix $R = (r_{ij})_{n \times 2}$ is obtained by normalizing and transforming the matrix by:

$$r_{ij} = \frac{\max_i a_{ij} - a_{ij}}{\max_i a_{ij} - \min_i a_{ij}}, i = 1, 2, \cdots, n. \tag{5}$$

The entropy of the j^th influencing factor can be calculated as:

$$h_j = -k \sum_{i=1}^{n} f_{ij} ln f_{ij}, \tag{6}$$

where $k = 1/lnn$ and $f_{ij} = \frac{r_{ij}}{\sum_{i=1}^{n} r_{ij}}$.

The objective weight of the j^th influencing factor is:

$$b_j = \frac{1 - h_j}{n - \sum_{j=1}^{2} h_j} \left(0 \le b_j \le 1, \sum_{1}^{2} b_j = 1 \right). \tag{7}$$

The calculation process of the subjective–objective combination weighting is shown as follows. Assuming that α and β are used to measure the importance of vector weights of influencing factors. The weight of the influencing factor calculated by the subjective weighting method is $a_j = (a_1, a_2)^T$ and the weight of the influencing factor calculated by the objective weighting method is $b_j = (b_1, b_2)^T$. Moreover, since $\alpha + \beta = 1$, then $\omega = \alpha a + \beta b$ is the weight determined by the subjective and objective combination weighting method.

$$\alpha = \frac{\sum_{i=1}^{n} \sum_{j}^{2} \left(r_j^- - r_{ij} \right) a_j}{\sum_{i=1}^{n} \sum_{j}^{2} \left(r_j^- - r_{ij} \right) (a_j + b_j)}, \tag{8}$$

$$\beta = \frac{\sum_{i=1}^{n} \sum_{j}^{2} \left(r_j^- - r_{ij} \right) b_j}{\sum_{i=1}^{n} \sum_{j}^{2} \left(r_j^- - r_{ij} \right) (a_j + b_j)}. \tag{9}$$

where r_j^- is the mean of the elements in column j of the evaluation matrix R.

The calculation process of TOPSIS is as follows. The indicator decision matrix $A = (a_{ij})_{n \times 2}$ is normalised using the vector normalisation method to obtain the matrix

$Y = (y_{ij})_{n\times 2}$, where $y_{ij} = \frac{a_{ij}}{\sqrt{\sum_l a_{ij}^2}}$ and the weighted normalization matrix is $V = (v_{ij})_{n\times 2} = (\omega_j y_{ij})_{n\times 2}$. The ideal solution and negative ideal solution are determined by

$$V^+ = \left(\min_{1\le i\le n} v_{ij} \middle| j \in J^-\right) = \{v_1^+, v_2^+\}, \quad (10)$$

$$V^- = \left(\max_{1\le i\le n} v_{ij} \middle| j \in J^-\right) = \{v_1^-, v_2^-\}. \quad (11)$$

The distance of parking space i to the positive ideal solution and negative ideal solution are S_i^+ and S_i^-, respectively, which are calculated as:

$$S_i^+ = \sqrt{\sum_{j=1}^{2}\left(v_{ij} - v_j^+\right)^2}, (i = 1, 2, \cdots, n), \quad (12)$$

$$S_i^- = \sqrt{\sum_{j=1}^{2}\left(v_{ij} - v_j^-\right)^2}, (i = 1, 2, \cdots, n). \quad (13)$$

The approximation of the value of each parking influence factor to the ideal solution can be calculated as:

$$C_i^+ = \frac{S_i^-}{S_i^- + S_i^+}, (i = 1, 2, \cdots, n). \quad (14)$$

If the value of the parking influence factor with the greatest posting progress is found in Equation (15), the parking space can be used as the optimal parking space for that pedestrian exit.

$$C_i = \max\left(C_1^+, C_2^+, \cdots C_n^+\right). \quad (15)$$

After completing the preliminary selection of parking spaces, the vehicle driving distance can be added to the factors affecting the parking space, and then the method described above can be used again to make a decision to select the optimal parking space. The vehicle driving distance is defined as the distance between the parking space and the entrance of the parking lot, which can be obtained by Dijkstra's algorithm [20].

2.2.2. Parking Space Final Selection Model

The autonomous vehicle may pass by some free parking spaces on its way to the target parking space. In a normal parking lot, the autonomous vehicle does not have access to information on whether the target parking space is occupied or not. Therefore, it needs to make a decision between the target parking space and the free parking space while passing by to determine the final parking space.

We have the option of using driver preferences for decision-making. The three driver preferences are classified as the shortest distance walked by the driver, the shortest distance travelled by the autonomous vehicle, and the shortest time taken by the driver to park. The driver chooses according to their own situation, and the default preference is the shortest time taken by the driver to park.

The shortest distance walked by the driver means that the driver walks the shortest distance from the parking space to the pedestrian exit. The preference can be determined by:

$$d_w = d_{wf} - (1 + p_z)\cdot d_{wt}, \quad (16)$$

where d_{wf} represents the distance from the passing free parking space to the pedestrian exit, d_{wt} represents the distance from the target parking space to the pedestrian exit, and p_z represents the occupied probability of the target parking space, which can be calculated as:

$$p_z = \frac{n_z}{n_i}, \tag{17}$$

where n_z represents the number of occupied parking spaces passed by the vehicle from the entrance of the parking lot to the current parking space, n_i represents the number of all parking spaces passed by the vehicle from the entrance of the parking lot to the current parking space.

When $d_w \geq 0$, the autonomous vehicle chooses to continue to the target parking space; otherwise, the autonomous vehicle chooses to park in a passing free parking space directly.

The second preference is the shortest distance travelled by the autonomous vehicle. It means that the total distance travelled by the autonomous vehicle in the parking lot should be minimized. The preference can be determined by:

$$d_d = d_{df} - (1 + p_z) \cdot d_{dt}, \tag{18}$$

where d_{df} represents the distance from the passing free parking space to the entrance of the parking lot and d_{dt} represents the distance from the target parking space to the entrance of the parking lot.

When $d_d \geq 0$, the autonomous vehicle chooses to continue to the target parking space; otherwise, the autonomous vehicle chooses to park in a passing free parking space.

The third preference is the shortest time taken by the driver to park. It means the shortest time from the entrance to the pedestrian exit of the parking lot. The preference can be determined by:

$$t = \frac{d_{wf}}{v_w} - (1 + p_z)\left(\frac{d_{wt}}{v_w} + \frac{d_{df_t}}{v_c}\right), \tag{19}$$

where d_{df_t} represents the distance from the passing free parking space to the target parking space, v_w represents the average walking speed of the driver, and v_c represents the average speed of the vehicle.

When $t \geq 0$, the autonomous vehicle chooses to continue to the target parking space; otherwise, the autonomous vehicle chooses to park in a passing free parking space.

When the autonomous vehicle reaches the target parking space and its sensors detect that the target parking space is free, the autonomous vehicle drives into the target parking space and completes the parking process.

There are also some special cases in the optimal parking space selection decision. When the autonomous vehicle travels to a target parking space and its sensors detect that the target parking space is occupied, then the autonomous vehicle needs to decide on travelling to the next target parking space. There are two choices, one is the nearest free parking space passed by and the other is the second optimal parking space decided according to the aforementioned multi-attribute decision method.

The next target parking space is determined by setting a threshold d_T. When $d_T \geq d_m$, the autonomous vehicle selects the nearest free parking space as the target parking space; otherwise, the autonomous vehicle selects the next optimal parking space as the target parking space, where d_m is the distance between the current position of the autonomous vehicle and the nearest free parking space.

2.3. Vehicle Driving Decision

The autonomous vehicle driving decision framework diagram is shown in Figure 5. It includes three main parts. In some specific situations, we can first predict the trajectory of the target vehicle driving in a straight lane. Then, we can use the behavior tree to make a decision on the vehicle's behavior and output the behavior that the vehicle follows or other behaviors, and finally input the result into the DQN method to output the vehicle's jerk and steering wheel angular speed.

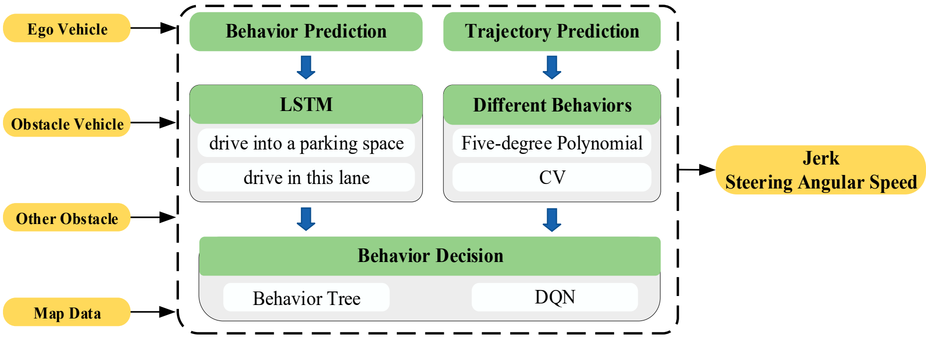


Figure 5. Driving decision framework.

