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RESEARCH ARTICLE

Dynamic Trajectory Planning and Optimization for Automated Driving on Ice and Snow Covered Road

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ABSTRACT The rapid development of 5G and Artificial Intelligence (AI) has promoted the widespread application of autonomous driving in various scenarios. Currently, autonomous vehicles (AVs) can autonomously perform operations such as turning, lane changing, and acceleration in accordance with road traffic rules. It is a challenge for autonomous vehicles (AVs) to plan a series of safe and efficient trajectories on ice and snow covered road (ISCR). This paper proposes an optimal trajectory planning algorithm based on the Frenet coordinate system, which ignores the influence of road curvature and improves the quality of trajectory. Specifically, the vehicle motion is decoupled into two dimensions using the Frenet coordinate system to build lateral and longitudinal trajectory planning models, respectively. Further, according to the information on the initial and target configuration, the corresponding trajectory sets of lateral and longitudinal motion were generated by sampling. Moreover, to improve the safety of autonomous vehicles (AVs) on ice and snow covered road (ISCR), the cost of driving distance and ice-obstacle distance is used as the core indicator to evaluate the trajectory planning cost, combined with the safe speed check. Simulation results show that this algorithm can plan an optimal trajectory for autonomous vehicles (AVs) that combines safety, comfort, and stability, especially on ice and snow covered road (ISCR).

INDEX TERMS Autonomous vehicles (AVs), ice and snow covered road (ISCR), simulation, trajectory planning.

I. INTRODUCTION

The commercialized test points of autonomous driving have been put into use one after another, which marks that the autonomous driving industry has entered a new stage. With the widespread application of autonomous driving technology in various fields [1], a new scenario of autonomous vehicles (AVs) driving on ice and snow covered road (ISCR) emerges as the times require. When the temperature is low after a snowfall, the road surface in some areas will always be covered with ice and snow. Studies [2] have shown that ISCR is the most common and serious type of traffic accidents caused by a variety of environments. The promotion of 5G and Artificial Intelligence (AI) has accelerated the development of AVs toward functionality and intelligence, but the safety, comfort, and stability of Intelligent Driving System still face challenges [3]. Therefore, planning the optimal trajectory for AVs on ISCR is a technical problem that must be solved.

At present, the algorithms of trajectory planning mainly include graph search, sampling, numerical optimization, and machine learning [4]. The graph-search-based algorithm is

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one of the most widely used and mature algorithms in traditional algorithms, which finds the optimal path from the initial position to the target position in a completely open environment, such as Dijkstra, A* and D*, etc [5]. The typical algorithm in graph search is Dijkstra, first proposed by Lavalle, which is used to compute the shortest path between any two nodes in a discrete space [6]. Kawabata proposed the Rapidly-Exploring Random Tree algorithm (RRT) based on the characteristics of the surrounding environment under the AVs driving behavior. The main improvement of this algorithm is to use the trajectory templates of other motions during AVs operation as the a priori information of RRT, which can significantly improve the computational efficiency of RRT in planning calculations [7]. Since it is not limited by the road environment, the algorithm is not suitable for the research of dynamic trajectory planning of AVs. The sampling-based algorithm plans a safe and comfortable trajectory through lateral and longitudinal sampling, which is very dependent on the sampling accuracy. The low sampling accuracy makes the trajectory planning deviation larger, and the high sampling accuracy consumes a lot of computing resources. Glaser proposes an optimal trajectory algorithm that takes into account the road environment and other AVs. The performance evaluation indicators of this algorithm include risk, speed, consumption, and comfort [8]. Wonteak proposes a hierarchical trajectory planning method for autonomous driving based on a combination of sampling and numerical optimization [9]. The upper planner searches to determine the macro-scale trajectory, and the lower planner obtains the optimal trajectory by discrete point fitting optimization. In contrast to algorithms such as graph search and sampling, numerical optimization describes trajectory planning as a multi-objective optimization problem, which is solved by quadratic programming to obtain the optimal trajectory [10]. The biggest advantage of this algorithm is that the optimal solution space is continuous and there is no large jump in the optimal solution between adjacent frames [11], [12]. However, the long time required for trajectory point optimization iterations leads to a slow solution speed for some frames, which cannot meet the real-time requirements in autonomous driving scenarios. To address the problem of poor applicability of reinforcement learning, LV improves deep reinforcement learning by building an empirical value evaluation network to allow intelligent products to understand environmental laws faster [13]. Schaul uses deep reinforcement learning with a preferred experience playback mechanism instead of probability sampling, which improves the utilization of effective samples [14]. The machine learning algorithm requires a large sample space and is prone to errors when faced with new scenarios and problems [15]. However, trajectory planning on ISCR cannot provide a large number of samples and has low fault tolerance.

The difficulty of dynamic trajectory planning for AVs is that the relative positional relationship between the AVs and the road cannot be accurately represented. AVs generally drive on structured roads such as highways and urban arterial roads, which have clear road markings and distinct geometric features [16]. Therefore, trajectory planning using the traditional Cartesian coordinate system has certain limitations, which prevent AVs from acquiring road positions in real-time, resulting in deviations from the center of lanes and even traffic violations [17], [18]. Moreover, the Cartesian coordinate system is difficult to represent the distance traveled in a certain period due to the curvature of the road. For structured roads, the Frenet coordinate system expresses the distance that the trajectory deviates from the road center in terms of the vertical distance relative to the base path. Since the road centerline is used as the basic path, the relative positional relationship between the AVs and the road is more clear.

The core of the trajectory planning on ISCR is to reduce the impact of ice and snow on AVs. Serious traffic accidents on ISCR are mainly caused by two reasons. On the one hand, ISCR has a serious impact on the driving environment. Compared with ordinary asphalt pavement, the road adhesion coefficient of ISCR asphalt pavement is significantly lower, which prolongs the actual braking and deceleration distance of AVs [19]. Secondly, the road surface covered with ice and snow may cover the road markings to varying degrees, which affects the identification of the lane lines and road boundaries. On the other hand, ISCR has a serious impact on the performance of AVs [20]. Driving on ISCR can greatly reduce the starting and braking performance, stability, and maneuverability of AVs [21]. To avoid traffic accidents caused by ISCR, the fundamental solution is to reduce speed. The lower speed allows the AVs driving system to have enough time to brake within a safe distance after recognizing the ISCR, and further plan the trajectory that can be passed safely. Moreover, the lower speed can also ensure that the AVs are within the controllable range in the face of emergency braking, and there will be no steering wheel failure, tire side slip, etc [22]. Therefore, the key to ensuring the safety of AVs is to stay within the safe speed calculated from the road adhesion coefficient.

The unique feature of ISCR as a new autonomous driving scenario is that AVs can pass through ice obstacles. At present, the references related to automatic driving trajectory planning only consider obstacles such as roadblocks and AVs that need to be strictly avoided [23]. Such obstacles are usually checked for collision in the two-dimensional plane by means of circular detection, axis-aligned bounding box, oriented bounding box, etc. However, ice and snow are special road obstacles that can be considered for planning the trajectory for AVs under the condition of reasonable speed control.

In order to apply autonomous driving technology more widely in various fields, this study mainly focuses on further exploring and researching new scenarios of AVs driving on ISCR. Compared to the existing references, this study offers the following three contributions to the dynamic trajectory planning of AVs on ISCR:

1) ISCR has a significant impact on the driving environment and AVs performance. This paper determines the safe driving speed based on the road adhesion coefficient and performs a safe speed check on the candidate trajectory, which improves the safety of AVs on ISCR.
2) This paper proposes an optimal trajectory planning algorithm based on the Frenet coordinate system, which ignores the influence of road curvature and improves the quality of trajectory. The algorithm includes four processes: sampling, synthesis, inspection, and evaluation. only the sampled trajectories that can pass the acceleration, curvature, collision, and safe speed check are output as the optimal trajectory.
3) The dynamic trajectory planning model for AVs on ISCR is formulated, which evaluates the trajectory cost based on the total distance traveled by the left and right front wheels of AVs on ISCR and the distance from the ice obstacles. The model can help AVs plan an optimal trajectory that combines safety, comfort, and stability, especially on ISCR.

