

Article

A Hierarchical Hybrid Trajectory Planning Method Based on a TTA-Driven Dynamic Risk Filtering Mechanism

Tao Huang¹, Lin Hu^{1,*} , Jing Huang² and Huakun Deng¹¹ College of Mechanical and Vehicle Engineering, Changsha University of Science and Technology, Changsha 410114, China² College of Mechanical and Vehicle Engineering, Hunan University, Changsha 410114, China

* Correspondence: hulin@csust.edu.cn

Abstract

To reduce the conservatism of local trajectory planning in dynamic road scenarios caused by redundant projection of predicted trajectories, this paper proposes a hierarchical hybrid trajectory-planning framework with a time-to-arrival (TTA)-driven dynamic risk-filtering mechanism. In the Frenet coordinate system, road boundaries, ego states, and static and dynamic obstacles are represented uniformly to construct an S–L fused risk field and an S–T spatiotemporal interaction graph, enabling the filtering of temporally irrelevant conflict regions based on TTA relationships. At the path-planning layer, risk-guided adaptive sampling is integrated with dynamic programming and quadratic programming to improve search efficiency and trajectory quality. At the speed-planning layer, spatiotemporal coordination is achieved through non-uniform discretization, safe-corridor extraction, and speed-profile optimization. Simulation results show that the proposed method generates safe, smooth, continuous, and executable local trajectories in scenarios involving static-obstacle avoidance, adjacent-vehicle cut-ins, non-motorized road-user crossings, and mixed multi-obstacle interactions, while reducing unnecessary deceleration and detours. Ablation results further indicate that adaptive sampling reduces the number of DP search nodes by approximately 50% and the average planning time by about 30%, while maintaining a nearly unchanged minimum safety distance. These findings demonstrate that the proposed framework effectively suppresses redundant conflict regions and improves planning efficiency, solution feasibility, and motion continuity without compromising safety.

Keywords: autonomous driving; trajectory planning; risk field; TTA filtering mechanism; dynamic programming



Academic Editor: Krzysztof Zboński

Received: 19 March 2026

Revised: 14 April 2026

Accepted: 18 April 2026

Published: 22 April 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Trajectory planning for autonomous driving determines how a vehicle moves in dynamic traffic environments and serves as a key module bridging environment perception, behavior decision-making, and vehicle control. This module is simultaneously constrained by safety, smoothness, trackability, and real-time performance, and therefore constitutes a core research topic in autonomous driving systems [1–4]. In structured-road and dynamic-interaction scenarios, planning algorithms must address not only spatial constraints such as road boundaries, static obstacles, and traffic rules, but also variations in the motion states of surrounding traffic participants and their temporal coupling with the ego vehicle. As scene complexity increases, trajectory planning algorithms are required to generate safe, feasible, and stable local trajectories under limited computational resources [5,6].

1.1. Related Work

To reduce the computational complexity of high-dimensional joint planning in dynamic scenarios, path–speed decoupling and hierarchical hybrid planning have become mainstream approaches. Lin et al. proposed a hierarchical decoupling framework that improves safety, comfort, and efficiency in automated lane changing by optimizing the path and speed separately [7]. Shi and Li reformulated dynamic conflict handling along a given spatial path as a one-dimensional speed-planning problem, thereby significantly reducing the problem dimensionality [8]. Guo et al. further showed, through a two-stage planning framework, that although hierarchical decomposition is beneficial for online implementation, the optimization performance still depends on the spatial topology generated in the front end [9]. To balance topological exploration and trajectory quality, Wang et al. combined sampling-based search with numerical optimization to establish a hybrid planning framework for dynamic road scenarios [10]. Subsequent studies further advanced hierarchical and hybrid planning through spatiotemporal lane-change gaps, decision–planning coordination, and oscillation suppression [11–13]. Related efforts also improved these frameworks through multi-reference-line modeling, dynamic consistency, and more efficient search strategies [14–18]. Overall, these methods provide a favorable balance between online efficiency and trajectory quality, but their performance still depends heavily on how effectively the path-layer planning space represents dynamic interactions.

In the construction of the path-layer planning space, risk-field methods have gradually become an important direction for enhancing dynamic environment representation [19]. Xia et al. proposed a geometric driver-perceived risk field that represents obstacle risk in a unified continuous geometric field [20]. To address the limitation that conventional risk fields are often instantaneous or quasi-static, Han et al. proposed the spatiotemporal risk field STRE, which describes dynamic traffic risk from a spatiotemporal coupling perspective [21]. Wang et al. further developed a data-driven spatiotemporal driving risk field to improve long-horizon risk assessment and path-planning performance [22]. Liu et al. constructed an integrated safety field composed of a static potential field, a dynamic-obstacle kinetic field, a lane-boundary field, and a target field, and directly used it for path generation and smoothing [23]. In addition, studies on 3D potential fields, dynamic-risk-driven lane changing, and integrated risk quantification have further improved the completeness of risk representation [24–26]. Localization uncertainty modeling, risk-map prediction, and prediction-driven planning have also improved the adaptability of risk-aware planning [27–30]. In general, risk-field methods have evolved from static geometric descriptions to spatiotemporally coupled, data-driven, and planning-coupled representations, continuously enhancing the path layer’s ability to characterize dynamic environments.

Relying solely on spatial representation at the path layer remains insufficient for complete trajectory planning in complex dynamic scenarios. Consequently, research has further shifted toward spatiotemporal coordination at the speed layer. Zhang et al. constructed a unified spatiotemporal feasible-region representation based on spatiotemporal voxels, organizing decision-making and trajectory planning within a common spatiotemporal framework [31]. On this basis, Chen et al. pointed out that relying only on uniformly processed prediction results is insufficient to capture multi-vehicle interaction relationships, and thus introduced an interaction reasoning mechanism into spatiotemporal planning [32]. In highly interactive system-level scenarios, Ding et al. proposed EPSILON, which uses hierarchical behavior planning, motion planning, and semantic spatiotemporal corridors to represent complex environmental constraints in a unified manner [33]. Zhang et al. further proposed an interactive spatiotemporal corridor method that decouples high-dimensional multi-vehicle conflicts into single-vehicle optimization problems within corridors [34]. In addition, deep reinforcement learning and compact spa-

tiotemporal joint optimization have further strengthened the unified handling of dynamic constraints and conflict relationships [35,36]. Joint optimization and iLQR-based methods have also improved the coordinated treatment of dynamic conflicts in spatiotemporal planning [37–39]. These methods enhance the representation and coordination of temporal conflicts, but they usually come at the cost of higher planning dimensionality and greater online computational burden.

In summary, although existing studies have made progress in hierarchical decomposition, path-layer risk representation, and speed-layer spatiotemporal coordination, further research is still needed on how to improve the path layer's ability to represent the temporal structure of dynamic interactions while maintaining real-time performance and how to effectively connect this representation with speed-layer spatiotemporal coordination. To this end, this paper proposes a hierarchical hybrid trajectory planning method based on a TTA-driven dynamic risk filtering mechanism. In the Frenet coordinate system, road boundaries, ego-vehicle states, static obstacles, and predicted trajectories of dynamic obstacles are mapped in a unified manner to construct an S–L fused risk field and an S–T spatiotemporal interaction graph. The former is used for dynamic risk screening in path planning, while the latter is used for temporal conflict handling in speed planning.