2.3.1. Behavior Tree Decision Model

The behavior tree is a more common rule-based behavioral decision-makingmethod [21]. The autonomous vehicle can classify the vehicle's current driving scenario based on information such as environmental perception and vehicle status. It can search the behavior tree model from the top down according to the formulated conditional rules to finally decide on the vehicle's behavior [22].

In the parking lot, surrounding obstacles include vehicles, pedestrians, other static obstacles, etc. [23]. The parking lot can be divided into three small scenarios for consideration: straight-line driving scenario, intersection driving scenario, and parking space driving scenario. The behavioral decision results may be different in different driving scenarios. Autonomous vehicles can enter different scenarios according to the access conditions of different scenarios in the behavior tree decision model. The access conditions of the straight-line driving scenario can be set as follows: the road segment that the autonomous vehicle is about to drive is a straight road, the distance between the vehicle position and the intersection center point is greater than 10 m, and the distance between the vehicle position and the target parking space is greater than 10 m. The scenario decision model diagram is shown in Figure 6.

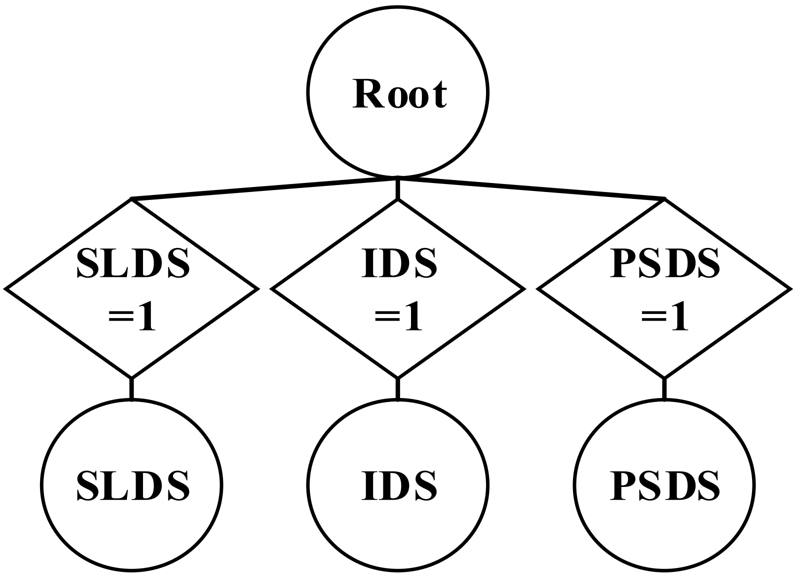


Figure 6. Scenario behavior tree decision model.

Autonomous vehicles enter the behavior tree decision model after meeting the access conditions of each scenario. The behavior tree models for the three scenarios are shown in

Figures 7–9. The meanings corresponding to the symbols in the behavior tree are shown in Table 2.

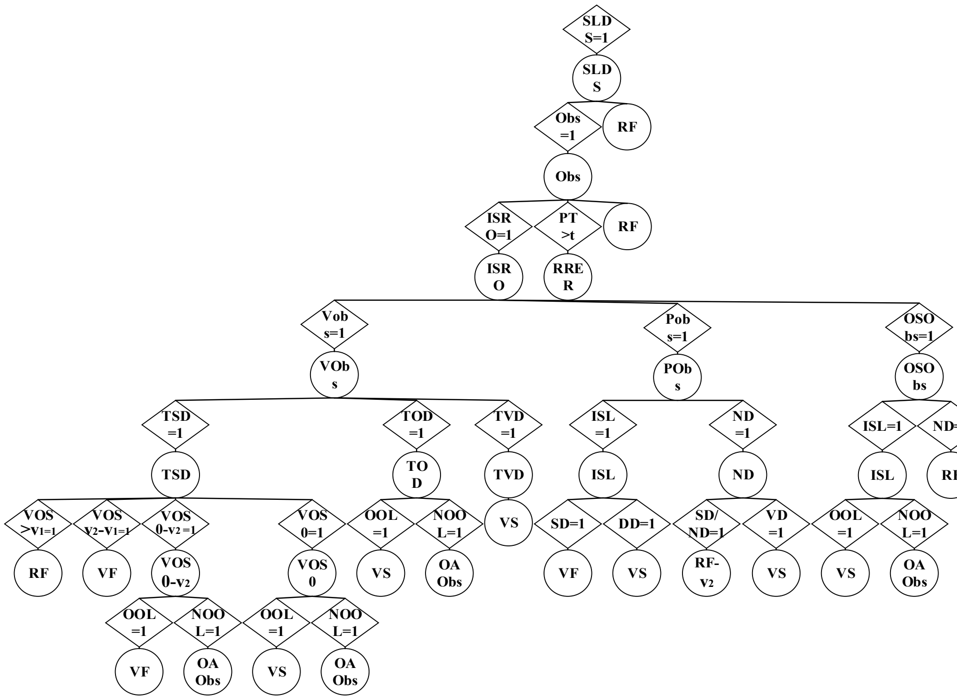


Figure 7. Straight-line driving scenario behavior tree decision model.

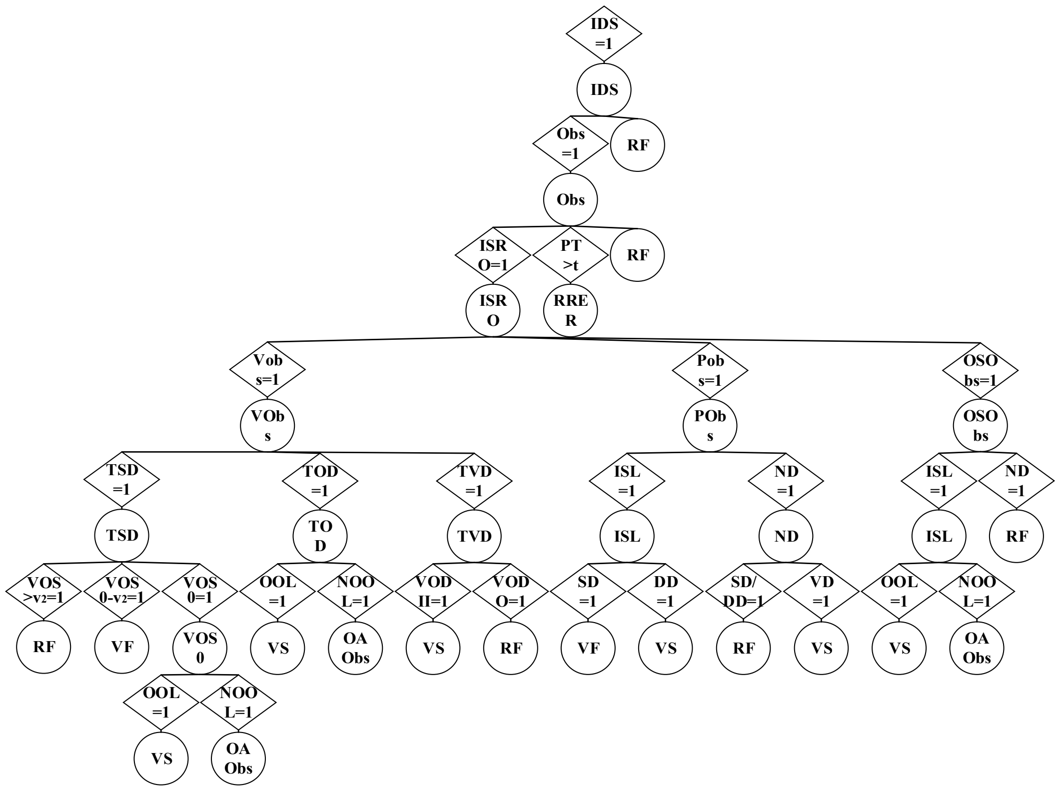


Figure 8. Intersection driving scenario behavior tree decision model.

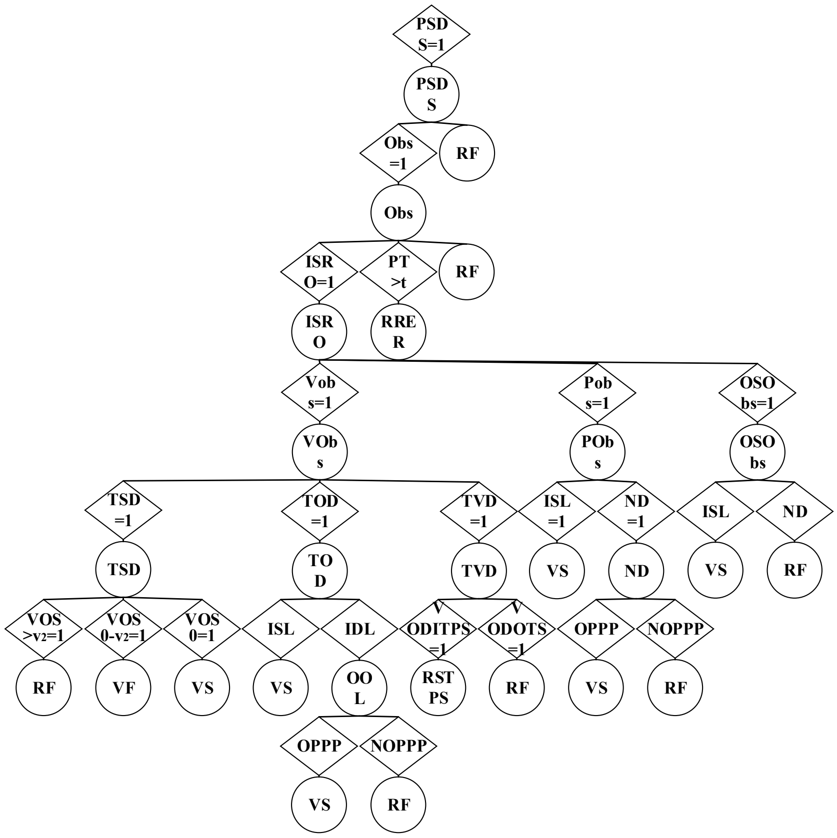


Figure 9. Parking space driving scenario behavior tree decision model.