The remainder of this paper is organized as follows. Section II provides problem descriptions and assumptions of this paper. Section III introduces and analyzes the dynamic trajectory planning model of AVs on ISCR. Section IV proposes a trajectory optimization algorithm centered on sampling, synthesis, inspection, and evaluation to improve the driving safety of AVs. Section V presents simulation experiments of ISCR to verify that the proposed trajectory planning algorithm is safe, stable, and comfortable. The conclusion of the paper and future research directions are summarized and discussed in Section VI.

II. PROBLEM DESCRIPTION

This study focuses on the two-dimensional trajectory optimization problem of AVs driving on ISCR without any intersections. The automatic level of all AVs is higher than the three-level set by the Society of Automotive Engineers. Specifically, our planning target is to provide reliable decision-making for AVs trajectory planning by building a dynamic trajectory planning model, which can be executed safely and stably on ISCR [24]. When AVs drive in a complex traffic scenario such as on a winding lane with or without a potential obstacle, as shown in Fig. 1, an infinite number of paths are possible for AVs, but not all alternative paths are safe and comfortable.

This paper proposes a trajectory planning algorithm to find the optimal path from an infinite number of alternative paths in a very short time. The details of the hypothesis are presented as follows:

Assumption 1: the AVs are treated as points.

Assumption 2: road attributes such as road boundary, lane line, and traffic infrastructure are available from communicating with roadside units.

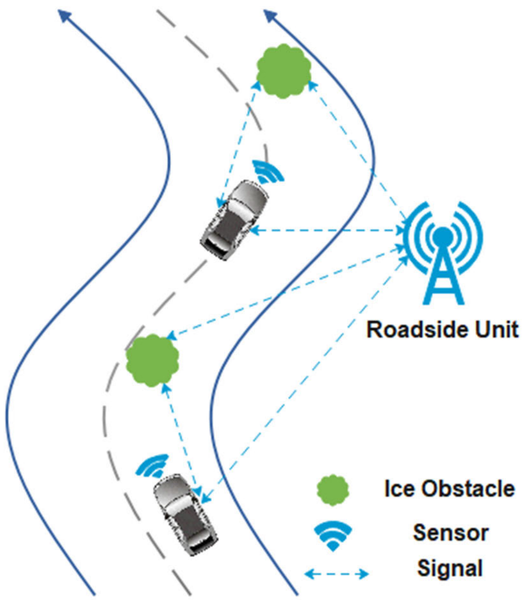

FIGURE 1. Autonomous vehicles driving in snow and ice scenarios.

Assumption 3: the geometry and road adhesion coefficient of ice obstacles can be obtained, and the road adhesion coefficient of the same obstacle is unique everywhere.

III. METHODOLOGY

A. PROBLEM ANALYSIS

AVs are prone to sideslip when driving on ISCR, which causes the tires to lose control and deviate from the original driving trajectory [25]. The skid resistance of ISCR can be directly reflected by the road adhesion coefficient. μ reflects the adhesion of tires on different road surfaces, expressed by the ratio of friction force to normal load. The research show that the road adhesion coefficient is significantly correlated with safe driving speed [26]. The more slippery the road surface, the smaller the road adhesion coefficient, the smaller the friction force, the weaker the controllability of AVs, and the smaller the safe driving speed [27]. It can be seen that the road adhesion coefficient is one of the main factors affecting safe driving speed, and the coefficient is positively correlated with speed. The analysis results shows that there is a linear functional relationship between safe driving speed and the road adhesion coefficient. The mathematical model is represented as follows:

$$v = f(\mu) \tag{1}$$

The model shows that each road state corresponds to a unique safe driving speed. AVs determine the safe driving speed according to the road adhesion coefficient obtained from their sensors and select the trajectory that can pass the safe driving speed check as the candidate trajectory.

1) FRENET COORDINATE SYSTEM

The Frenet coordinate system is used to easily determine the position of the lane centerline, which significantly reduces

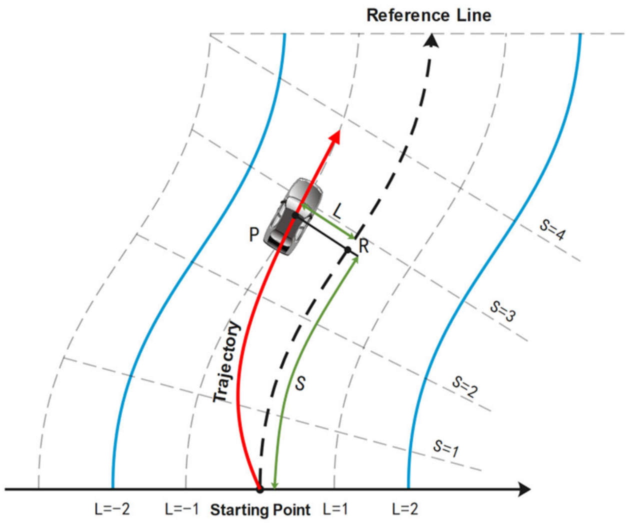

FIGURE 2. Autonomous vehicle trajectory representation in the frenet coordinate system.

computation and improves computing efficiency. The reference line is the vertical axis, and the longitudinal offset (S) represents the distance the AVs travels along the road. The direction perpendicular to the reference line is the horizontal axis, and the lateral offset (L) represents the distance the AVs deviates from the center of the road. The motion state is described by the Frenet coordinate system, as shown in Fig. 2. Make a smooth reference line. The AVs position are marked as P, and the projection point of AVs on the reference line are marked as R. S represents the path length from the starting point of the reference line to the projected point. L represents the distance from the AVs position to the projected point.

B. TRAJECTORY PLANNING MODEL

The beginning and end states of AVs correspond to position, velocity, and acceleration, respectively, resulting in six boundary conditions [28]. If the driving conditions such as parking and following are not considered in the longitudinal trajectory planning, the position s_1 of the final state is not required. In order to saturate the constraint, a quartic polynomial curve is used to establish the longitudinal trajectory planning model of AVs [29]. The longitudinal trajectory polynomial is formulated as follows:

$$s(t) = a_0 + a_1 t + a_2 t^2 + a_3 t^3 + a_4 t^4 \tag{2}$$

$$\dot{s}(t) = a_1 + 2a_2 t + 3a_3 t^2 + 4a_4 t^3 \tag{3}$$

$$\ddot{s}(t) = 2a_2 + 6a_3 t + 12a_4 t^2 \tag{4}$$

$$\text{When } t = t_0 = 0,\ a_0 = s(t_0),\ a_1 = \dot{s}(t_0),\ a_2 = \ddot{s}(t_0)/2; \tag{5}$$

when $t = t_1 > 0$, the solution equation of coefficient a_3 and a_4 is as follows:

$$\begin{bmatrix} \dot{s}(t_1) \\ \ddot{s}(t_1) \end{bmatrix} = \begin{bmatrix} 1 & 2t_1 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} + \begin{bmatrix} 3t_1^2 & 4t_1^3 \\ 6t_1 & 12t_1^2 \end{bmatrix} \begin{bmatrix} a_3 \\ a_4 \end{bmatrix} \tag{6}$$

The longitudinal offset, velocity, and acceleration of AVs at t_0 are s_0, $\dot{s}_0$, $\ddot{s}_0$, respectively. Initial configuration is $S_0 = [s_0, \dot{s}_0, \ddot{s}_0]$. The longitudinal offset, velocity, and acceleration of AVs at t_1 are s_1, $\dot{s}_1$, $\ddot{s}_1$, respectively. Target configuration is $S_1 = [s_1, \dot{s}_1, \ddot{s}_1]$. If the initial and target configurations are known [30], the longitudinal trajectory equation $s(t)$ can be solved by combining (6)-(7).