1.2. Contributions

The main contributions of this paper are as follows.

- (1) A hierarchical hybrid trajectory-planning framework is proposed, in which a TTA-based temporal relevance filtering mechanism is introduced into spatial risk representation and further integrated into risk-guided adaptive sampling, path search, and path optimization processes.
- (2) A dynamic risk-field modeling method based on the TTA filtering mechanism is proposed. By eliminating invalid risk contributions according to the arrival-time relationship, the proposed method reduces redundant high-risk regions and mitigates planning conservatism caused by the direct projection of predicted trajectories.
- (3) A spatiotemporal coordination method for speed planning is proposed. By constructing time-varying non-traversable regions, the proposed method enables accurate conflict constraints and smooth speed-profile optimization.

2. Trajectory Planning Framework

To address the coordinated requirements of safety, smoothness, and real-time performance for autonomous vehicles in dynamic road scenarios, this paper proposes a hierarchical hybrid trajectory-planning method based on a TTA-driven dynamic risk-filtering mechanism. Building upon a global reference line, the method uniformly maps road boundaries, ego-vehicle states, static obstacles, and predicted trajectories of dynamic obstacles in the Frenet coordinate system. On this basis, an S–L fused risk field and an S–T spatiotemporal interaction graph are constructed to enable a hierarchically decoupled solution of path planning and speed planning.

As illustrated in Figure 1, the proposed method consists of four main components: planning-space construction, path planning, speed planning, and trajectory fusion. During the planning-space construction stage, the road scene is first represented in a structured manner in the Frenet coordinate system. A static risk field and a dynamic risk field filtered by the TTA mechanism are then superimposed to form the S–L fused risk field for path planning. Meanwhile, an S–T spatiotemporal interaction graph is established along the planned path for speed planning, so as to characterize the potential temporal conflicts between the ego vehicle and dynamic obstacles.

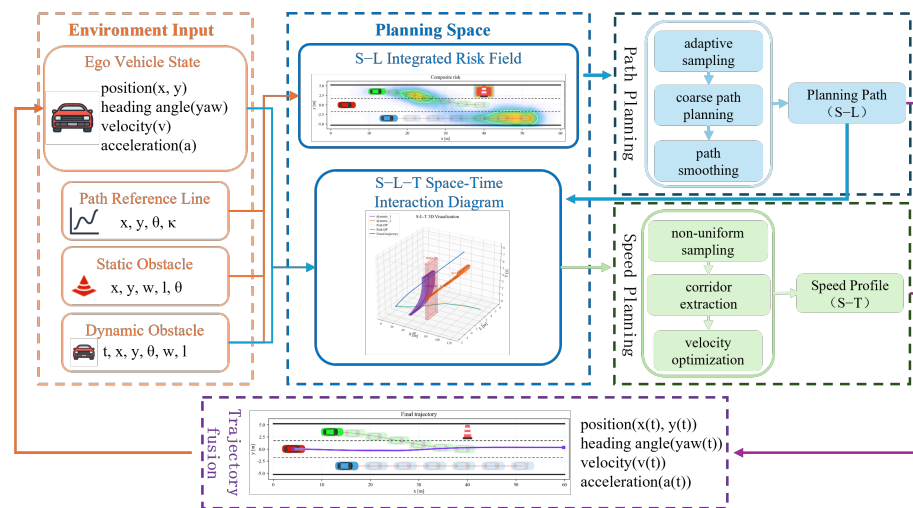


Figure 1. Hierarchical Hybrid Trajectory Planning under a TTA-Driven Dynamic Risk Filtering Framework.

In the path-planning stage, a hierarchical solution strategy combining dynamic programming and quadratic programming is adopted in the S–L space. Adaptive sampling is first performed according to the risk distribution, and adjacent sampling nodes are connected using quintic polynomials to generate candidate paths and conduct coarse path search. Subsequently, quadratic programming is introduced on the basis of the discrete reference path to further satisfy smoothness requirements and vehicle kinematic constraints, thereby yielding a continuous and executable local path. This stage mainly addresses the spatial traversability of the vehicle.

In the speed-planning stage, the spatiotemporal coordination between the ego vehicle and dynamic obstacles is handled in the S–T space. Time-varying non-traversable regions are first constructed through non-uniform spatiotemporal discretization and obstacle projection based on the Minkowski sum, from which a safe spatiotemporal corridor is extracted. A quadratic programming model is then formulated within the feasible region to jointly optimize velocity, acceleration, and jerk, thereby generating a smooth speed profile that satisfies dynamic constraints. This stage mainly addresses the temporal allocation problem of the vehicle.

Finally, the path-planning result and the speed-planning result are fused and mapped back to the Cartesian coordinate system to obtain a local trajectory that satisfies the requirements of safety, smoothness, and trackability, thus completing trajectory planning in dynamic scenarios.

3. Planning Space

Constructing a complete trajectory planning space is a prerequisite for the trajectory planner proposed in this paper. This planning space mainly consists of road geometry, static obstacles, dynamic obstacles and their predicted trajectories, and the global path. In the S–L space, an S–L fused risk field is constructed for path planning; in the S–T space, an S–T spatiotemporal interaction graph between the ego vehicle and dynamic obstacles is established for speed planning.

3.1. Frenet Coordinate Mapping

In complex road topologies, such as curved segments and sections with gradually varying curvature, directly evaluating environmental risk in the global Cartesian coordinate system makes it difficult to intuitively capture the relative interactions between surrounding obstacles and the ego vehicle in both the longitudinal and lateral directions

along the roadway. To address this issue, before constructing the underlying risk field, this paper first introduces a Frenet coordinate system (i.e., the S–L coordinate system) that is compatible with the geometric characteristics of the road. Based on the global reference line provided by the upstream routing module, the ego-vehicle state, road boundaries, and the positions and predicted trajectories of all surrounding obstacles in the Cartesian coordinate system are uniformly transformed and projected into the S–L space. In this space, the s -axis denotes the longitudinal arc length along the reference line, whereas the l -axis represents the lateral offset perpendicular to the reference line. This spatial reconstruction not only decouples the vehicle's longitudinal and lateral kinematics but also establishes the mathematical foundation for the subsequent computation of static and dynamic risk fields on a structured grid.

3.2. Risk Field

In collision-avoidance navigation for autonomous driving, potential-field methods are often employed to quantitatively assess the potential risks posed by surrounding obstacles. However, conventional potential-field approaches are primarily suited to adaptive cruise control (ACC) or purely static scenarios. In dynamic traffic environments, such methods often lack an effective representation of the continuous motion tendencies of vehicles and therefore fail to accurately characterize the distribution of risk during dynamic interactions. To address this limitation, this paper develops an improved driving risk-field model in which the motion states of obstacles are explicitly incorporated into the risk assessment associated with spatial position. This model provides the risk-field input for the subsequent TTA-based trajectory planning framework. The improved risk field consists of two components, namely a static component and a dynamic component: the former is determined by the inherent attributes and geometric shape of obstacles, whereas the latter is governed by the relative motion states between the obstacles and the ego vehicle. The specific construction process is described as follows.