Table 2. Symbol meaning cross-reference table.

Symbol	Meaning	Symbol	Meaning
SLDS	Straight-Line Driving Scenario	RF	Routes Follow
IDS	Intersection Driving Scenario	VF	Vehicles Follow
PSDS	Parking Space Driving Scenario	OAObs	Overtaking Avoiding Obstacles
Obs	Obstacles	VS	Vehicles Stop
VObs	Vehicle Obstacles	TSD	Traveling Same Direction
PObs	Pedestrian Obstacles	TOD	Traveling Opposite Direction
OSObs	Other Static Obstacles	TVD	Traveling Vertical Direction
OOL	Obstacle in Opposite Lane	ISL	In the Same Lane
NOOL	No Obstacle in Opposite Lane	IDL	In the Different Lane
SD	Same Direction	ND	Near the Driveway
DD	Different Direction	VOS	Vehicle Obstacles Speed
VD	Vertical Direction	RRER	Route Re-routing
ISRO	In Safe Range Outside	RF	Parking Time
VODII	Vehicle Obstacle Driving Into Intersections	OPPP	Overlap with Parking Plan Paths
VODOI	Vehicle Obstacle Driving Out of Intersection	NOPPP	No Overlap with Parking Plan Paths
VODITPS	Vehicle Obstacle Driving Into Target Parking Space	RSTPS	Re-select Target Parking Space
VODOTPS	Vehicle Obstacle Driving Out of Target Parking Space		

2.3.2. DQN Decision Model

During the driving process of autonomous vehicles, sudden changes in speed and steering angle can occur during the switching and execution process of behavior decided by the behavior tree. To address this issue, the study used the DQN method to model different behaviors separately.

First, the kinematics of the autonomous vehicle is modelled, as shown in Equations (20)–(25).

$$a_{t+1} = \int_t^{t+1} j dt + a_t \tag{20}$$

$$v_{t+1} = \int_t^{t+1} a dt + v_t \tag{21}$$

$$\delta_{t+1} = \int_t^{t+1} kw dt + \delta_t \tag{22}$$

$$\theta_{t+1} = \int_t^{t+1} \frac{v \cdot \tan \delta}{L} dt + \theta_t \tag{23}$$

$$y_{t+1} = \int_t^{t+1} v \cdot \sin \theta dt + y_t \tag{24}$$

$$x_{t+1} = \int_t^{t+1} v \cdot \cos \theta dt + x_t \tag{25}$$

where j represents the jerk, a represents the acceleration, v represents the speed, k represents the ratio of steering wheel speed to front wheel steering angular speed, δ represents the front wheel steering angle, θ represents the transverse sway angle, x represents the longitudinal displacement, and y represents the lateral displacement.

As the state space, action space, and reward function considered in the DQN are different, the models are conducted as below.

1. Car following behavior.

Since under the car following behavior, the autonomous vehicle follows a planned global trajectory, we only need to replan its speed here:

$$S = \{\Delta d_x, v, a, j\}, \tag{26}$$

$$A = \{j\}, \tag{27}$$

where S represents the state space, Δd_x represents the relative longitudinal distance to the vehicle ahead, and A represents the action space, with $3 \geq j \geq -3$ and a discrete interval of 0.1.

The reward function consists of the following components: The first influencing factor is the time to collision (TTC) [24], which represents the time to collide with the autonomous vehicle at the current speed and lane, and is derived by:

$$TTC = \frac{\Delta d_x}{v - v_z}, \tag{28}$$

where v_z represents the speed of the vehicle ahead.

The second influencing factor is the minimum safe distance (MSD) between the autonomous vehicle and the vehicle ahead.

The third influencing factor is the vehicle interval time (IVT), which indicates the time it would take for a collision to occur if the vehicle ahead stopped and the autonomous vehicle continued at its current speed and lane.

For each of the three influences mentioned above, the value-at-risk definition can be derived by:

$$R_{TTC} = \begin{cases} 1 & TTC < t_1 \\ 0 & otherwise \end{cases}, \tag{29}$$

$$R_{MSD} = \begin{cases} 1 & MSD < d_a \\ 0 & otherwise \end{cases}, \tag{30}$$

$$R_{IVT} = \begin{cases} 1 & IVT < t_2 \\ 0 & otherwise \end{cases}, \tag{31}$$

where t_1 represents the TTC threshold, d_a represents the MSD threshold, t_2 represents the IVT threshold, R_{TTC} represents the TTC risk value, R_{MSD} represents the MSD risk value, and R_{IVT} represents the IVT risk value.

The reward value for the safety component can be derived by:

$$R_F = \begin{cases} r_f & R_{TTC} + R_{MSD} + R_{IVT} \geq 1 \\ 0 & otherwise \end{cases}, \tag{32}$$

where r_f represents the penalty value for the safety component, which is negative.

The second part is the desired speed of the vehicle; it can be derived by:

$$R_V = r_v \times |v - v_{desire}|, \tag{33}$$

where r_v represents a negative coefficient and v_{desire} represents the desired speed of the autonomous vehicle.

The third part is the choice of vehicle actions, mainly the acceleration of the vehicle, trying to avoid frequent acceleration and deceleration, which can be derived by:

$$R_A = \begin{cases} r_a \times a^2 & a \neq 0 \\ 0 & otherwise \end{cases}, \tag{34}$$

where r_a represents a negative coefficient.

The fourth part is the penalty for a vehicle collision; it can be derived by:

$$R_R = \begin{cases} r_r & \Delta d = 0 \\ 0 & otherwise \end{cases}, \tag{35}$$

where r_r represents a large negative value.

The fifth part is the desired relative distance of the vehicle; it can be derived by:

$$R_D = r_d \times |\Delta d_x - \Delta d_{desire}|, \tag{36}$$

where r_d represents a negative coefficient and Δd_{desire} represents the desired relative distance to the vehicle ahead.

The sixth part is the reward for the autonomous vehicle reaching the desired state; it can be derived by:

$$R_T = \begin{cases} r_t & v = v_{desire}, \Delta d_x = \Delta d_{desire} \\ 0 & otherwise \end{cases}, \tag{37}$$

where r_t represents a positive reward value.

In conclusion, the value of the reward for autonomous vehicle following behavior can be derived by:

$$R = w_1 R_F + w_2 R_V + w_3 R_A + w_4 R_R + w_5 R_D + w_6 R_T, \tag{38}$$

where w_1~w_6 are the coefficients for each partial award value.

2. Overtaking and obstacle avoidance behavior.

If obstacles occupy the planned global trajectory under the overtaking obstacle avoidance behavior, both the speed and lateral displacement of the autonomous vehicle need to be considered to ensure reasonable obstacle avoidance.

$$S = \{\Delta d_x, \Delta d_y, v, a, j, \theta, \delta\} \tag{39}$$

$$A = \{j, w\} \tag{40}$$

where Δd_y represents the relative lateral distance from the autonomous vehicle to other obstacles, with $3 \geq w \geq -3$ and a discrete interval of 0.1.

The reward function consists of the following components: The first part is the relative lateral distance expected by the autonomous vehicle from other obstacles; the value can be derived by:

$$R_D = \begin{cases} r_d \times \left|\Delta d_y - \Delta d_{desire1}\right| & \Delta d_x < d_a \\ r_d \times \left|\Delta d_y - \Delta d_{desire2}\right| & otherwise' \end{cases} \tag{41}$$

where r_d represents a negative coefficient, $\Delta d_{desire1}$ represents the desired relative lateral distance while lane changing, $\Delta d_{desire2}$ represents the desired relative lateral distance without lane change, and d_a represents the safe distance.

The second part is the desired speed of the vehicle, which can be derived in Equation (33).

The third part is the choice of vehicle actions; trying to avoid frequent acceleration, deceleration, and lateral oscillation, the value can be derived by:

$$R_A = \begin{cases} r_a \times a^2 + r_w \times w^2 & a \neq 0, w \neq 0 \\ 0 & otherwise \end{cases}, \tag{42}$$

where r_a and r_w represent negative coefficients.

The fourth part is the penalty for a vehicle collision, which can be derived in Equation (35).