The position, velocity, and acceleration of the beginning and end states are all considered in lateral trajectory planning [31]. Therefore, the quintic polynomial curve is used to establish the lateral trajectory planning model of AVs. Lateral motion is induced by longitudinal motion, so the lateral offset L is designed as a function of the longitudinal offset S. The lateral trajectory polynomial is formulated as follows:

$$l(s) = b_0 + b_1 s + b_2 s^2 + b_3 s^3 + b_4 s^4 + b_5 s^5 \tag{7}$$

$$\dot{l}(s) = b_1 + 2b_2 s + 3b_3 s^2 + 4b_4 s^3 + 5b_5 s^4 \tag{8}$$

$$\ddot{l}(s) = 2b_2 + 6b_3 s + 12b_4 s^2 + 20b_5 s^3 \tag{9}$$

$$\text{When } s = s_0 = 0,\ b_0 = l(s_0),\ b_1 = \dot{l}(s_0),\ b_2 = \ddot{l}(s_0)/2; \tag{10}$$

when $s = s_1 > 0$, the solution equation of coefficient b_3, b_4, b_5 is as follows:

$$\begin{bmatrix} l(s_1) \\ \dot{l}(s_1) \\ \ddot{l}(s_1) \end{bmatrix} = \begin{bmatrix} 1 & s_1 & s_1^2 \\ 0 & 1 & 2s_1 \\ 0 & 0 & 2 \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ b_2 \end{bmatrix} + \begin{bmatrix} s_1^3 & s_1^4 & s_1^5 \\ 3s_1^2 & 4s_1^3 & 5s_1^4 \\ 6s_1 & 12s_1^2 & 20s_1^3 \end{bmatrix} \begin{bmatrix} b_3 \\ b_4 \\ b_5 \end{bmatrix} \tag{11}$$

The lateral offset, velocity, and acceleration of AVs at t_0 are $l_0, \dot{l}_0, \ddot{l}_0$, respectively. Initial configuration is $L_0 = [l_0, \dot{l}_0, \ddot{l}_0]$. The lateral offset, velocity, and acceleration of AVs at t_1 are $l_1, \dot{l}_1, \ddot{l}_1$, respectively. Target configuration is $L_1 = [l_1, \dot{l}_1, \ddot{l}_1]$. If the initial and target configurations are known, the lateral trajectory equation $l(s)$ can be solved by combining (12)-(13).

IV. TRAJECTORY PLANNING ALGORITHM

A. TRAJECTORY SAMPLING

The distance between the position and the look-ahead point determined by the AVs speed is used as the longitudinal sampling offset. If the sampling length is short, the AVs in an emergency situation lacks sufficient safety distance to transition smoothly, resulting in dangerous behaviors such as sharp turns or excessive acceleration. Moreover, too many times of invalid planning will result in a waste of computing resources. The AVs visibility is so limited in the turning section that it cannot accurately detect the road conditions ahead. If the sampling length is too long, the environmental information between the current AVs position and the sampling point cannot be effectively identified. The accuracy measured by the on-board sensor is higher only when it is within the effective detection distance. Therefore, too long sampling lengths may lead to inaccurate information for decision-making and trajectory planning. A reasonable lateral trajectory sampling interval set by the lane width must include all possible lateral motion states of AVs.

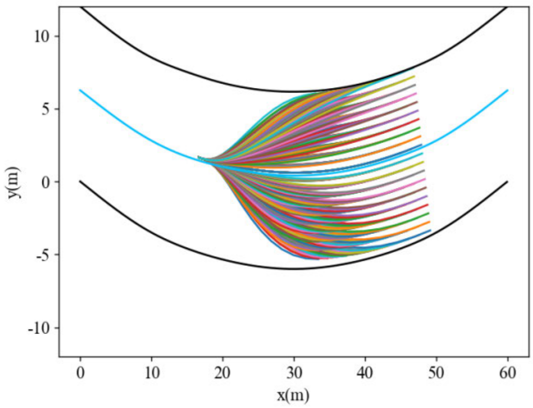

FIGURE 3. Trajectory sets in the cartesian coordinate system.

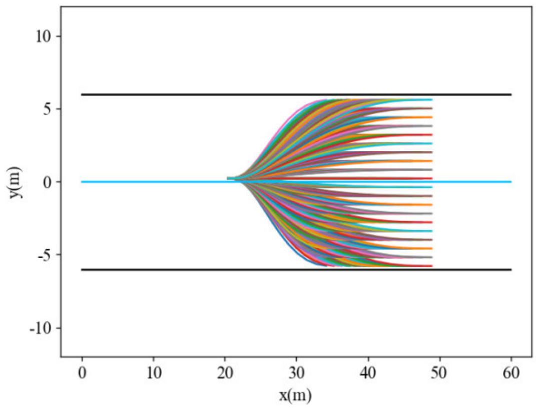

FIGURE 4. Trajectory sets in the frenet coordinate system.

B. TRAJECTORY SYNTHESIS

Trajectory planning with too short time intervals do not have enough ability to cope with unexpected situations, whereas with too long time intervals are less reliable. Therefore, the time interval is limited to the range $T_{\min}$ to $T_{\max}$. Discrete the lateral and longitudinal trajectories using time intervals.

According to the solved longitudinal trajectory equation $s(t)$ and lateral trajectory equation $l(s)$, the corresponding longitudinal offset $s* = s(t*)$ and lateral offset $l* = l(s*)$ can be obtained at given $t*$. A series of longitudinal and lateral offsets are obtained at different times, corresponding to the longitudinal and lateral trajectory sets. Finally, multiple complete candidate trajectories are formed using the Frenet coordinate system. Trajectory sets in the coordinate system are shown in Fig. 3-4:

The AVs drive along the center of the lane as the reference line. Fig. 3 is a set of trajectories in the Cartesian coordinate system. Fig. 4 is a set of trajectories in the Frenet coordinate system. It can be seen that the AVs ignore the influence of curvature by using the Frenet coordinate system on curved road sections. Compared with the Cartesian coordinate system used in the traditional algorithm, the Frenet coordinate system has more advantages in establishing a dynamic trajectory planning model for AVs, which can effectively improve the computing speed and reduce the trajectory planning difficulty.

C. TRAJECTORY CHECK

AVs are subject to kinematics and dynamics constraints during trajectory planning, such as curvature and acceleration, which have limited conditions [9], [32]. AVs will increase the risk of loss of control and collision when the curvature and acceleration increase [33]. Moreover, AVs driving at high speed on ISCR is prone to sideslip [34]. In order to obtain an optimal collision-free smooth trajectory that satisfies the constraints, the trajectory is checked for curvature limit, acceleration limit, safe speed, and collision.

The curvature check is as follows:

$$q[i] \leq q_{\max} \tag{12}$$

where $q[i]$ represents the curvature of trajectory i and $q_{\max}$ represents the maximum curvature that can be achieved by the trajectory planning of AVs on ISCR.

The acceleration check is as follows:

$$a[i] \leq a_{\max} \tag{13}$$

where $a[i]$ represents the acceleration of trajectory i and $a_{\max}$ represents the maximum acceleration that can be achieved by the trajectory planning of AVs on ISCR.

The safe speed check is as follows:

$$v[i] \leq v_{\max} \tag{14}$$

where $v[i]$ represents the speed of trajectory i and $v_{\max}$ represents the maximum speed that can be achieved by the trajectory planning of AVs on ISCR. The road adhesion coefficient μ continuously provided by the AVs sensors is substituted into (1) to obtain the safe speed $v_{\max}$.