3.2.1. Static Risk Field

The static risk field is primarily used to characterize the fundamental spatial constraints and collision risks imposed on the ego vehicle by fixed obstacles in the road environment, such as parked vehicles and roadblocks. Conventional artificial potential-field methods typically adopt standard Gaussian distributions or simple inverse-proportional functions; however, such formulations tend to produce geometric distortions when representing the rectangular contours of vehicle bodies, thereby excessively occupying the surrounding effectively drivable space and leading to overly conservative planning results. To overcome this limitation and to provide a globally continuous and differentiable cost map for subsequent TTA-based spatial path planning, this study adopts a two-dimensional super-Gaussian distribution to construct the static risk model.

As illustrated in Figure 2, compared with the standard Gaussian function, the super-Gaussian function can more compactly envelop the true physical boundary of an obstacle through its higher-order exponent parameters, while maintaining an excellent smooth transition at the boundary of the risk influence region. Specifically, the spatial coordinates (x, y) of static obstacle i are first transformed into the Frenet coordinate system generated by the global path, yielding the new coordinates (s, l) . The resulting risk value is defined as $R_i^s(s, l)$:

$$R_i^s(s, l) = A_s \exp \left[- \left(\left| \frac{s - s_{\text{obs}}}{\sigma_s} \right|^n + \left| \frac{l - l_{\text{obs}}}{\sigma_l} \right|^n \right) \right] \quad (1)$$

where A_s denotes the maximum risk magnitude in the central region of the static obstacle; $(s_{\text{obs}}, l_{\text{obs}})$ represents the geometric center coordinates of the static obstacle; σ_s and σ_l

denote the diffusion coefficients of the risk influence along the longitudinal s direction and the lateral l direction, respectively, whose values are typically determined jointly by the actual physical dimensions of the obstacle and a preset safety buffer distance; and n is an even-order shape parameter controlling the distribution profile (typically chosen as $n \geq 4$). As n increases, the contour of the risk field gradually transitions from an elliptical shape toward the true rectangular boundary, thereby maximizing the utilization of the ego vehicle's traversable space while ensuring collision-avoidance safety.

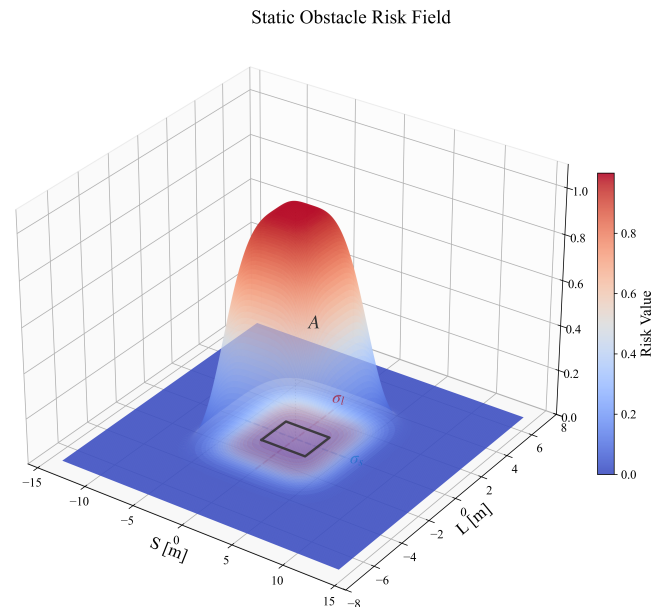


Figure 2. Static Risk Field of Obstacles.

3.2.2. Dynamic Risk Field Based on TTA Filtering

The dynamic risk field is intended to quantify the potential collision risk imposed on the ego vehicle by moving objects in the traffic environment, such as surrounding vehicles, over their future spatiotemporal evolution. Unlike the static case, the positions of dynamic obstacles vary continuously over time. If the risk fields corresponding to an entire predicted trajectory are directly superimposed onto the planning space, redundant virtual high-risk regions can easily be introduced, thereby causing the ego vehicle to behave in an overly conservative manner. To address this issue, this paper proposes, within the Frenet coordinate system (i.e., the S–L coordinate system), a spatiotemporal risk-field modeling method that accounts for the evolution of uncertainty, and further introduces a TTA filtering mechanism to provide a more accurate representation of environmental risk for the subsequent trajectory planning framework.

To characterize the spatiotemporal evolution of dynamic obstacles, this paper defines the underlying risk field as a three-dimensional S–L–T region that varies with the prediction time t . Considering that the uncertainty of trajectory prediction gradually increases over time, time-varying variance coefficients are introduced to quantify the expansion effect of the underlying Gaussian potential field along the predicted trajectory. Let the predicted state of dynamic obstacle j at future time t , after being projected into the S–L coordinate system, be denoted by $[s_p^j(t), l_p^j(t), \theta_{\text{rel}}^j(t), v_{\text{obs}}^j]$, where $\theta_{\text{rel}}^j(t)$ is the local heading angle and v_{obs}^j is the target velocity. The time-varying asymmetric Gaussian risk field generated by this target at time t and spatial position (s, l) is defined as:

$$R_d^j(s, l, t) = A_d \cdot \exp \left(- \left(\frac{(S_j)^2}{2\sigma_s(t)^2} + \frac{(L_j)^2}{2\sigma_l(t)^2} \right) \right) \quad (2)$$

where A_d denotes the maximum amplitude weight of the dynamic risk field, and $[S_j, L_j]^T$ represents the relative coordinates in a local coordinate system whose origin is located at the predicted position of the obstacle and whose positive direction is aligned with its heading angle. The corresponding transformation is given by

$$\begin{bmatrix} S_j \\ L_j \end{bmatrix} = \begin{bmatrix} \cos \theta_p^j(t) & \sin \theta_p^j(t) \\ -\sin \theta_p^j(t) & \cos \theta_p^j(t) \end{bmatrix} \begin{bmatrix} s - s_p^j(t) \\ l - l_p^j(t) \end{bmatrix} \quad (3)$$

To quantify the uncertainty of the predicted trajectory in both the longitudinal and lateral directions, the diffusion coefficients $\sigma_s(t)$ and $\sigma_l(t)$ are defined as monotonically increasing functions of time t , namely, $\sigma_s(t) = \sigma_{s0} + k_s t$ and $\sigma_l(t) = \sigma_{l0} + k_l t$. Here, σ_{s0} and σ_{l0} denote the equivalent inflation terms corresponding to the target's initial geometric dimensions, while k_s and k_l are the uncertainty expansion coefficients. This model indicates that the risk influence region of the target in the S–L–T space expands progressively as the prediction horizon increases.