The fifth component is the penalty for driving out of the lane. The value can be derived by:

$$R_S = \begin{cases} r_s & outline \\ 0 & otherwise' \end{cases} \tag{43}$$

where $outline$ represents a vehicle out of the lane and r_s represents a negative coefficient.

In conclusion, the value can be derived by:

$$R = w_1 R_D + w_2 R_V + w_3 R_A + w_4 R_R + w_5 R_S, \tag{44}$$

where $w_1 \sim w_5$ are the coefficients for each partial award value.

3. Stop behavior.

As vehicles generally stop along a global trajectory, the vehicle stop behavior can be modelled in the same way as the vehicle following behavior, but with some differences in the assignment of parameters.

2.3.3. Target Vehicle Trajectory Prediction in Parking

At present, many scholars have focused on the trajectory prediction of vehicles driving in the lane [25,26]. Most of the scenarios in the parking lot can refer to the above papers for vehicle trajectory prediction. However, the scenario shown in Figure 10 cannot be realized, so this paper chooses this scenario for target vehicle trajectory prediction to make up for the above deficiencies. Since the target vehicle will not affect the driving of the autonomous vehicle when driving in this lane but may affect it when driving into a parking space, the behavior of the target vehicle is simplified to continue driving along this lane or driving out of this lane into a parking space.

At present, few researchers have predicted the behavior and trajectory of vehicles in the parking lot, so there is no public dataset of vehicles driving in the parking lot. This study firstly uses MATLAB to build the dataset, which includes the location of lane lines, the location of parking spaces, and the coordinates, speed, and behavioral information of vehicles. As the study only considers the prediction of the behavior and trajectory of the target vehicle in the aforementioned scenario, two types of behaviors are considered when building the dataset: continuing to drive along this lane or driving out of this lane into the parking space.

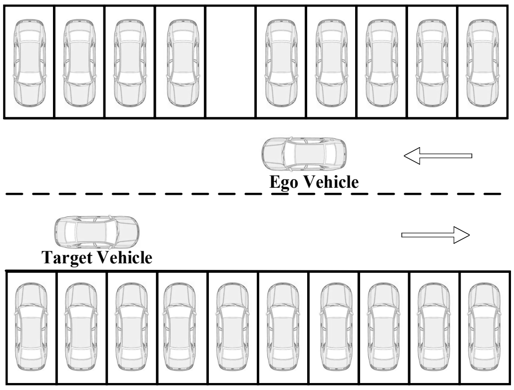


Figure 10. Trajectory prediction scenario.

It is necessary to divide the departure zone in the dataset. The two zones are when the heading angle ($\theta_2 \sim \theta_4$) of the target vehicle at three consecutive coordinate points is detected to be greater than the heading angle θ_1 of the previous point, and when the distance from the lane line is less than a certain threshold (since most vehicles are between 1.4 m and 1.6 m wide, the threshold is set to 1 m). The behavior of the target vehicle is then identified in the dataset as performing the act of driving out of this lane into the target parking space, and the rest of the behavior is identified as continuing to drive along this lane, as shown in Figure 11.

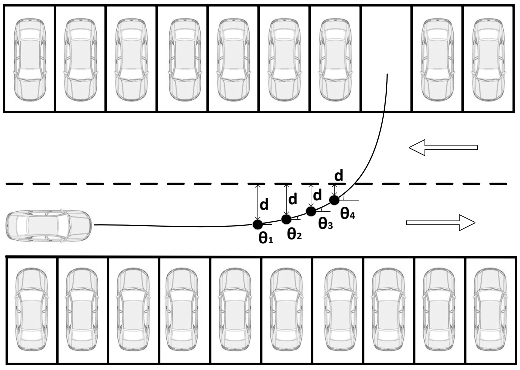


Figure 11. Diagram of exiting this lane into the target lane.

Based on the specificity of the parking lot, the study divides the datasets into continuing to drive along this lane and driving out of this lane, where the datasets of driving out of this lane contains driving into the left and right parking spaces. The LSTM model for predicting driving behavior is trained using these datasets.

When the behavior of the target vehicle is to continue to drive along this lane, the trajectory of the target vehicle can be predicted using the CV motion model.

$$X = [x, \dot{x}, y, \dot{y}] \tag{45}$$

$$X_{k+1} = \begin{bmatrix} 1 & t & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & t \\ 0 & 0 & 0 & 1 \end{bmatrix} X_k + \begin{bmatrix} t^2/2 & 0 \\ t & 0 \\ 0 & t^2/2 \\ 0 & t \end{bmatrix} W_k \tag{46}$$

where (x, y) represents the position coordinates, $\dot{x}$ represents the vehicle velocity along the x direction, $\dot{y}$ represents the velocity along the y direction, X represents the vehicle state matrix, t represents the prediction time, and W_k represents the Gaussian noise, which is simplified to 0.

When the behavior of the target vehicle is to drive out of this lane into a parking space, the end position of the target vehicle is known as driving into a free parking space. At this point, we can use a five-degree polynomial to predict the trajectory of the target vehicle.

$$y(x) = c_0 + c_1 x + c_2 x^2 + c_3 x^3 + c_4 x^4 + c_5 x^5 \tag{47}$$

$$y'(x) = c_1 + 2c_2 x + 3c_3 x^2 + 4c_4 x^3 + 5c_5 x^4 \tag{48}$$

$$y''(x) = 2c_2 + 6c_3 x + 12c_4 x^2 + 20c_5 x^3 \tag{49}$$

where $c_0 \sim c_5$ represent the coefficients of the five-degree polynomial. In Equations (47)–(49), we can find out the coefficients $c_0 \sim c_5$ by only knowing the coordinates of the vehicle at the starting point (x_s, y_s) and the ending point (x_g, y_g), and the corresponding first and second order derivatives, where (x_s, y_s) represents the coordinates of the current point of the vehicle and (x_g, y_g) represents the target parking position scaled by the vehicle center of rear axle point. The nearest free parking space on the left and right side is used as the target parking space. The first and second order derivatives of y with respect to x at the starting point can be found from three points: the starting point, the first point before the starting point, and the second point before the starting point. The first and second order derivatives of y with respect to x at the end point can be obtained empirically.

The parking behavior can be simplified into a uniform deceleration motion with a speed of 0 at the end point, so that the total time required for the target vehicle to drive out of this lane into the target parking space can be found.

3. Simulation Validation

Different maps of parking lots are built based on different levels of decision-making methods, which are used to validate the soundness of the proposed methods.

3.1. Simulation Validation of Optimal Parking Space Selection

The parking lot established in this section is shown in Figure 12. A joint simulation experiment using MATLAB and PRESCAN can verify the feasibility of the proposed method.

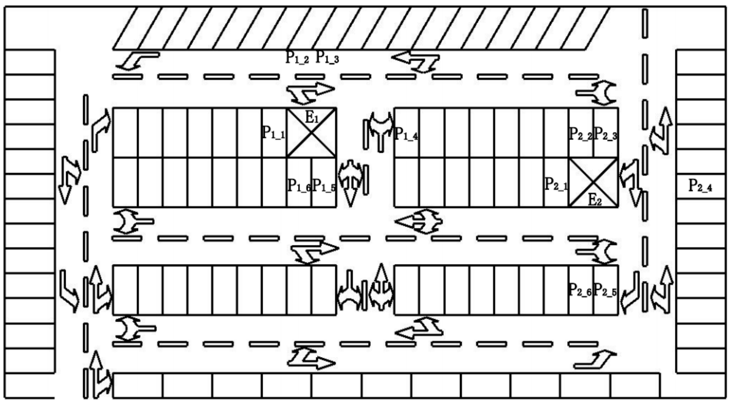


Figure 12. Parking lot map.

In Figure 12, there are two pedestrian exits and six parking spaces around each pedestrian exit, where pedestrian exits and parking spaces are indicated by letters and numbers. For example, E_1 is pedestrian exit number 1 and P_{1_1} is one of the parking spaces around pedestrian exit number 1.

3.1.1. Parking Space Preliminary Selection

The attributes of the 12 parking spaces around the pedestrian exits in the parking lot are shown in Table 3, the parking difficulty of the bias shape parking space and the T shape parking space are both between 3 and 5, and the parking difficulty of the line shape parking space is between 5 and 7 [27]. We set the parking difficulty of the three parking spaces as 3, 5, and 7.

Table 3. Parking space attributes.

Pedestrian Exit Number	Parking Space Number	Walking Distance	Parking Difficulty
E1	P1_1	4.50	5
	P1_2	13.00	3
	P1_3	13.34	3
	P1_4	11.50	5
	P1_5	6.19	5
	P1_6	6.19	5
E2	P2_1	4.50	5
	P2_2	6.19	5
	P2_3	6.19	5
	P2_4	13.01	5
	P2_5	13.09	5
	P2_6	13.09	5

As walking distance is far more important than the parking difficulty, the judgement matrix is expressed by:

$$W_{2\times 2} = \begin{bmatrix} 1 & 5 \\ 1/5 & 1 \end{bmatrix} \quad (50)$$

Inputting the parameters above into the multi-attribute decision method, we can initially select parking spaces as follows: the optimal parking space for pedestrian exit E_1 is P_{1_1} and the optimal parking space for pedestrian exit E_2 is P_{2_1}.