The collision check is as follows:

$$(x_i - x_{obs})^2 + (y_i - y_{obs})^2 > (r_i - r_{obs})^2 \tag{15}$$

where $[x_i, y_i]$ represents the position of trajectory i and $[x_{obs}, y_{obs}]$ represents the obstacle position of trajectory i. r_i represents the radius of AVs and r_{obs} represents the radius of the obstacles.

D. TRAJECTORY EVALUATION

Evaluation indicators such as safety, comfort, and efficiency are usually considered in trajectory planning for AVs [35], [36]. Improving trajectory security mainly includes the following two aspects. Stay away from obstacles to reduce the risk of collision and reduce the contact area with ice obstacles to reduce the risk of sideslip. Trajectory comfort is usually expressed in Jerk (changing rate of acceleration) [37]. The bigger the Jerk, the less comfortable the AVs are. The planning period is the main measure of AVs efficiency. The shorter the trajectory planning period, the more efficient the AVs are.

The AVs may deviate from the road reference line due to obstacle avoidance. However, proximity to road boundaries

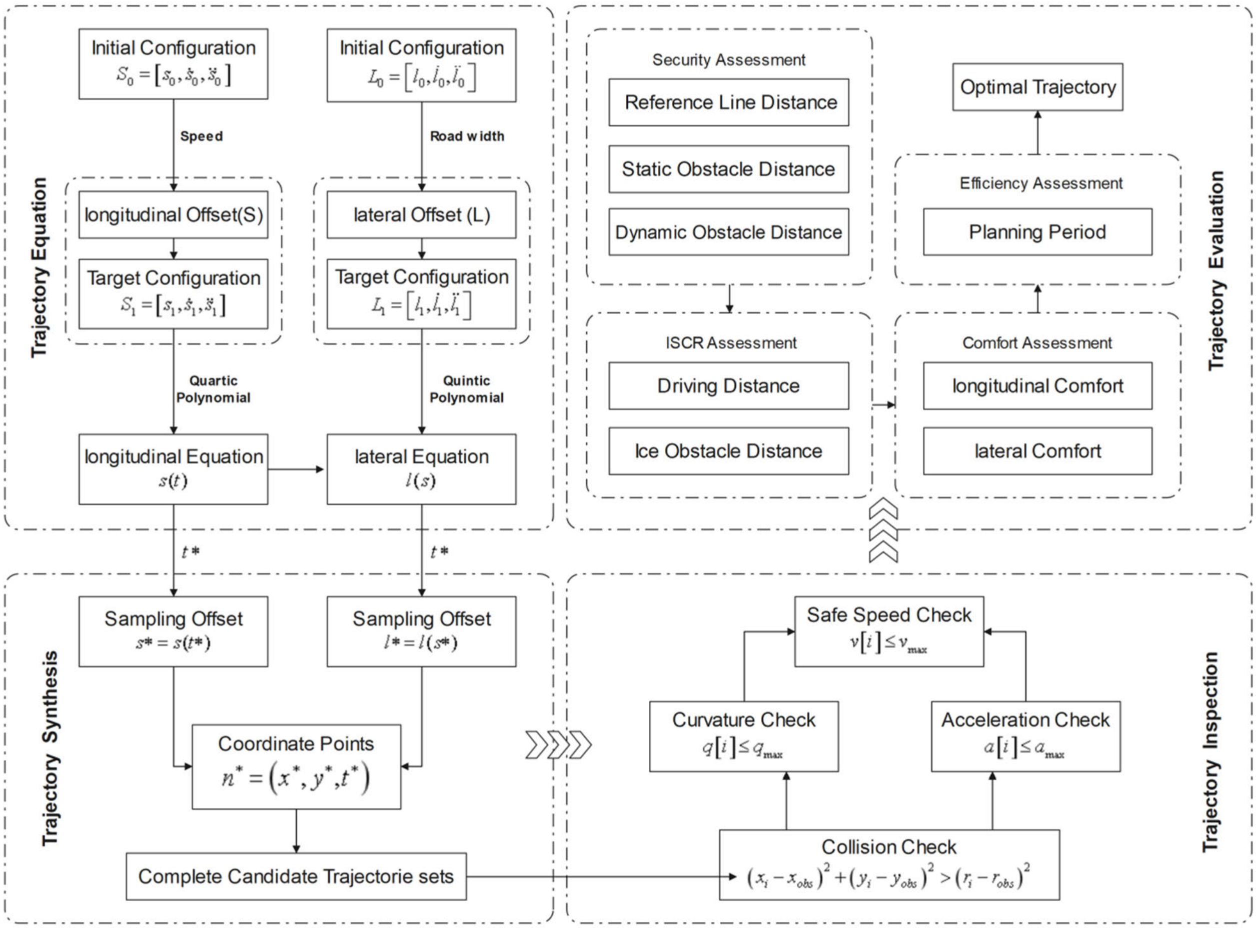

FIGURE 5. Trajectory planning algorithm process.

TABLE 1. Evaluation index for trajectory planning on ISCR.

Parameter	Physical Significance	Effect
c_T	Trajectory planning period	Efficiency
c_{ice-x}	Driving distance on ice and snow covered road	Safety
c_{ice-z}	Distance between the AVs and the ice obstacle	Safety
c_h	Distance between the AVs and the reference line	Safety
c_{obs-s}	Distance between the AVs and the static obstacle	Safety
c_{obs-d}	Distance between the AVs and the dynamic obstacle	Safety
J_s	Changing rate of longitudinal acceleration	Comfort
J_l	Changing rate of lateral acceleration	Comfort

TABLE 2. Simulation parameters for trajectory planning on ISCR.

Parameter	Description	value
$q_{\max}\left(m/s^{-1}\right)$	Maximum curvature	0.5
$a_{\max}\left(m/s^{2}\right)$	Maximum acceleration	4.6
r_i / m	Radius of vehicle collision	2
r_{obs} / m	Radius of obstacle collision	2
L_d / m	Road width	12
Δd / m	Lateral sampling interval	0.8
S_N	Number of longitudinal sampling	1
$\Delta\dot{s}/(m/s)$	Longitudinal velocity sampling interval	1.39
ΔT / s	Time sampling interval	0.2
$T_{\max}$ / s	Maximum prediction time	4.2
$T_{\min}$ / s	Minimum prediction time	3.5

creates a potential risk of AVs colliding with roadblocks. The greater the degree of deviation, the higher the trajectory cost. Moreover, approaching obstacles increases the risk of collision, and the trajectory cost increases accordingly. Obstacles that AVs may encounter on ISCR can be divided into three categories: static obstacles, dynamic obstacles, and ice obstacles. Static obstacles are mainly considered as barricades, parked vehicles, etc. Dynamic obstacles are mainly considered as moving vehicles, etc. Therefore, the cost function for evaluating trajectory safety is as follows:

$$C_a = w_h c_h + w_{obs-s} c_{obs-s} + w_{obs-d} c_{obs-d} \tag{16}$$

where c_h represents the maximum distance between the AVs and the reference line. c_{obs-s} and c_{obs-d} represent the straight-line distance between the AVs and static and dynamic obstacles, respectively. w_h, w_{obs-s}, w_{obs-d} are the weight coefficients of c_h, c_{obs-s}, c_{obs-d}, respectively.

The road adhesion coefficient of ISCR is significantly reduced, which may cause the AVs to slip out of control. In order to ensure safe driving, the AVs should be kept away from ice obstacles. If driving on ISCR cannot be avoided, the AVs should minimize contact with ice obstacles. Therefore, the cost function for evaluating ISCR is as follows:

$$C_{ice} = w_{ice-x}c_{ice-x} + w_{ice-z}c_{ice-z} \tag{17}$$

where c_{ice-x} represents the total distance traveled by the left and right front wheels of the AVs on ISCR, and c_{ice-z} represent the straight-line distance between the AVs and ice obstacles. w_{ice-x} and w_{ice-z} are the weight coefficients of c_{ice-x} and w_{ice-z}, respectively.