After constructing the three-dimensional S–L–T risk field, this paper further designs an adaptive TTA filtering mechanism to reduce the field to a two-dimensional S–L space for path topological search. The criterion for this mechanism is defined as follows: the dynamic risk at spatial position (s, l) is retained only when the difference between the estimated arrival times of the ego vehicle and the obstacle at that position falls within a valid temporal window; otherwise, the region is regarded as collision-free. Let the current reference speed of the ego vehicle be v_{ego} . The estimated time for the ego vehicle to reach the longitudinal position s is denoted by $TTA_{\text{ego}}(s)$, and the estimated arrival time of dynamic obstacle j is denoted by $TTA_{\text{obs}}^j(s)$. These two quantities are approximated as

$$TTA_{\text{ego}}(s) = \frac{s - s_{\text{ego}}}{v_{\text{ego}}} \quad (4)$$

$$TTA_{\text{obs}}^j(s) = t \quad \text{s.t.} \quad s_p^j(t) = s. \quad (5)$$

Based on the above arrival times, the arrival-time difference between the ego vehicle and obstacle j at spatial position s is defined as

$$\Delta TTA^j(s) = |TTA_{\text{ego}}(s) - TTA_{\text{obs}}^j(s)|. \quad (6)$$

To balance safety and feasible solution space, the time-tolerance window $\tau(\Delta v^j)$ is adaptively adjusted according to the relative speed between the two vehicles. In scenarios involving high relative-speed interactions, the window is enlarged to increase the safety margin, whereas in low-speed following scenarios, it is reduced to limit unnecessary occupation of the feasible space. Its functional form is defined as

$$\tau(\Delta v^j) = \tau_{\text{base}} + c_v |v_{\text{ego}} - v_{\text{obs}}^j| \quad (7)$$

where τ_{base} is the base time tolerance, and c_v is the velocity sensitivity coefficient. Accordingly, after introducing the TTA mechanism, the dynamic-obstacle risk field is defined as

$$R_d^j(s, l) = \max_j \begin{cases} R_d^j(s, l, TTA_{\text{obs}}^j(s)), & \Delta TTA^j(s) \leq \tau(\Delta v^j), \\ 0, & \Delta TTA^j(s) > \tau(\Delta v^j). \end{cases} \quad (8)$$

After TTA filtering, the maximum risk over all predicted time instants is taken along the temporal dimension to obtain a two-dimensional dynamic risk field. According to the

threshold R_{thd} , the risk region can be further divided into a hard-constrained region and a soft-constrained region.

The proposed TTA-based filtering mechanism relies on short- to medium-horizon trajectory predictions of surrounding dynamic obstacles at each replanning cycle. In the receding-horizon framework, both obstacle predictions and the corresponding TTA-based filtering results are continuously updated. To reflect the increase in prediction uncertainty over time, the dynamic risk field adopts time-varying diffusion coefficients, so that long-horizon predicted risk is represented with a larger spatial spread.

3.2.3. Fused Risk Field

After the static risk field and the dynamic risk field are superimposed, they together constitute the vehicle's driving risk field, which is given by

$$R(s, l) = \sum_i R_i^s(s, l) + \sum_j R_d^j(s, l) \quad (9)$$

Figure 3 illustrates a complex traffic scenario involving multiple traffic participants together with their corresponding driving risk fields. In this study, the driving risk field is constructed in the Frenet coordinate system, where the forward lane direction is defined as the s -axis and the perpendicular direction as the l -axis. The intensity distribution of the risk field can intuitively characterize the potential risk at each position and primarily serves as a compact spatial prior for downstream path planning, while providing the spatial interaction basis for the subsequent hierarchical spatiotemporal coordination.

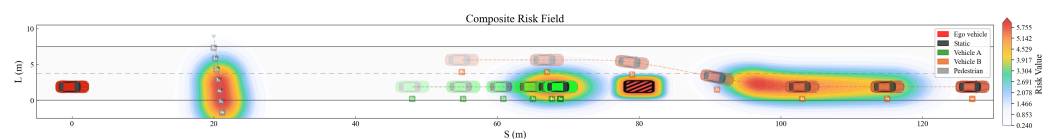


Figure 3. Visualization of the composite risk field in the Frenet coordinate system for a complex traffic scenario. The heat map illustrates the risk distribution generated by various traffic participants, including a static obstacle, dynamic vehicles, and a pedestrian.

4. Trajectory Planning with TTA-Driven Dynamic Risk Filtering

4.1. Adaptive Sampling in the S–L Space

To improve the search efficiency of dynamic programming in the S–L space, an adaptive sampling method is developed based on the constructed path risk field $R(s, l)$. The main idea is to adjust the longitudinal sampling density according to the projected risk distribution along the reference-line direction, such that denser samples are allocated in high-risk regions, and sparser samples are used in open regions. In this way, local search accuracy is preserved while redundant nodes are reduced.

First, for each longitudinal position s , the maximum risk along the lateral dimension is extracted to obtain the longitudinal risk envelope:

$$R_{\text{max}}(s) = \max_{l \in [l_{\text{min}}, l_{\text{max}}]} R(s, l) \quad (10)$$

This smoothing step diffuses isolated local peaks in the longitudinal risk envelope and enables nearby regions ahead of and behind obstacles to influence the subsequent sampling-density distribution. As a result, the generated longitudinal station sequence varies more continuously and avoids abrupt spacing transitions.

To ensure that the regions ahead of and behind obstacles are also reflected in the sampling-density distribution, a one-dimensional smoothing operation is applied to $R_{\max}(s)$, yielding

$$G(s) = \frac{1}{\sqrt{2\pi}\sigma_g} \exp\left(-\frac{s^2}{2\sigma_g^2}\right) \quad (11)$$

$$\bar{R}(s) = R_{\max}(s) * G(s) \quad (12)$$

where σ_g denotes the standard deviation of the Gaussian kernel. This operation spreads isolated local peaks in the longitudinal risk envelope to their neighboring regions, so that areas immediately ahead of and behind obstacles also contribute to the subsequent sampling-density distribution. As a result, the sampling density varies more continuously around obstacle regions, avoiding abrupt changes in the longitudinal sampling interval. The smoothed envelope is then normalized to obtain the longitudinal risk-distribution factor:

$$I_{\text{obs}}(s) = \frac{\bar{R}(s) - \min_s \bar{R}(s)}{\max_s \bar{R}(s) - \min_s \bar{R}(s)} \quad (13)$$

where $I_{\text{obs}}(s) \in [0, 1]$, and a larger value indicates a stronger local risk concentration along the longitudinal direction and therefore a higher demand for sampling resolution. On this basis, rather than directly adopting a piecewise step-size function, a continuous longitudinal sampling density function is defined as

$$\rho(s) = \rho_{\min} + (\rho_{\max} - \rho_{\min})(I_{\text{obs}}(s))^\gamma \quad (14)$$

$$\rho_{\min} = \frac{1}{\Delta s_{\max}}, \quad \rho_{\max} = \frac{1}{\Delta s_{\min}} \quad (15)$$

where $\Delta s_{\max}$ and $\Delta s_{\min}$ denote the maximum and minimum longitudinal sampling intervals, respectively, and γ is the density shaping coefficient. This formulation establishes a continuous mapping between obstacle distribution and sampling resource allocation, such that higher-risk regions correspond to higher sampling densities. Subsequently, the cumulative density function is introduced as

$$C(s) = \int_0^s \rho(u) du \quad (16)$$

and uniform sampling is then performed in the cumulative-density space with a fixed interval Δc , namely,

$$C(s_i) = i \Delta c, \quad i = 0, 1, \dots, N \quad (17)$$

By inversion, the longitudinal sampling station sequence $\{s_i\}$ can be obtained. This method avoids abrupt interval transitions caused by local step-size recursion, allowing the spacing between longitudinal sampling stations to vary continuously with the risk distribution.

In the lateral direction, to maintain a regular search-network structure, discrete sampling is performed with a fixed step size:

$$l_j = l_{\min} + j \Delta l, \quad j = 0, 1, \dots, M \quad (18)$$

In this way, a lateral node set $\{(s_i, l_j)\}$ is formed at each longitudinal station s_i , thereby ultimately constructing a complete S–L search network.