The attributes of the two initially screened parking spaces are shown in Table 4.

Table 4. Preliminary screened parking attributes.

Pedestrian Exit Number	Parking Space Number	Walking Distance	Driving Distance	Parking Difficulty
E1	P1_1	4.50	132	5
E2	P2_1	4.50	162	5

For drivers of autonomous vehicles, three influencing factors are ranked in order of importance: walking distance > vehicle driving distance > parking difficulty. The judgement matrix is expressed by:

$$W_{3\times 3} = \begin{bmatrix} 1 & 3 & 5 \\ 1/3 & 1 & 3 \\ 1/5 & 1/3 & 1 \end{bmatrix} \quad (51)$$

Inputting the parameters into the multi-attribute decision method, the optimal target parking space is P_{1_1}.

3.1.2. Parking Space Final Selection

The current parking spaces are used as shown in Figure 13, but the autonomous vehicle has no access to information such as the utilization rate. The red car is the autonomous vehicle. The vehicle travels at about 3 m/s and the pedestrian walks at about 1 m/s.

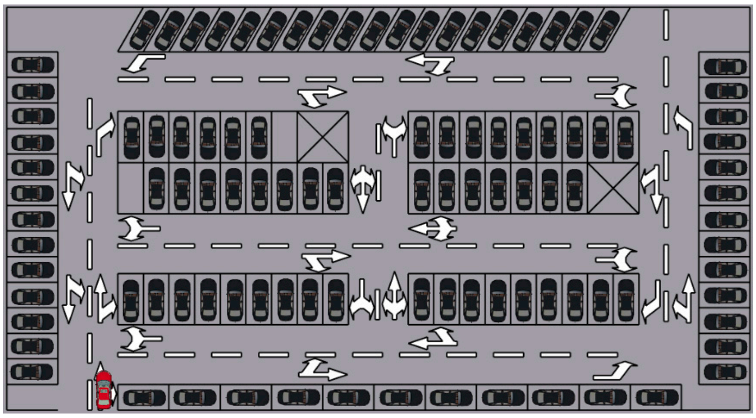
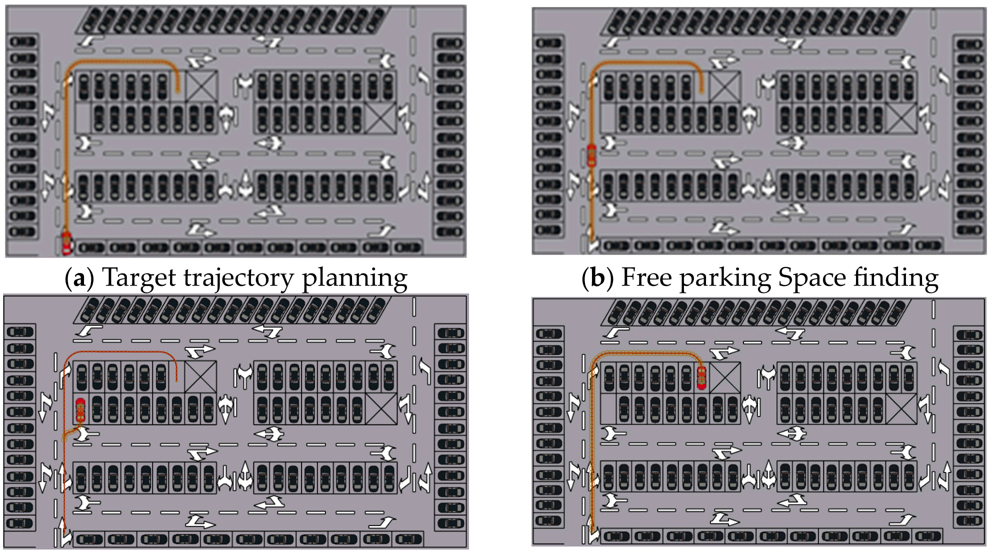


Figure 13. Parking space occupancy map.

As shown in Figure 14a, when the autonomous vehicle is at the entrance of the parking lot, a trajectory towards the target parking space is planned based on the information from the multi-attribute decision method and the parking lot map. When the autonomous vehicle travels to the location shown in Figure 14b, its sensing system will find a free parking space. The autonomous vehicle will then make a choice based on the driver's preference in the target parking space and free parking space decision. When the driver's preference is the shortest total distance by the autonomous vehicle and the shortest time taken by the driver to park, the autonomous vehicle will park in the parking space shown in Figure 14c. When the driver's preference is the shortest distance walked by the driver, the autonomous vehicle will park in the parking space shown in Figure 14d.



(**a**) Target trajectory planning (**b**) Free parking Space finding

(**c**) shortest total distance and time (**d**) shortest driver walking distance

Figure 14. Autonomous vehicle driving process and results.

3.2. Simulation Validation of Vehicle Driving Decision

The section first validates the autonomous vehicle driving decision method with examples such as a straight-line driving scenario and an intersection driving scenario, as shown in Figures 15 and 16; then, a straight-line driving scenario is constructed to validate the driving decision method with a fusion prediction method, as shown in Figure 17.

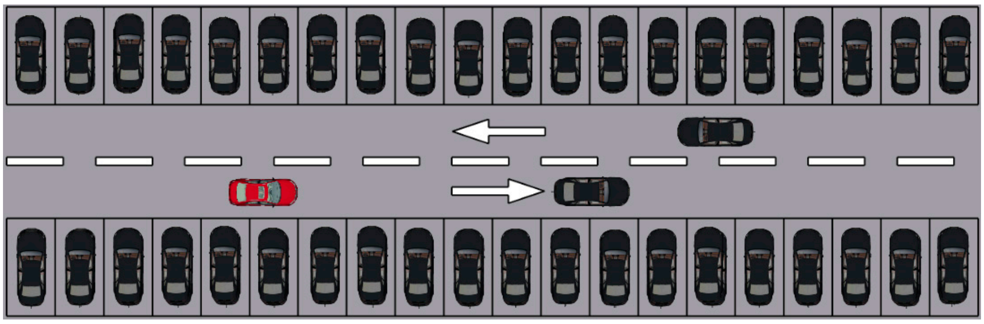


Figure 15. Straight-line driving scenario.

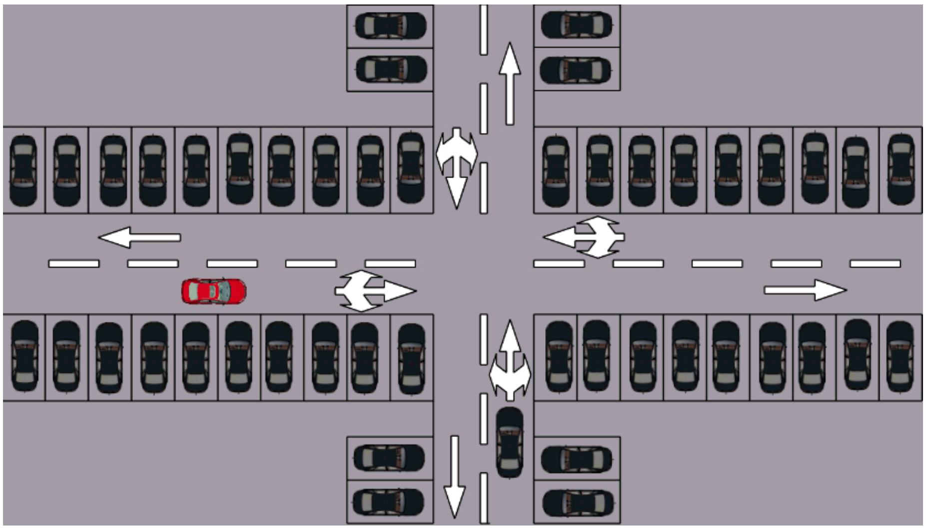


Figure 16. Intersection driving scenario.

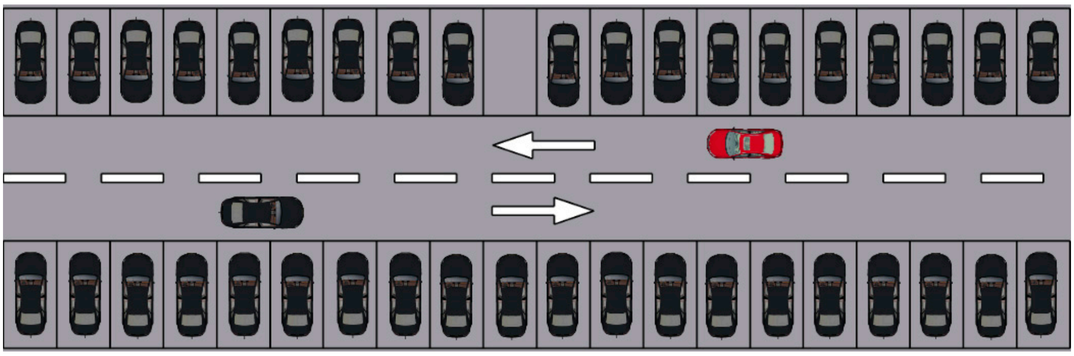
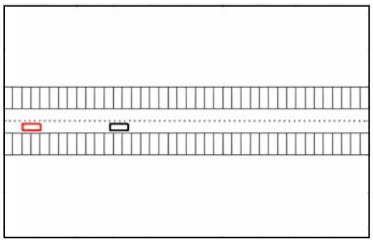


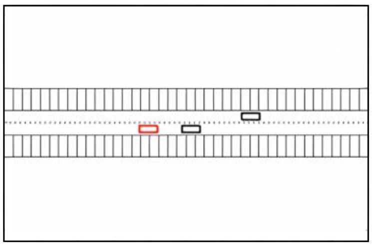
Figure 17. Straight-line driving scenario in the presence of a target vehicle.