Research shows that Jerk can be used as an effective indicator to describe AVs comfort. The cost of the longitudinal trajectory comfort can be expressed by the integral of $\dddot{s}^2(t)$ from t_0 to t_1, and the lateral trajectory can be expressed by the integral of $\dddot{l}^2(s)$ from t_0 to t_1.

Therefore, the cost function for evaluating trajectory comfort is as follows:

$$J_s = \int_{t_0}^{t_1} \dddot{s}^2(t)dt \tag{18}$$

$$J_l = \int_{t_0}^{t_1} \dddot{l}^2(s)ds \tag{19}$$

The total cost function of trajectory planning for AVs on ISCR is as follows:

$$C_{total}[i] = k_a C_a[i] + k_{ice}C_{ice}[i] + k_s J_s[i] + k_l J_l[i] + k_T C_T[i] \tag{20}$$

where i is the trajectory index; C_a and C_T are cost-weighted items for evaluating trajectory safety and efficiency, respectively. C_{ice} is the cost-weighted item for evaluating ISCR. J_s and J_l are cost-weighted items for evaluating the comfort of longitudinal and lateral trajectories, respectively. k_a, k_{ice}, k_s, k_l, k_T are the weight coefficients of C_a, C_{ice}, C_s, C_l, C_T, respectively.

The cost items and the weight coefficients together determine the trajectory cost function. Comfort and safety are often not compatible. When the emphasis is on comfort, the AVs tend to reduce lateral excursion, which decreases the risk of a collision. When focusing on safety, the vehicle tends to stay away from obstacles, which can increase discomfort.

The trajectory planning algorithm process of AVs driving on ISCR includes four parts: equation, synthesis, inspection, and evaluation, as shown in Fig. 5. First, the initial and target configuration information of AVs is obtained, specifically the position, velocity, and acceleration. Then, the quartic and quintic polynomial curves are used to

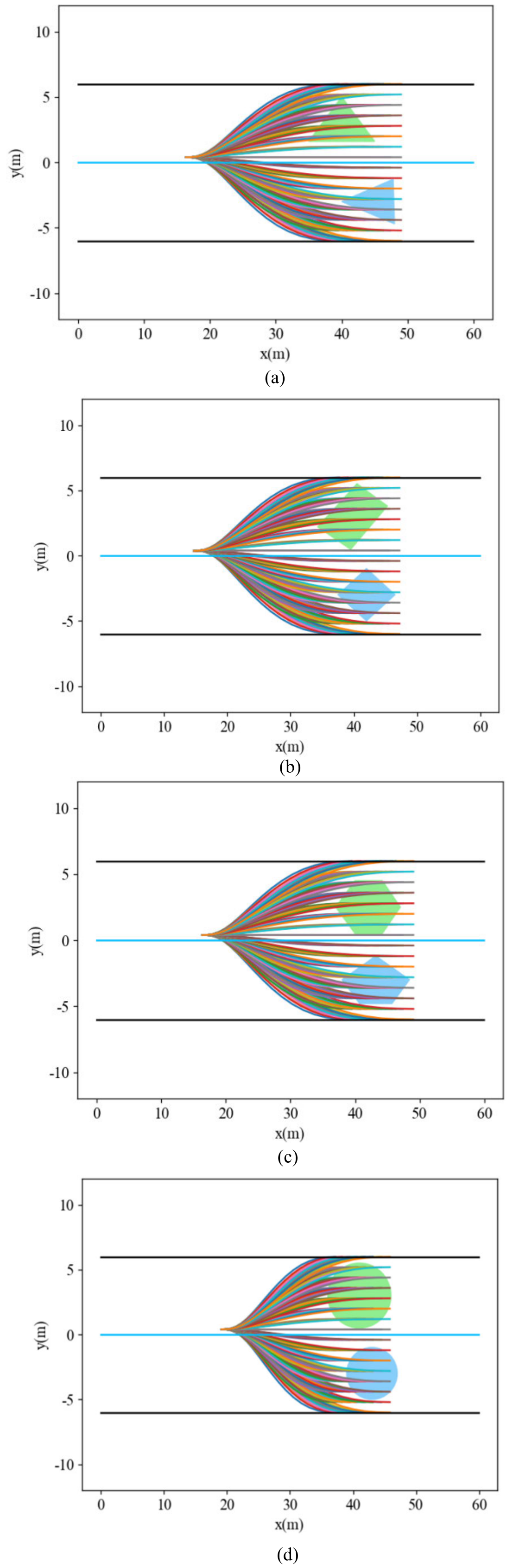

FIGURE 6. Ice obstacles schematic. (a) Triangular ice obstacles. (b) Rectangular ice obstacles. (c) Polygonal ice obstacles. (d) Round ice obstacles.