As shown in Figure 4, the projected longitudinal risk envelope captures the spatial variation of risk along the reference-line direction. After Gaussian smoothing and normalization, the resulting risk-distribution factor becomes continuous, and the high-risk peaks

around obstacle regions are broadened to their neighboring longitudinal intervals. Consequently, the constructed sampling-density function forms smoother and wider density peaks in the vicinity of obstacles, rather than producing abrupt local concentration only at isolated positions. Through inverse sampling in the cumulative-density space, the final longitudinal station sequence therefore becomes denser near obstacle regions and changes more gradually in open areas, which helps reduce redundant nodes while preserving local search resolution.

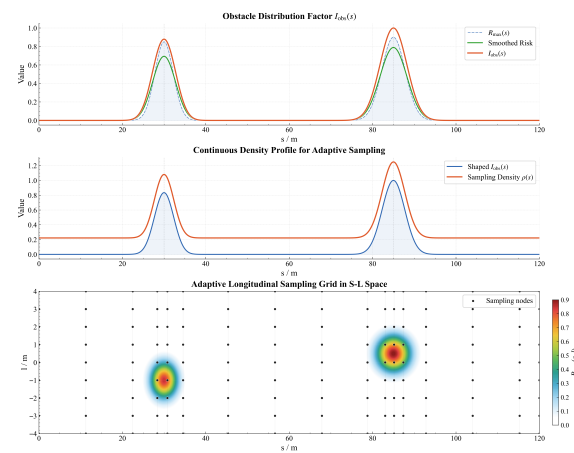


Figure 4. Schematic illustration of risk-distribution-driven adaptive sampling in the S–L space.

4.2. Path Planning

4.2.1. Candidate Path Generation

After adaptive sampling of the discrete spatial nodes, it is necessary to construct local geometric connections between nodes in adjacent longitudinal layers, thereby generating a directed acyclic graph for global optimization via dynamic programming. As illustrated in Figure 5, to satisfy the nonholonomic constraints of vehicle motion and to ensure C^2 continuity of the planned trajectory in terms of lateral offset, heading angle, and curvature, this paper adopts quintic polynomials to generate smooth curves between nodes.

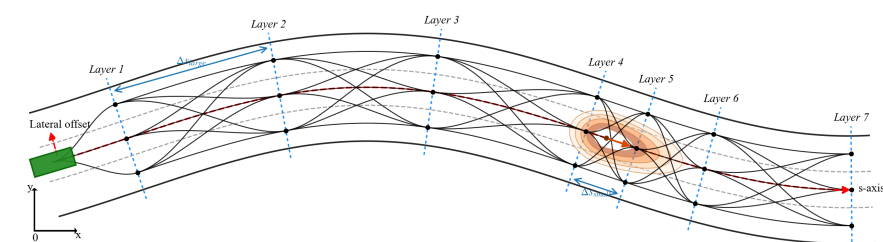


Figure 5. Methodology for candidate path generation based on adaptive sampling. Quintic polynomials are employed to construct continuous trajectories between discrete nodes across multiple sampling layers. The varying longitudinal density of the layers demonstrates the TTA-driven adaptive resource allocation in the S–L search space.

Let a sampled node at the i th longitudinal layer s_i be denoted as the starting point P_i , and a sampled node at the $(i + 1)$ th layer s_{i+1} as the terminal point P_{i+1} . In the Frenet coordinate system, the local smooth curve $l(s)$ connecting these two points can be modeled as a quintic polynomial function of the longitudinal arc length s :

$$l(s) = a_0 + a_1(s - s_i) + a_2(s - s_i)^2 + a_3(s - s_i)^3 + a_4(s - s_i)^4 + a_5(s - s_i)^5 \quad (19)$$

where a_0 through a_5 are the polynomial coefficients. These coefficients are uniquely determined by six boundary constraints at the start and end points, namely the boundary

states (l_i, l'_i, l''_i) and $(l_{i+1}, l'_{i+1}, l''_{i+1})$. To effectively reduce the dimensionality of the state space during the dynamic-programming search stage, it is commonly assumed—except for the current initial state of the ego vehicle—that the desired driving posture at the remaining candidate nodes is parallel to the road reference line. Accordingly, the first- and second-order lateral derivatives are relaxed to zero.

4.2.2. Cost Evaluation

After constructing the discrete state network composed of local polynomial connections, the path-planning problem can be reformulated as the search for a globally optimal path sequence in a directed acyclic graph. To simultaneously account for trajectory safety, kinematic feasibility, and reference-line tracking performance, this paper constructs, for the local polynomial curve $l(s)$ between two adjacent nodes P_i and P_{i+1} , a composite cost function that integrates smoothness, reference-line deviation, and environmental risk.

Let the longitudinal span of the curve segment be $[s_i, s_{i+1}]$. The total local cost $C_{\text{edge}}(P_i, P_{i+1})$ is defined as the weighted sum of the individual evaluation terms:

$$C_{\text{edge}}(P_i, P_{i+1}) = w_{\text{smooth}} C_{\text{smooth}} + w_{\text{ref}} C_{\text{ref}} + w_{\text{risk}} C_{\text{risk}} \quad (20)$$

To quantify the kinematic smoothness and ride comfort of the trajectory, quadratic penalties are imposed on the first-order lateral derivative of the polynomial curve (heading-angle deviation), the second-order derivative (curvature), and the third-order derivative (rate of curvature change). The corresponding integral form along the longitudinal arc length s is given by

$$C_{\text{smooth}} = \int_{s_i}^{s_{i+1}} \left(w_{dl} [l'(s)]^2 + w_{ddl} [l''(s)]^2 + w_{dddl} [l'''(s)]^2 \right) ds \quad (21)$$

where w_{dl} , w_{ddl} , and w_{dddl} are the sub-weights associated with the penalty terms for the first-, second-, and third-order derivatives, respectively.

To guide the ego vehicle to travel along the desired lane center in the absence of obstacle-avoidance requirements, a reference-line deviation cost is introduced to constrain the lateral position error of the trajectory:

$$C_{\text{ref}} = \int_{s_i}^{s_{i+1}} [l(s)]^2 ds \quad (22)$$

To achieve effective avoidance of surrounding obstacles, the two-dimensional composite risk field $R(s, l)$ constructed in the previous section is introduced. The cost incurred when the local polynomial curve traverses this risk field is quantified by the spatial path integral:

$$C_{\text{risk}} = \int_{s_i}^{s_{i+1}} R(s, l(s)) ds \quad (23)$$

Within the discrete solution framework, this integral term can be approximately evaluated by numerical accumulation using fixed-step sampling along the longitudinal arc length. The introduction of the risk-field cost imposes a substantial penalty on graph-search edges that pass through high-risk regions, thereby guiding the planning algorithm to avoid potential collision zones during spatial optimization.

4.2.3. Path Smoothing

Although the optimal discrete path produced by dynamic programming satisfies the preliminary requirements of obstacle avoidance and topological consistency, its derivative-level smoothness remains insufficient to directly meet the control demands imposed by

the underlying vehicle dynamics, owing to the limited resolution of the discretized state space. To address this issue, this paper introduces a quadratic programming algorithm to perform refined trajectory smoothing. Taking the reference path generated by the DP module as the baseline, the system resamples it along the longitudinal arc length s using a higher-resolution uniform step size, thereby generating a discrete longitudinal sequence $s_1, s_2, \dots, s_n$. The corresponding lateral coordinate sequence $[l_1, l_2, \dots, l_n]$ in the Frenet coordinate system then serves as the core decision variable of the QP module.