3.2.1. Behavioral Decision-Making in Straight-Line Driving Scenarios

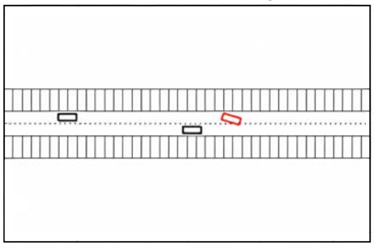
A straight-line driving simulation scenario in the parking lot is established as shown in Figure 15, in which the red vehicle is the autonomous vehicle, and the black vehicles are the obstacle vehicles. The obstacle vehicle in the same lane as the autonomous vehicle drives at a speed of 2.5 m/s and then gradually decreases to 0. The obstacle vehicle in the lane different to the autonomous vehicle first stops and then drives at a speed of 3 m/s, and finally the speed decreases to 0. The effect diagrams are shown in Figures 18–22.



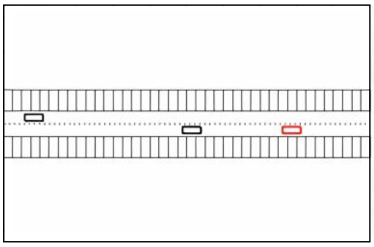
(**a**) Start driving



(**b**) Encounter the opposite lane obstacle



(**c**) Surpass the obstacle



(**d**) Move away from all obstacles

Figure 18. Autonomous vehicle driving process.

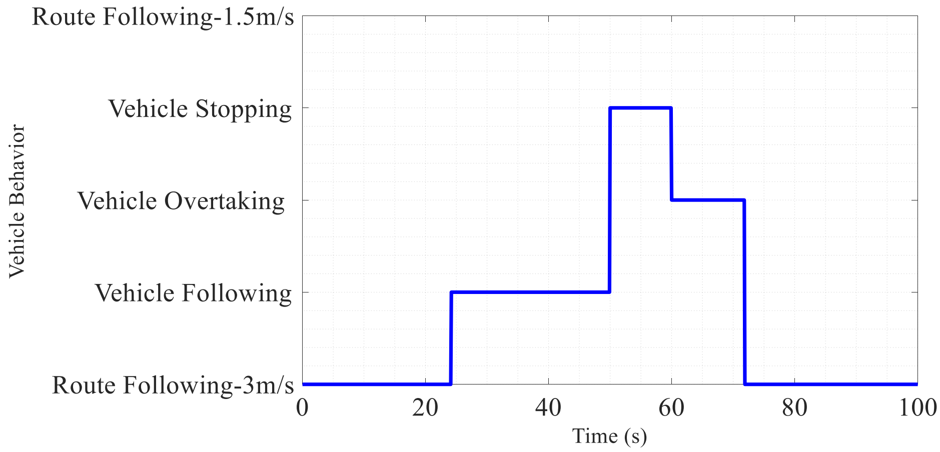


Figure 19. Autonomous vehicle behavior decision results.

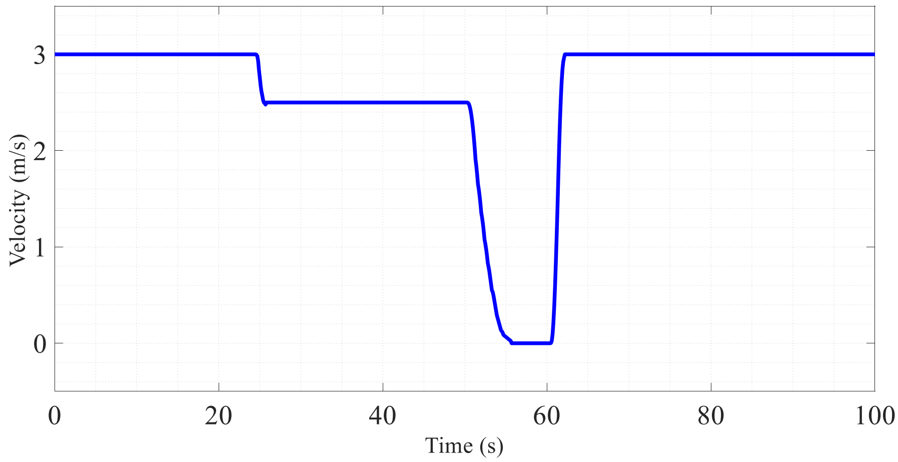


Figure 20. Autonomous vehicle speed.

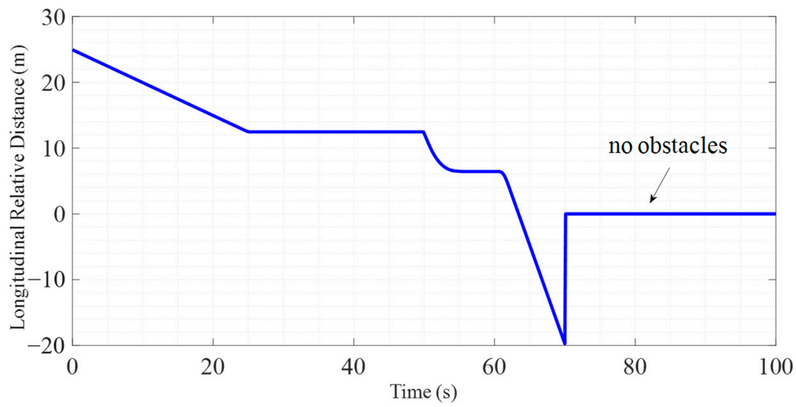


Figure 21. Relative longitudinal distance between the autonomous vehicle and the vehicle ahead.

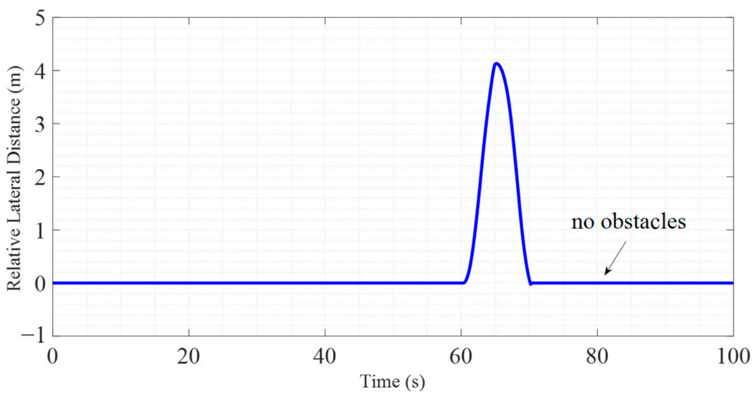


Figure 22. Relative lateral distance between the autonomous vehicle and the vehicle ahead.

In Figure 18, the red vehicle is the autonomous vehicle, driving in the right direction, and the black vehicle in the same lane as the red vehicle is the obstacle vehicle, driving in the same direction as the autonomous vehicle. The black vehicle in the other lane is an obstacle vehicle, traveling in the opposite direction to the self-driving vehicle. The figure from a to d is the process diagram of the key points of the interaction process.

In terms of vehicle behavior decision, according to the behavior tree decision model, the autonomous vehicle enters the straight-line driving scenario, and performs corresponding behaviors according to the surrounding environment. The behavior is shown in Figure 19, including the output result of the decision tree model decisions such as vehicle stopping in the interaction process. Figure 20 shows the speed information decided by the autonomous vehicle through the DQN in this interaction process. When the vehicle ahead stops with no obstacles in the opposite lane, the autonomous vehicle performs a vehicle overtaking behavior, which helps to improve vehicle driving efficiency. The safety of the autonomous vehicle is ensured by the fact that at least one of the horizontal and vertical relative distances from the vehicle obstacles is greater than 0 when performing any behavior, as shown in Figures 21 and 22. Figure 21 shows the relative longitudinal distance between the autonomous vehicle and the vehicle in front of it. Figure 22 shows the relative lateral distance between the autonomous vehicle and the vehicle in front of it.

3.2.2. Behavioral Decision-Making in Intersection Driving Scenarios

A parking lot intersection driving simulation scenario is built as shown in Figure 16, where the red vehicle is the autonomous vehicle, and the black vehicle is the obstacle vehicle. The effect of the obstacle vehicle in the lane driving at 2.5 m/s is shown in Figures 23–26.