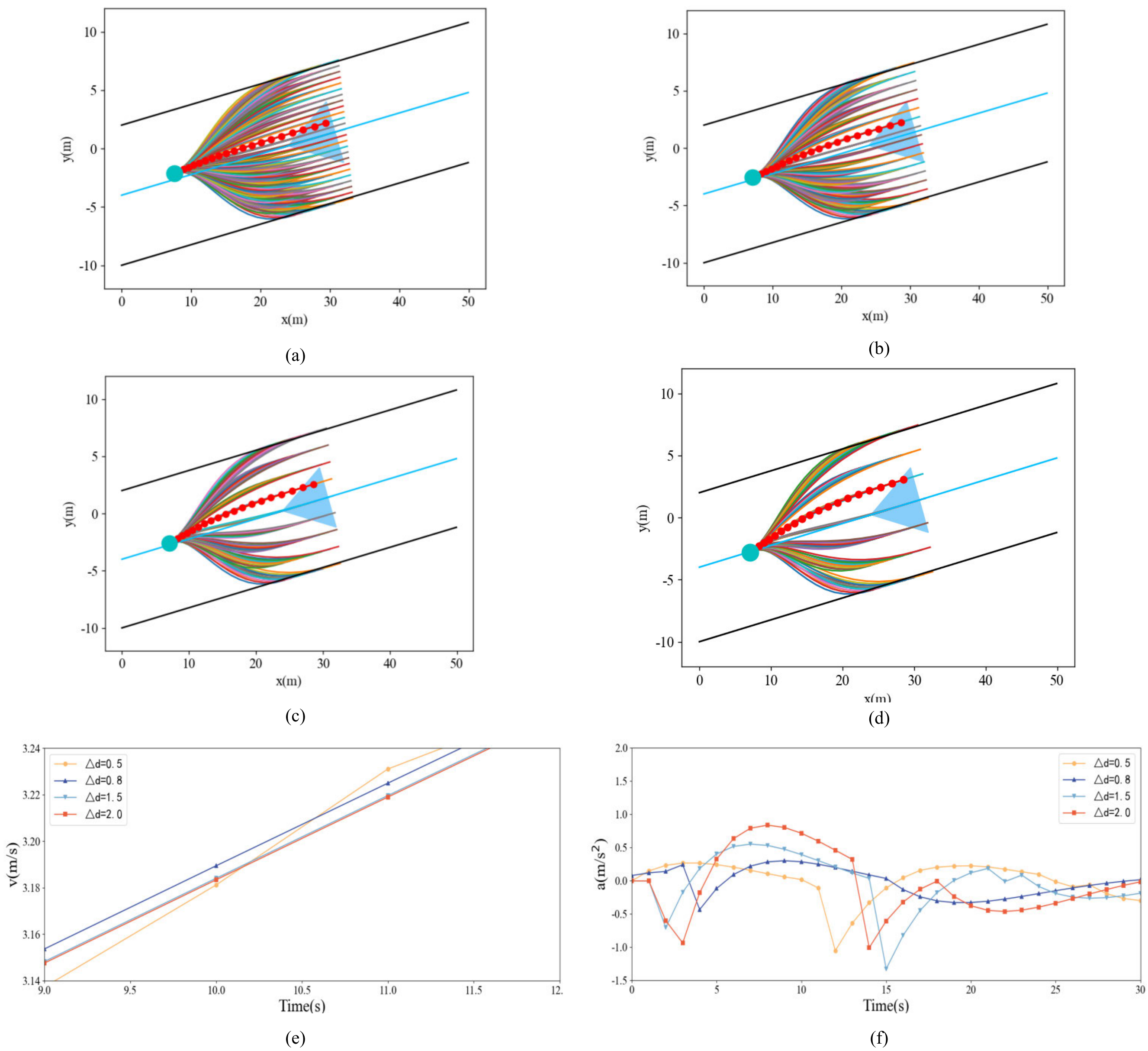

FIGURE 7. Impact of lateral sampling interval on trajectory planning. (a) $\Delta d = 0.5$ m. (b) $\Delta d = 0.8$ m. (c) $\Delta d = 1.5$ m. (d) $\Delta d = 2.0$ m. (e) Speed-Time. (f) Acceleration-Time.

establish the longitudinal and lateral trajectory planning equations, respectively. The longitudinal and lateral trajectories are synthesized at the corresponding moments. Finally, multiple complete candidate trajectories are formed using the Frenet coordinate system. The candidate trajectories are checked for collision, curvature, acceleration, and safe speed in turn. Only candidate trajectories that pass each check can proceed to the trajectory evaluation stage.

The trajectory planning of AVs usually considers evaluation indicators such as safety, comfort, and efficiency. Safety is one of the most important indicators. Trajectory safety is expressed by the distance of AVs from the road centerline, static obstacles, and dynamic obstacles. In particular, trajectory safety in snow and ice scenarios is represented by the distance traveled on ISCR and the distance between the AVs and the ice obstacles.

V. SIMULATION RESULTS ANALYSIS

A. SIMULATION SCENE

Ice obstacles are generally distributed on the road in an irregular shape. However, irregular shapes cannot be accurately described by simple curve equations, which increases the difficulty of obtaining information such as the distance between the AVs and the ice obstacles and the AVs travel on ISCR. Moreover, the boundaries of ice obstacles in real situations are often blurred and cannot be accurately identified. Therefore, this study considers an approximate

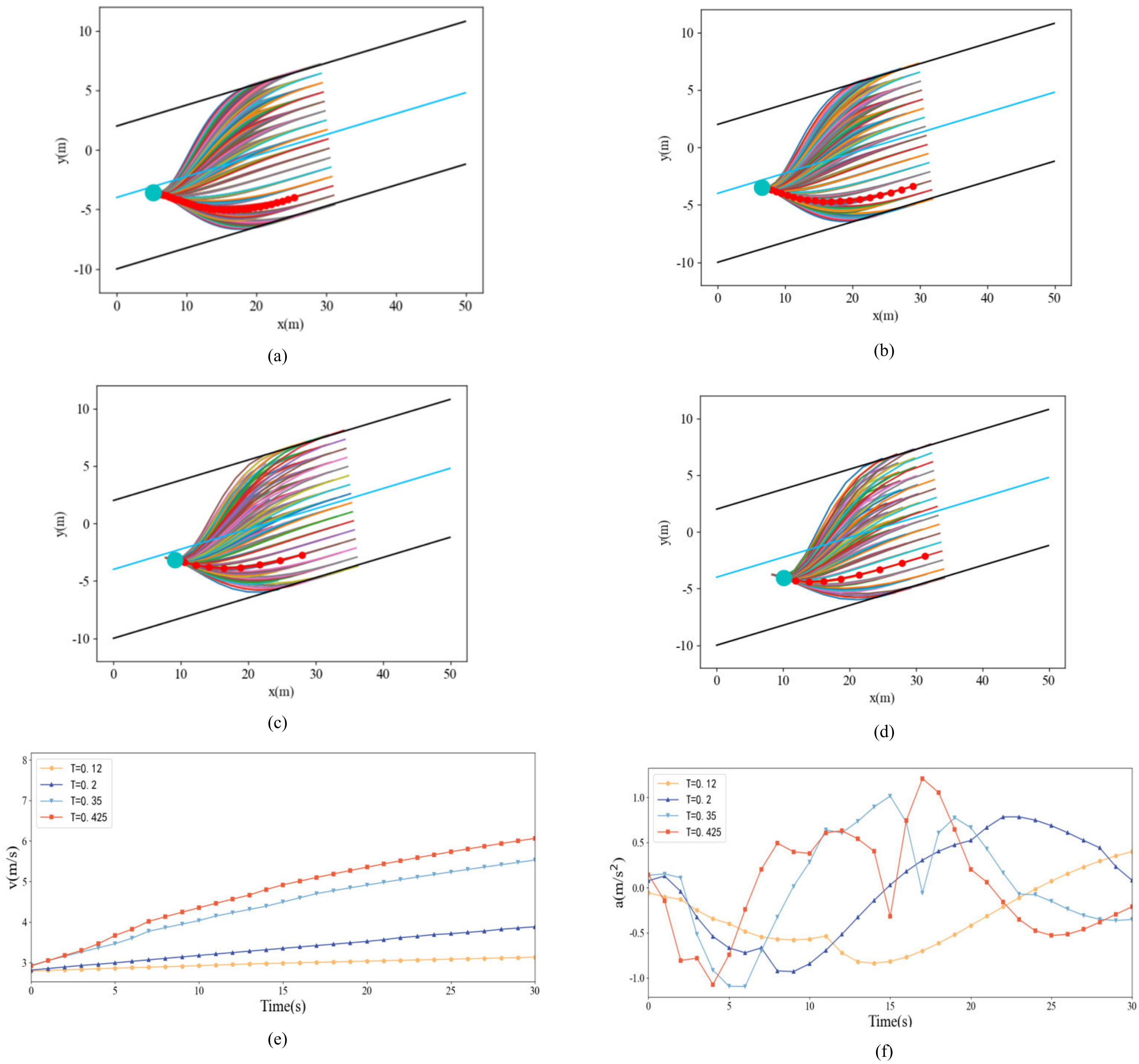

FIGURE 8. **Impact of time sampling interval on trajectory planning. (a) $\Delta T = 0.12$ m. (b) $\Delta T = 0.2$ m. (c) $\Delta T = 0.35$ m. (d) $\Delta T = 0.425$ m. (e) Speed-Time. (f) Acceleration-Time.**

alternative treatment for irregular ice obstacles. Common regular shapes such as triangles, rectangles, polygons, and circles can be used as an approximate substitute for all irregular ice obstacles. The selected shape is required to completely cover the ice obstacle and conform to its original shape to the greatest extent possible. As shown in Fig. 6, the travel distances of candidate trajectories on ISCR are different. The longer the vehicle drives, the higher the safety cost. In addition, the melting of the ice surface caused by the rising temperature makes it difficult to identify the boundaries of ice obstacles. The candidate trajectories that have a shorter driving distance on ice obstacles and are farther away from them are preferentially selected as optimal trajectories.