To balance trajectory smoothness, tracking accuracy, and risk avoidance, the objective function is composed of the following components. To ensure passenger comfort, a trajectory smoothness cost function is first introduced:

$$J_{\text{smooth}} = w_1 \sum_i (l'_i)^2 + w_2 \sum_i (l''_i)^2 + w_3 \sum_i (l'''_i)^2 \quad (24)$$

where w_1 , w_2 , and w_3 are the cost weights associated with the lateral velocity, acceleration, and jerk, respectively. In addition, to guide the ego vehicle to remain as close as possible to the path planned by the DP module when obstacle avoidance is not required, a reference-line tracking cost is introduced:

$$J_{\text{ref}} = \sum_i (l_i - l_{\text{ref}})^2 \quad (25)$$

where l_{ref} denotes the reference path generated by the DP module in the previous subsection. For the risk-field avoidance cost, considering that the composite risk field $R(s, l)$ is strongly nonlinear, this paper performs a second-order Taylor expansion at the DP reference node $l_{\text{dp},i}$ and transforms it into an approximate quadratic cost that satisfies the convexity requirements of quadratic programming:

$$J_{\text{risk}} = \sum_i \left(\frac{\partial R}{\partial l} \bigg|_{l_{\text{dp},i}} l_i + \frac{1}{2} \frac{\partial^2 R}{\partial l^2} \bigg|_{l_{\text{dp},i}} l_i^2 \right) \quad (26)$$

To achieve a comprehensive optimum with respect to trajectory smoothness, tracking accuracy, and risk avoidance, the final objective cost function of the quadratic programming problem is formulated as

$$F_{\text{cost}} = J_{\text{smooth}} + w_{\text{ref}} J_{\text{ref}} + w_{\text{risk}} J_{\text{risk}} \quad (27)$$

In the quadratic programming formulation, this paper imposes curve constraints using a piecewise-jerk optimization method. Assuming that the third-order derivative of the curve $f(s)$ connecting l_i and l_{i+1} remains constant, the fourth-order and higher-order derivatives of the curve are therefore zero. Under this assumption, l_{i+1} and l'_{i+1} can be expressed by finite Taylor expansions as follows:

$$l_{i+1} = l_i + l'_i \Delta s + \frac{1}{2} l''_i \Delta s^2 + \frac{1}{6} \left(\frac{l''_{i+1} - l''_i}{\Delta s} \right) \Delta s^3 \quad (28)$$

$$l'_{i+1} = l'_i + l''_i \Delta s + \frac{1}{2} \left(\frac{l''_{i+1} - l''_i}{\Delta s} \right) \Delta s^2 \quad (29)$$

In terms of inequality constraints, the true geometric boundary of the vehicle must be taken into account in order to construct physical collision-avoidance constraints. In this paper, the vehicle is equivalently modeled as a rigid rectangular body. Let the total vehicle width be w , and let the distances from the center of mass to the front and rear ends of the

vehicle be denoted by d_1 and d_2 , respectively. Under the small-angle assumption $\theta \approx l'_i$, the lateral coordinates of the four corners of the equivalent rectangle can be approximated as $l_i + d_1 l'_i \pm \frac{w}{2}$ and $l_i - d_2 l'_i \pm \frac{w}{2}$. To ensure physical safety, the coordinates of these four points must be strictly enclosed within the QP convex-space bounds $[lb_i, ub_i]$.

By solving the resulting quadratic programming model, a continuous obstacle-avoidance path that satisfies vehicle dynamic constraints can be obtained while simultaneously accounting for both comfort and safety.

4.3. Speed Planning

4.3.1. Spatiotemporal Corridor Extraction

To balance global computational efficiency and local obstacle-avoidance accuracy, this paper adopts a non-uniform discretization strategy along the longitudinal S-axis, with dense sampling in the near field and sparse sampling in the far field. Specifically, a finer grid is employed in the proximal interaction region, whereas a coarser grid is used in the distal region, thereby reducing the scale of the state space while preserving the accuracy of local planning. In particular, the near field is discretized with a fine grid interval Δs_{near} , whereas the far field is discretized with a coarse grid interval Δs_{far} .

In complex dynamic interaction scenarios, directly projecting the predicted trajectories of surrounding vehicles onto the S-T plane may introduce invalid collision regions, because such a treatment ignores both the relative heading difference between the obstacle and the reference path and the lateral geometric separation between the obstacle and the selected path. To obtain a more accurate non-traversable region for speed planning, a two-dimensional geometric projection based on the Minkowski-sum concept is introduced in the Frenet coordinate system.

Consider a dynamic obstacle at time t , whose center is projected onto the reference path as $(s_{\text{obs}}(t), d_{\text{obs}}(t))$, and whose heading angle relative to the tangent direction of the reference path is denoted by $\Delta\theta(t)$. The obstacle is approximated by a rectangle with length L_{obs} and width W_{obs} , while the ego vehicle is approximated by a rectangle with length L_{ego} and width W_{ego} . For a rectangular obstacle, the projection of its footprint onto the lateral axis of the Frenet frame is $L_{\text{obs}}|\sin \Delta\theta(t)| + W_{\text{obs}}|\cos \Delta\theta(t)|$, whereas its projection onto the longitudinal axis is $L_{\text{obs}}|\cos \Delta\theta(t)| + W_{\text{obs}}|\sin \Delta\theta(t)|$.

Based on the Minkowski-sum interpretation, the geometric dimensions of the ego vehicle are absorbed into the obstacle footprint to form an equivalent collision envelope. The effective lateral and longitudinal extents of the obstacle with respect to the ego vehicle are then expressed as

$$D(t) = W_{\text{ego}} + L_{\text{obs}}|\sin \Delta\theta(t)| + W_{\text{obs}}|\cos \Delta\theta(t)| \quad (30)$$

$$S(t) = L_{\text{ego}} + L_{\text{obs}}|\cos \Delta\theta(t)| + W_{\text{obs}}|\sin \Delta\theta(t)| \quad (31)$$

Here, $D(t)$ denotes the effective collision width in the lateral direction, and $S(t)$ denotes the effective collision length in the longitudinal direction. Geometrically, Equations (30) and (31) first project the obstacle rectangle onto the Frenet axes according to the relative heading angle $\Delta\theta(t)$, and then enlarge the projected obstacle by the ego-vehicle dimensions to obtain the collision-relevant envelope.

Let d_{margin} be the lateral safety margin. The non-traversable region induced by the obstacle at time t is defined as

$$\Omega_{\text{obs}}(t) = \left\{ s \mid |d_{\text{obs}}(t)| \leq \frac{1}{2}D(t) + d_{\text{margin}}, |s - s_{\text{obs}}(t)| \leq \frac{1}{2}S(t) \right\} \quad (32)$$

Equation (32) indicates that the obstacle contributes a longitudinally non-traversable interval only when the selected path satisfies the lateral overlap condition

$$|d_{\text{obs}}(t)| \leq \frac{1}{2}D(t) + d_{\text{margin}}$$

If this condition is not satisfied, the obstacle does not produce an effective conflict interval at the current time, and thus

$$\Omega_{\text{obs}}(t) = \emptyset$$

Therefore, the proposed projection removes dynamic targets that are laterally separated from the selected path while preserving the longitudinal collision envelope for obstacles that may actually interact with the ego vehicle.