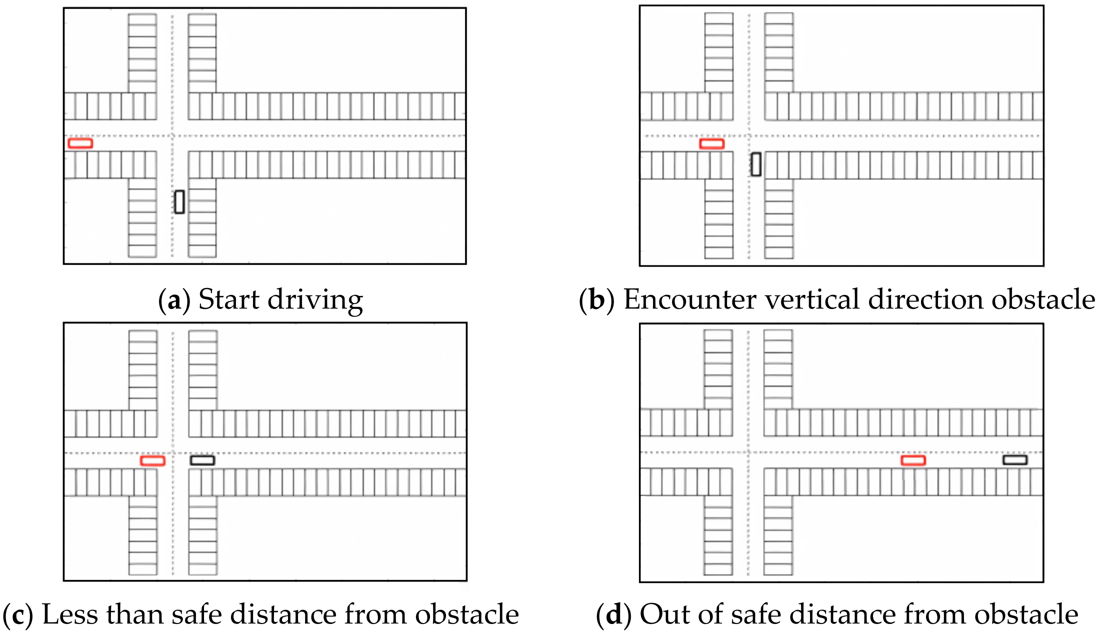


Figure 23. Autonomous vehicle driving process.

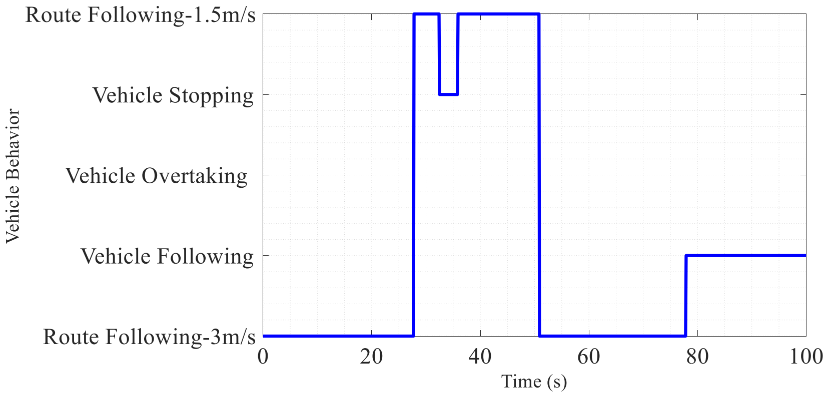


Figure 24. Autonomous vehicle behavior decision results.

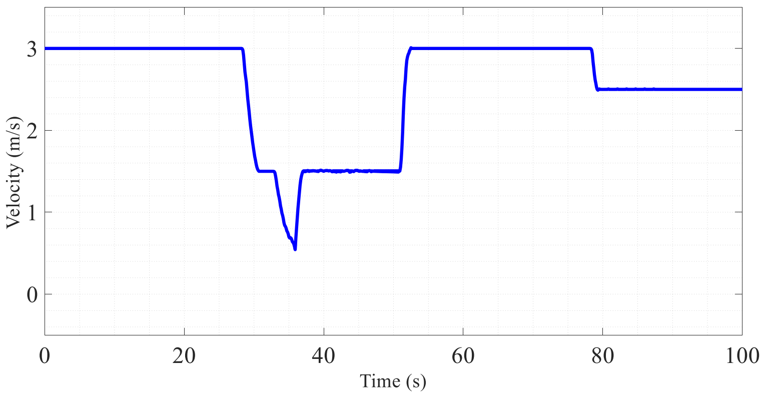


Figure 25. Autonomous vehicle speed.

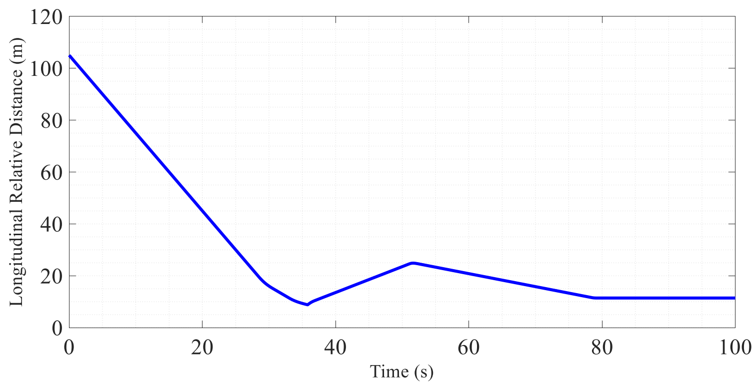


Figure 26. Relative longitudinal distance between the autonomous vehicle and the vehicle ahead.

In terms of vehicle behavior decision, according to the behavior tree decision model, the autonomous vehicle enters the following scenarios in turn, the straight-line driving scenario, intersection driving scenario, and straight-line driving scenario, and performs corresponding behaviors according to the surrounding environment. The behavior is shown in Figure 24. Ensuring that the autonomous vehicle slows down during the intersection driving scenario, in terms of the relative distance between the vehicle and the obstacle, if the longitudinal relative distance between the autonomous vehicle and the vehicle obstacle is greater than 0 when performing any behavior, the safety can be ensured as shown in Figure 26.

3.2.3. Combined Prediction for Autonomous Vehicle Driving Decisions

A straight-line driving simulation scenario is built as shown in Figure 17, in which the behavior of the target vehicle is predicted by using the LSTM method, and the prediction results are shown in Figures 27 and 28. Between 0 and about 45 s, the probability of a vehicle performing the behavior of continuing to drive along this lane is close to 1; between 45 s and 52 s, the probabilities of the three behaviors change, with the probability of a vehicle performing the behavior of continuing to drive along this lane decreasing and the probability of a vehicle performing the behavior of driving out of this lane into the left parking space increasing and eventually approaching 1; after 52 s, the probability of a vehicle's behavior does not change, as shown in Figure 27. The vehicle's behavior prediction results also overlap with its real behavior, and the behavior prediction results predict that the vehicle is about to perform the act of driving out of this lane into the left parking space about 0.1 s earlier than the real results as shown in Figure 28. The predicted and actual trajectories are shown in Figure 29. The error values of the two trajectories are shown in Figure 30. The maximum error value occurs when the target vehicle is driving out of this lane.

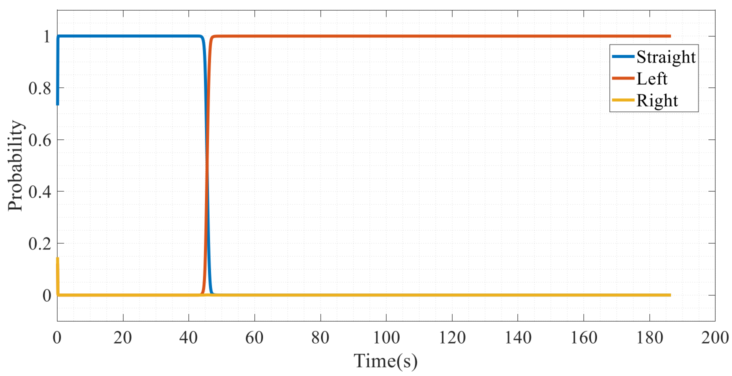


Figure 27. Predicted probability of vehicle behavior.

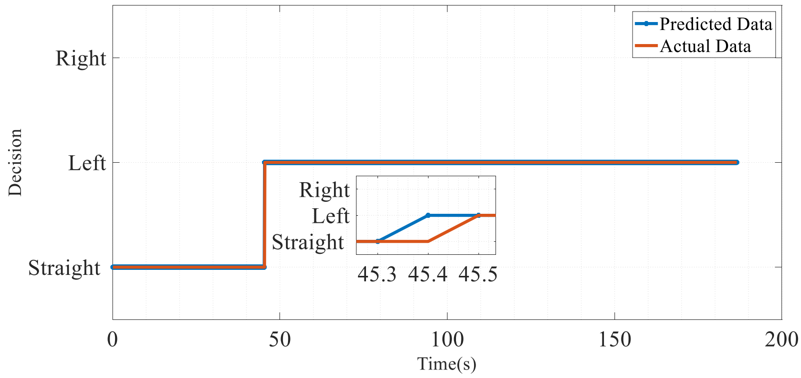


Figure 28. Predicted vehicle behavior results.