B. SIMULATION PARAMETERS

Assuming that the minimum turning radius is 2 m, the maximum curvature $q_{\max}$ is 0.5 m^{-1}. The maximum acceleration of the vehicle is 4.6 m/s^2. In order to facilitate the simulation, the vehicle is covered with a circle with a radius of 2 m, and the circle radius is the collision radius of the AVs. The collision parameters of the environmental and the experimental vehicles are consistent. Lateral trajectory planning cannot exceed the road width limit. In order to clearly show the visualization effect of vehicles passing through ice obstacles, the road width is 12 m, and the lateral sampling interval is 0.8 m. The longitudinal velocity sampling interval is 5.0 km/h $\approx$ 1.39 m/s. This paper uses the optimal parameters to solve the problem through data analysis. The specific simulation parameters are shown in Table 2:

C. SAMPLING ACCURACY ANALYSIS

Sampling parameters play a decisive role in the trajectory planning of AVs. Improving the sampling accuracy can enhance the richness of candidate trajectories and improve the optimal trajectory quality. The key sampling parameters mainly include the lateral sampling interval Δd and the time sampling interval ΔT.

The width of the road is constrained by environmental factors, and the lateral sampling interval Δd can only be changed within the range of the road width. Δd mainly affects the number of lateral trajectory sets. Fig. 7 shows the simulation results of trajectory planning when Δd is 0.5 m, 0.8 m, 1.5 m, and 2.0 m respectively. It can be seen that the larger the sampling interval, the sparser the sampling trajectory. Sparse sampling trajectories cannot accurately describe the state of vehicles passing through ice obstacles, which reduces the quality of trajectory planning on ISCR. As the sampling interval increases, the velocity variation is generally smooth, but the acceleration fluctuates significantly. The vehicle acceleration varied considerably at sampling intervals of 0.5 m, 1.5 m, and 2 m when the vehicle passed the ice obstacle. The candidate trajectories with a sampling interval of 0.5 m have a relatively gentle change in acceleration, with no drastic changes.

ΔT mainly affects the frequency of trajectory planning. Fig. 8 shows the simulation results of trajectory planning when ΔT is 0.12 s, 0.2 s, 0.35 s, and 0.425 s, respectively. It can be seen that the larger the sampling interval, the more drastic the acceleration fluctuation. When the sampling interval is greater than 0.2 s, the number of drastic acceleration changes becomes increasingly apparent. If the trajectory planning frequency is low, the AVs need to consume time to track the optimal solution of the last trajectory planning, which will lead to AVs instability. If the trajectory planning frequency is high, the vehicle may suddenly find an ice obstacle at the corner, which cannot be avoided in time because it is too close. Therefore, an appropriate increase in sampling accuracy helps AVs plan an optimal trajectory that combines safety, comfort, and stability in ice and snow scenarios.

D. ICE AND SNOW SCENARIO ANALYSIS

AVs are prone to skidding on ISCR, with a high risk of loss of control. This paper proposes to use the distance the AVs travel on ISCR as an evaluation index to measure the trajectory planning cost, and the longer the distance, the higher the cost. Fig. 9 shows that if the cost of driving distance is not considered, the vehicle will move forward along the reference line, which has a large contact area with the ice obstacle. With the effect of driving distance cost, the trajectory cost is higher near the ice obstacle in the center of the road, whereas the trajectory cost is lower from the obstacle to the road boundary range. Candidate trajectories immediately adjacent to the boundary of the obstacle are selected, as shown in Fig. 9(b). The obstacle boundary trajectory has the smallest deflection angle compared with other candidate trajectories within the obstacle and road boundary. Therefore, the trajectory with a short driving distance and a small deflection angle is selected as the optimal trajectory.

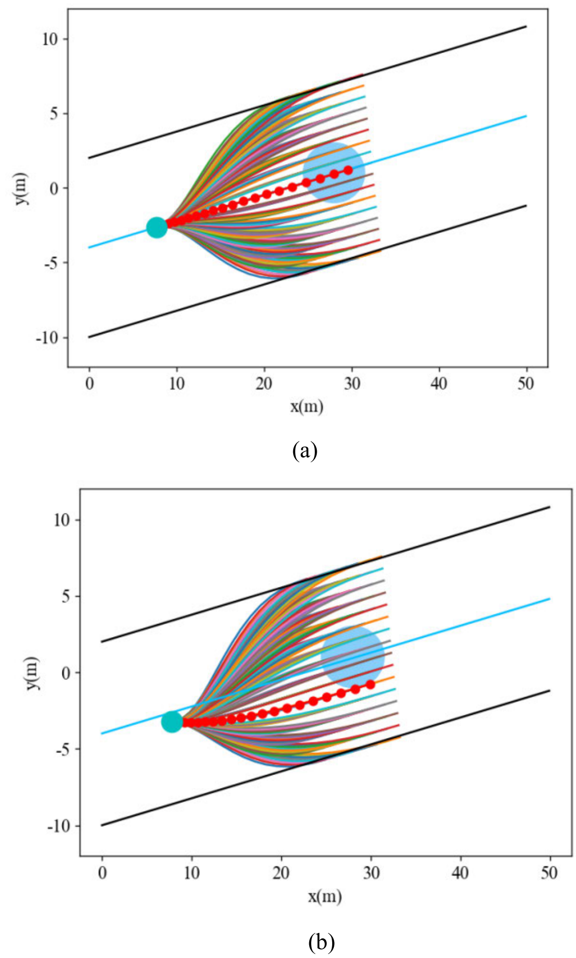

FIGURE 9. Impact of driving distance on trajectory planning. (a) Not considering the driving distance. (b) Consider the driving distance.

If only the driving distance cost is considered, the planning algorithm will choose the trajectory close to the ice obstacle, whereas the ice obstacle boundary cannot be accurately identified due to easy melting, which has certain dangers. Therefore, obstacle distance is also an important indicator for cost assessment of trajectory planning on ISCR. Fig. 10 shows that if the obstacle distance cost is not considered, the AVs drive along the road center reference line close to the ice obstacles. With the effect of obstacle distance cost, the AVs deflect in the direction away from the obstacle due to the higher cost near the obstacle, which improves the trajectory safety. Figure 10(c) shows more concisely the trajectory planning process of in the two cases of considering the obstacle distance and not considering the obstacle distance.