In implementation, $\Omega_{\text{obs}}(t)$ is first evaluated at each discrete time layer of the S–T graph. For each time instant t_k , the corresponding values of $D(t_k)$ and $S(t_k)$ are computed for every dynamic obstacle, and the lateral overlap condition is then checked. If the condition is satisfied, the obstacle generates a longitudinal non-traversable interval

$$\left[s_{\text{obs}}(t_k) - \frac{1}{2}S(t_k), s_{\text{obs}}(t_k) + \frac{1}{2}S(t_k) \right]$$

Otherwise, the obstacle contributes no forbidden interval at that time layer. For multi-obstacle scenarios, the intervals at the same time layer are merged to form the overall non-traversable region of that layer.

It should be noted that Equation (32) defines the obstacle-induced forbidden interval at an individual time instant, whereas the final non-traversable space used for speed planning is obtained by connecting these intervals across successive time layers, thereby forming continuous time-varying obstacle bands in the S–T graph, as illustrated in Figure 6. When the lateral overlap condition remains satisfied over adjacent time layers, the corresponding longitudinal intervals evolve continuously along the time axis and jointly define a continuous obstacle region. When the lateral condition is no longer satisfied, the associated obstacle band naturally terminates. Therefore, the lateral overlap condition determines whether an obstacle contributes to an effective conflict region at a given time layer, while the connected intervals across time constitute the continuous non-traversable space used in the subsequent search process. In this way, dynamic obstacles that are laterally separated from the selected path are excluded, and only geometrically relevant conflict regions are preserved in the S–T graph.

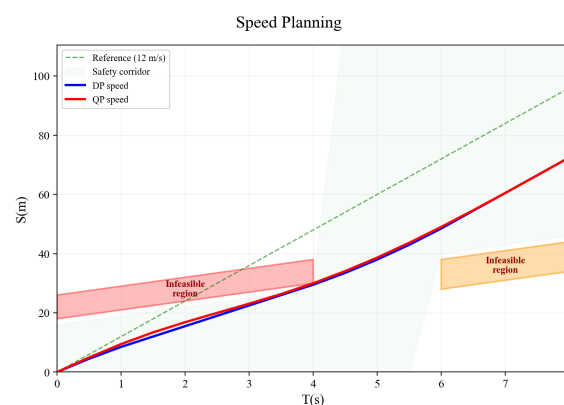


Figure 6. Velocity profile optimization.

Based on the resulting continuous non-traversable space, dynamic programming is performed on the non-uniform S–T graph to search for a coarse-grained velocity profile that is globally optimal with respect to the overall cost. The cost function jointly considers speed-tracking performance, acceleration smoothness, jerk smoothness, and obstacle-avoidance cost:

$$J = \sum_i \left[w_v (\dot{s}_i - v_r)^2 + w_a \ddot{s}_i^2 + w_j \dddot{s}_i^2 + w_o \phi(d_i) \right] \quad (33)$$

Here, $\phi(d_i)$ denotes the obstacle penalty term constructed according to the distance between the current node and the time-varying non-traversable region. Through this formulation, a coarse-grained safe velocity profile with globally minimal cost can be efficiently obtained on the non-uniform S–T graph. Furthermore, the free space between adjacent obstacle bands can be extracted to generate a safe spatiotemporal corridor $[s_{\min}, s_{\max}]$, which serves as the feasible domain for the subsequent quadratic programming stage.

4.3.2. Multi-Objective Velocity Profile Smoothing

Although the heuristic search provides a safe spatiotemporal corridor, the resulting discrete trajectory does not possess continuity at the level of the second-order derivative. Therefore, under the convex spatial constraints established in the previous subsection, this study constructs a quadratic programming model based on piecewise jerk to generate a smooth velocity profile consistent with the physical behavior of the vehicle.

The discrete system state vector is defined as

$$X = [s_0, \dots, s_n, v_0, \dots, v_n, a_0, \dots, a_n]^T \in \mathbb{R}^{3(n+1)},$$

with jerk taken as the control input. The optimization objective is to minimize the reference-speed tracking error, acceleration effort, and jerk penalty. Accordingly, the cost function f_{cost} is formulated as

$$f_{\text{cost}} = w_1 \sum_{i=0}^n (v_i - v_r)^2 + w_2 \sum_{i=0}^n a_i^2 + w_3 \sum_{i=0}^{n-1} j_i^2. \quad (34)$$

Here, w_1 , w_2 , and w_3 are dimensionless weighting coefficients. After matrix reformulation, the above cost function can be cast into the standard quadratic form $\frac{1}{2} X^T H X + g^T X$. The positive semidefiniteness of the sparse Hessian matrix ensures the convexity of the optimization problem and thereby enables efficient computation of the global optimum.

To ensure a smooth acceleration transition in the generated trajectory without abrupt changes, accurate kinematic and boundary constraints must be imposed on the system. Assuming that the jerk remains constant within each discrete time step Δt , the Taylor-expansion-based expressions can be written as

$$s_{i+1} = s_i + \dot{s}_i \Delta t + \frac{1}{2} \ddot{s}_i \Delta t^2 + \frac{1}{6} \left(\frac{\ddot{s}_{i+1} - \ddot{s}_i}{\Delta t} \right) \Delta t^3, \quad (35)$$

$$\dot{s}_{i+1} = \dot{s}_i + \ddot{s}_i \Delta t + \frac{1}{2} \left(\frac{\ddot{s}_{i+1} - \ddot{s}_i}{\Delta t} \right) \Delta t^2. \quad (36)$$

By replacing the control input with the finite-difference expression $j_i = \frac{a_{i+1} - a_i}{\Delta t}$, the above higher-order integral relations can be transformed into linear equality constraints among the state variables, from which the sparse equality-constraint matrix A_{eq} is constructed.

Meanwhile, the optimization must remain strictly confined within the safe corridor generated in the previous subsection and must also satisfy the vehicle's dy-

dynamic constraints. Specifically, the state variables are required to satisfy the position bounds $s_{\min} \leq s_i \leq s_{\max}$, the speed limits $0 \leq v_i \leq v_{\max}$, and the acceleration bounds $a_{\min} \leq a_i \leq a_{\max}$. In particular, the jerk constraint is explicitly imposed through the difference equation $j_{\min}\Delta t \leq a_{i+1} - a_i \leq j_{\max}\Delta t$. Figure 6 illustrates the optimized velocity profile.

In summary, this study achieves decoupled path and speed planning in the Frenet coordinate system. Through inverse coordinate transformation, the trajectory jointly generated from the S–L and S–T graphs is mapped back into the global Cartesian space, ultimately yielding a complete spatiotemporal state vector with high-order continuity $q = [x, y, v, a, \theta, \kappa]^T$.

5. Simulation and Verification

To verify the effectiveness of the proposed method, simulations were conducted under several representative scenarios, including static-obstacle avoidance, adjacent-vehicle cut-in, non-motorized road-user crossing, and mixed interactions with multiple obstacles. The main simulation parameters are listed in Table 1.