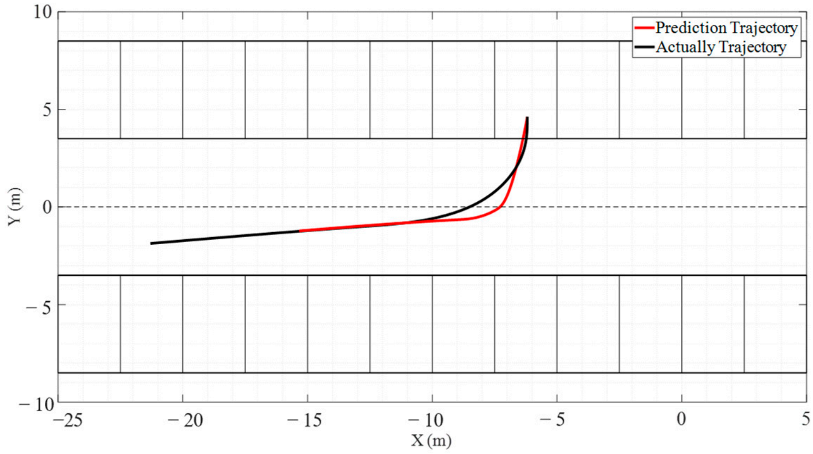


Figure 29. Comparison of vehicle trajectories.

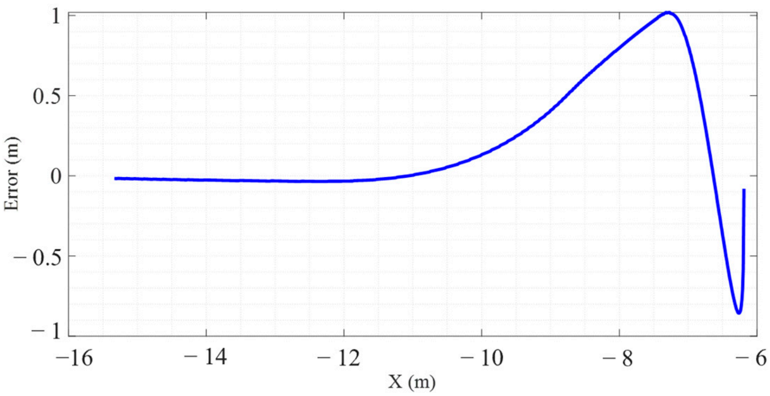
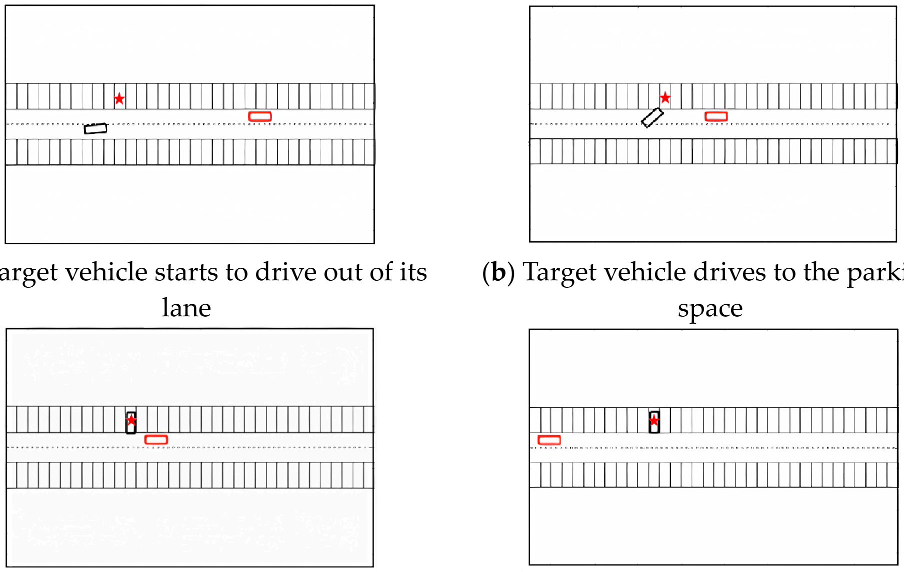


Figure 30. Vehicle trajectory error diagram.

The results of autonomous vehicle driving decisions using the fusion prediction method are shown in Figures 31–34. Figure 31a–d describe the driving process diagram of the interaction between the autonomous vehicle and the target vehicle, and it can be found that no dangerous accidents such as collisions occur between the target vehicle and the autonomous vehicle.



(**a**) Target vehicle starts to drive out of its lane (**b**) Target vehicle drives to the parking space

(**c**)Target vehicle enters the parking space (**d**) Driving away from the target vehicle

Figure 31. Diagram of vehicle movement.

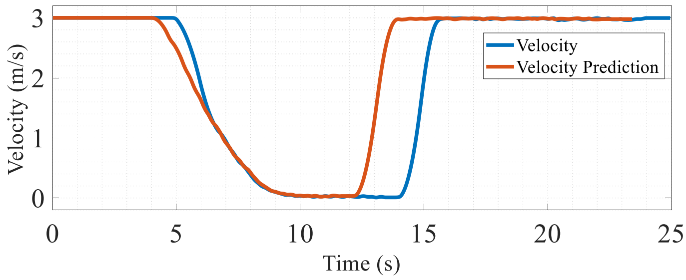


Figure 32. Speed comparison chart for autonomous vehicles.

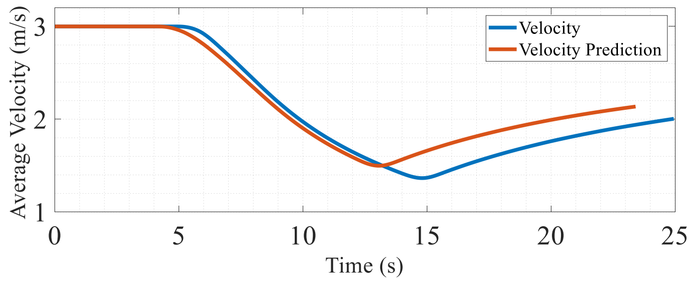


Figure 33. Average speed comparison of autonomous vehicles.

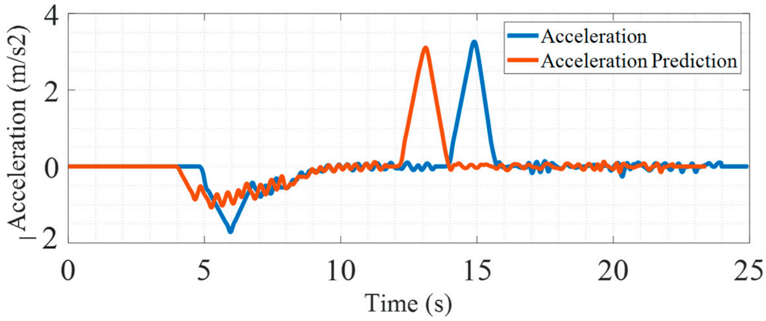


Figure 34. Acceleration comparison of autonomous vehicles.

The speed comparison is shown in Figure 32, where the autonomous vehicle, in the decision of the fusion prediction method, performs an early deceleration when it is about to interact with the target vehicle, and an early acceleration when the target vehicle pulls into a parking space.

The average speed comparison is shown in Figure 33. The average speed of the autonomous vehicle in the decision of the fusion prediction method is greater than in the decision of the non-fusion prediction method.

The acceleration comparison is shown in Figure 34. The acceleration of the autonomous vehicle in the decision of the fusion prediction method is less than in the decision of the non-fusion prediction method for the same scenario.

4. Conclusions

This paper proposes two aspects of decision-making for an APS in the parking lot, aiming to provide a method for optimal parking space selection and vehicle driving decision. In terms of selecting the optimal parking space decision, we select the optimal parking space by using a multi-attribute decision-making method considering the type of parking space, walking distance, and vehicle driving distance. In terms of vehicle driving decision, we first use a prediction method to predict the behavior and trajectory of the target vehicle, and then use a combination of rule-based and learning-based decision-making methods to make decisions on autonomous vehicle behaviors in the APS. The simulation results show that both aspects of decision-making can produce better decision effects. The paper can serve as a guide or reference for future vehicle decision research in parking lots.

Compared with the existing research, the parking space selection decision method based on multi-attribute decision making in the paper only needs to use a plane map of the parking lot to select a better parking space purposefully. In addition, at present, there are few studies on parking lot decision-making, which mainly uses rule-based methods. This paper proposes a decision-making method combining behavior trees and deep Q-learning, which can improve the driving efficiency and comfort of intelligent vehicles on the premise of ensuring safety. However, the proposed method still has some limitations. Although the decision model based on the behavior tree can make decisions for most scenarios, it cannot traverse all possible cases when making behavior tree rules due to the limitations of rule-based methods such as behavior tree. Therefore, to solve the problem, future research can incorporate a learning-based approach into the upper-level decision-making, to adapt to more complex parking lot situations.

Author Contributions: Formal analysis, M.G.; writing—original draft preparation, M.H. (Mulin Han); writing—review and editing, Z.Q. and Z.X.; project administration, H.Q. and M.H. (Manjiang Hu) All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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