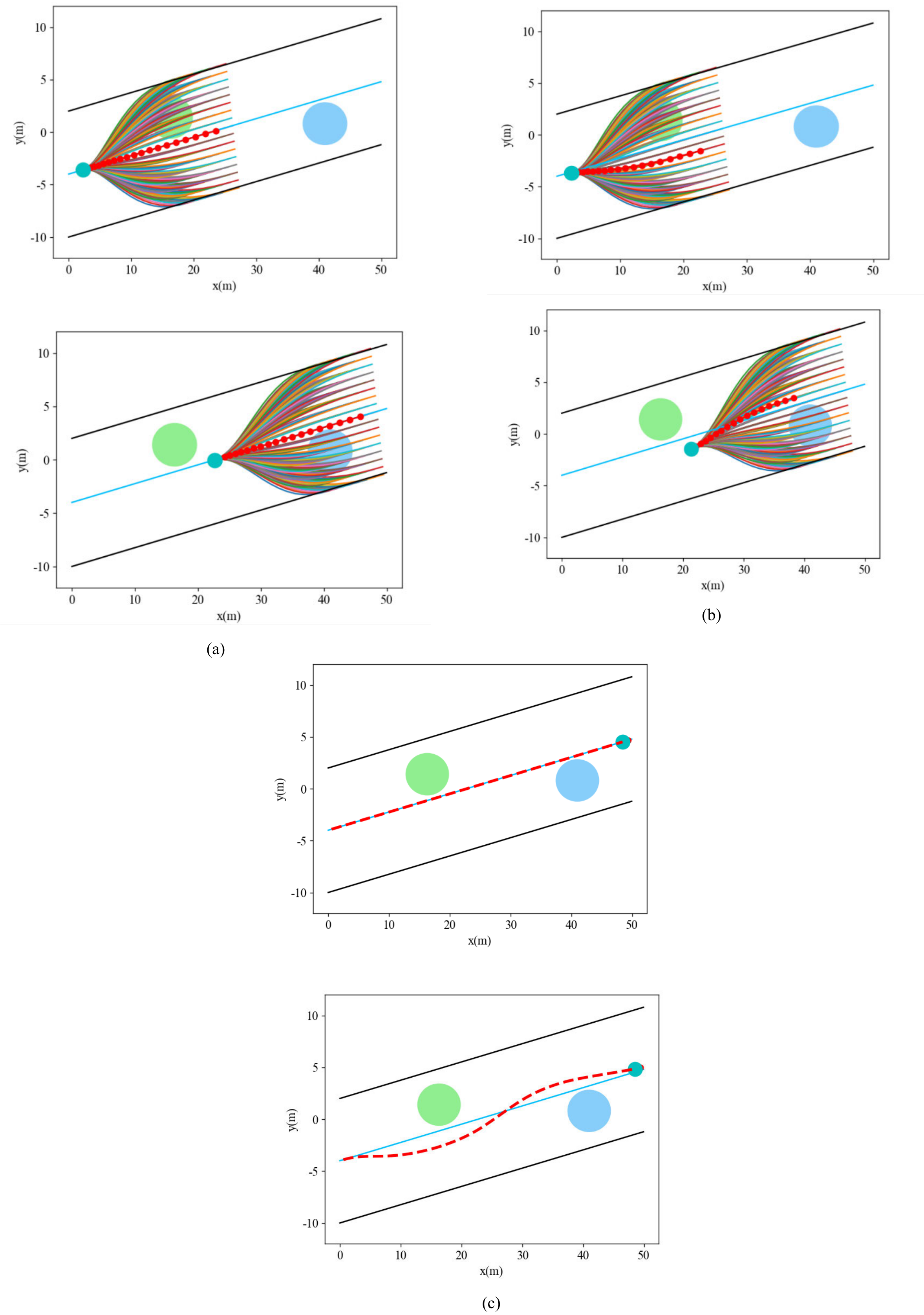

FIGURE 10. Impact of obstacle distance on trajectory planning. (a) Not considering the obstacle distance. (b) Consider the obstacle distance. (c) Optimum trajectory display.

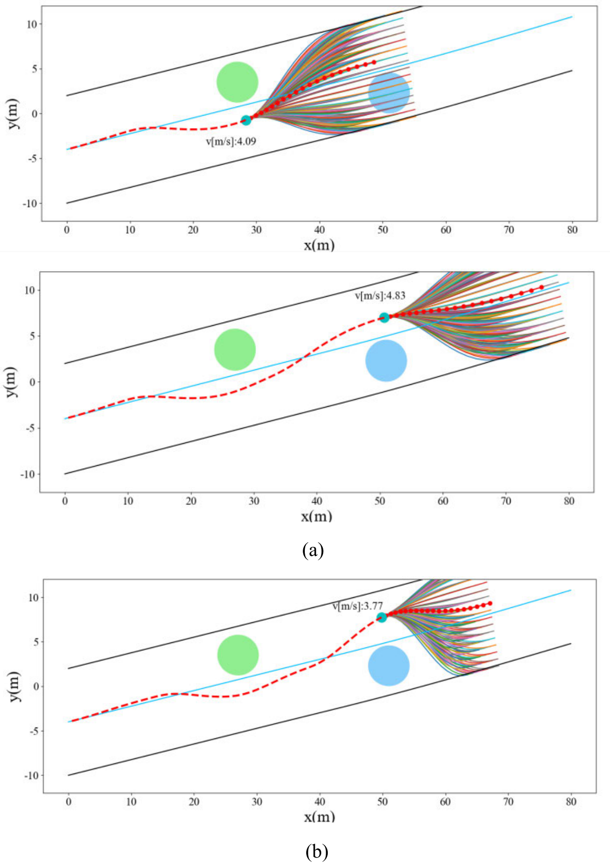

FIGURE 11. Impact of safe speed check on trajectory planning. (a) Not considering safe speed check. (b) Consider safe speed check.

E. SAFE SPEED ANALYSIS

The main reason why AVs are prone to slipping on ISCR is the low road adhesion coefficient. The more slippery the road, the slower the safe driving speed. This shows that safe driving speed is positively related to the road adhesion coefficient. Assuming that the adhesion coefficient of ISCR is known, the safe driving speed of the vehicle is 17 km/h $\approx$ 4.7 m/s. As shown in Fig. 11, this paper enhances trajectory safety through the safe speed check. If there is no safe speed check, the vehicle accelerates toward the target speed 30 km/h $\approx$ 8.3 m/s and passes the second obstacle at a speed of 4.83 m/s, exceeding the safe speed. However, after considering the safe speed check, the planning algorithm screens out trajectories that exceed the safe speed and outputs trajectories that pass the second obstacle with speed 3.77 m/s, which meets the safe speed requirement.

VI. CONCLUSION

Autonomous driving technology is divided into four core modules: perception, cognition, decision-making, and execution. The decision-making module is a direct factor in determining the safety and comfort of AVs, which mainly includes two parts: behavior decision-making and motion planning. Trajectory planning as a major component of motion planning needs to be completed more accurately and efficiently to serve the safe driving for AVs in snow and ice scenarios. Firstly, the current position, velocity, and acceleration state of the AVs are determined. Then, after getting the target state command from the decision-making module, the road environment information such as lane line and ice obstacle position is obtained based on sensors and radars. Finally, a safe and executable trajectory sequence is planned for the purpose of controlling the AVs to complete the target motion. This paper proposes an optimal trajectory planning algorithm based on the Frenet coordinate system, which provides reliable decisions for AVs trajectory planning in snow and ice scenarios. The main conclusions are summarized as follows:

1) The Frenet coordinate system expresses the distance that the trajectory deviates from the road center in terms of the vertical distance relative to the base path. This allows for an accurate representation of the relative position relationship between the AVs and the road. Moreover, compared to the Cartesian coordinate system, the Frenet coordinate system ignores the influence of road curvature and reduces the trajectory planning difficulty.
2) Evaluation indicators such as safety, comfort, and efficiency are usually considered in trajectory planning for AVs. The trajectory comfort is usually expressed in Jerk (changing rate of acceleration). The trajectory safety is expressed by the distance of the AVs from the road centerline, static obstacles, and dynamic obstacles. In particular, the safety of the trajectory in the snow and ice scenario is expressed by the distance traveled on ISCR and the distance between the AVs and the ice obstacles.
3) To reduce the impact of ISCR on trajectory planning, AVs must control the speed within a safe range. The road adhesion coefficient is one of the main influencing factors of safe speed. AVs determine the safe driving speed according to the road adhesion coefficient obtained from their sensors and select the trajectory that can pass the safe driving speed check as the candidate trajectory.
4) The sampling accuracy affects the richness as well as the quality of the trajectory. The key sampling parameters mainly include the lateral sampling interval Δd and the time sampling interval ΔT. Δd mainly affects the number of lateral trajectory sets. ΔT mainly affects the frequency of trajectory planning. A reasonable increase in sampling accuracy can plan an optimal trajectory for AVs that combines safety, comfort, and stability, especially on ISCR.

Simulation results show that this algorithm provides a reference on how to plan a safe, comfortable and stable trajectory for AVs on ISCR. This study broadens the application scenario of AVs and has practical significance for the development of intelligent transportation technology. In future work, it is proposed to apply temperature, humidity, and tire parameters in trajectory cost assessment to construct a more accurate trajectory planning algorithm.

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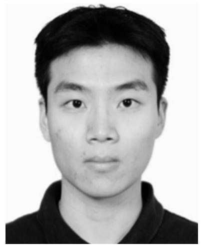

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