Table 1. Main algorithm parameters.

Parameter	Value	Description
W_{road}	3.75 m	Road width
L_{ego}	4.8 m	Length of the ego vehicle
W_{ego}	2.0 m	Width of the ego vehicle
σ_l	0.12	Lateral diffusion coefficient of the risk field
σ_s	0.25	Longitudinal diffusion coefficient of the risk field
γ	1	Risk-field density shaping coefficient
Δt	0.1 s	Planning cycle
a^c	$[-6, 4] \text{ m/s}^2$	Acceleration range
$j_{\max}$	4 m/s^3	Maximum jerk

5.1. Static Obstacle Avoidance

As illustrated in Figure 7, this scenario corresponds to a two-lane curved road segment with a lane width of 3.75 m and a local planning horizon of 120 m. The ego vehicle has an initial speed of 36 km/h (10 m/s). A static obstacle, such as a parked vehicle, is placed 55 m ahead of the ego vehicle. The obstacle is located at the center of the current lane and has dimensions of $4.5 \text{ m} \times 1.8 \text{ m}$. The vehicle is required to complete a local bypass maneuver while satisfying the road-boundary constraints.

Under this scenario, the proposed planner generates a continuous and collision-free local trajectory. As shown in Figure 7c, the dynamic-programming stage is already capable of identifying the correct obstacle-bypassing topology; however, the resulting path still exhibits noticeable oscillations before and after the obstacle, accompanied by substantial fluctuations in the curvature profile. This indicates that, although the discrete search result is feasible, it remains inadequate for direct vehicle execution. After quadratic-programming-based refinement, the final trajectory produces a single and continuous lateral deviation in the vicinity of the obstacle and gradually returns to the target lane after passing it. As can be seen from Figure 7a, the longitudinal acceleration varies relatively smoothly throughout the maneuver, indicating that the vehicle completes obstacle avoidance primarily through lateral steering rather than pronounced deceleration. The peak lateral acceleration is concentrated during the obstacle-bypassing phase and is well aligned with the trajectory offset, suggesting that the planned motion can respond promptly to obstacle constraints by appropriately adjusting the vehicle state. These results demonstrate that the proposed method can effectively coordinate road-boundary constraints and obstacle-avoidance requirements

in curved-road scenarios with static obstacles, while also improving the geometric quality of the coarse path.

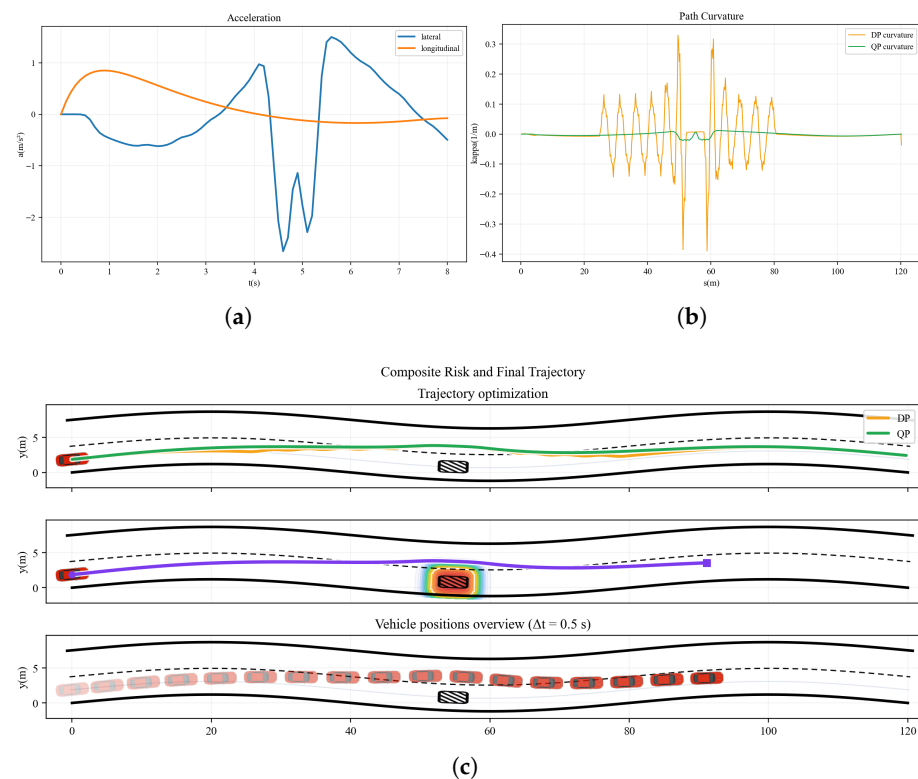


Figure 7. Static Obstacle Avoidance: (a) Lateral and longitudinal acceleration profiles; (b) Lateral and longitudinal path curvature; (c) Comparison of vehicle trajectory optimization results and schematic illustration of vehicle positions at 0.5 s intervals. In this comparison, the orange line segment represents the DP planning result, the green line segment indicates the QP optimization result, and the purple line segment denotes the final fused trajectory curve.

5.2. Interactive Scenarios

5.2.1. Adjacent-Vehicle Cut-In

In this scenario, the environment is configured as a two-lane straight road segment with a total road length of 120 m, a lane width of 3.75 m, a local planning horizon of 120 m, and a speed limit of 50 km/h. The ego vehicle travels with an initial speed of 10 m/s. An adjacent vehicle, initially located 30 m ahead of the ego vehicle, cuts into the ego lane at a speed of 6 m/s and subsequently decelerates at 1 m/s^2 until coming to a stop.

As shown in Figure 8, under this scenario, the proposed method does not maintain a continuous car-following strategy. Instead, as the dynamic risk ahead gradually intensifies, it identifies the feasible space that reopens in the adjacent lane and generates a single, continuous lane-change trajectory, before resuming stable driving after traversing the conflict region, without exhibiting noticeable rollback behavior or repeated corrections throughout the process. As shown in Figure 8d, the high-risk region is mainly concentrated in front of the cut-in vehicle and within the area occupied after it decelerates to a stop, indicating that the proposed method is capable of compressing the temporal conflict induced by the dynamic obstacle into a localized region directly relevant to the actual interaction, and of accordingly guiding the vehicle toward lower-risk space. The evolution of acceleration is broadly consistent with the trajectory variation. The longitudinal acceleration remains relatively smooth overall, without pronounced emergency braking; the peaks in lateral acceleration mainly correspond to the lane-change initiation and recovery phases; and both longitudinal and lateral jerk exhibit only brief fluctuations at the initial stage of trajectory

adjustment, followed by rapid attenuation. By contrast, in the absence of TTA filtering, the cut-in vehicle imposes a persistently occupied obstacle constraint on the left side. When further combined with the risk field, its predicted trajectory expands into a continuous diagonal high-risk band in the planning space, compressing the traversable region of the left lane and making the planner more inclined to decelerate and yield or to initiate avoidance prematurely. After introducing the TTA mechanism, the proposed method is able to capture the critical temporal cue that the left lane becomes available again once the vehicle completes the lane-change maneuver, thereby preserving the effective feasible region and triggering a rational lane-change decision. These results demonstrate that the TTA filtering mechanism can suppress redundant risk propagation and improve planning traversability.

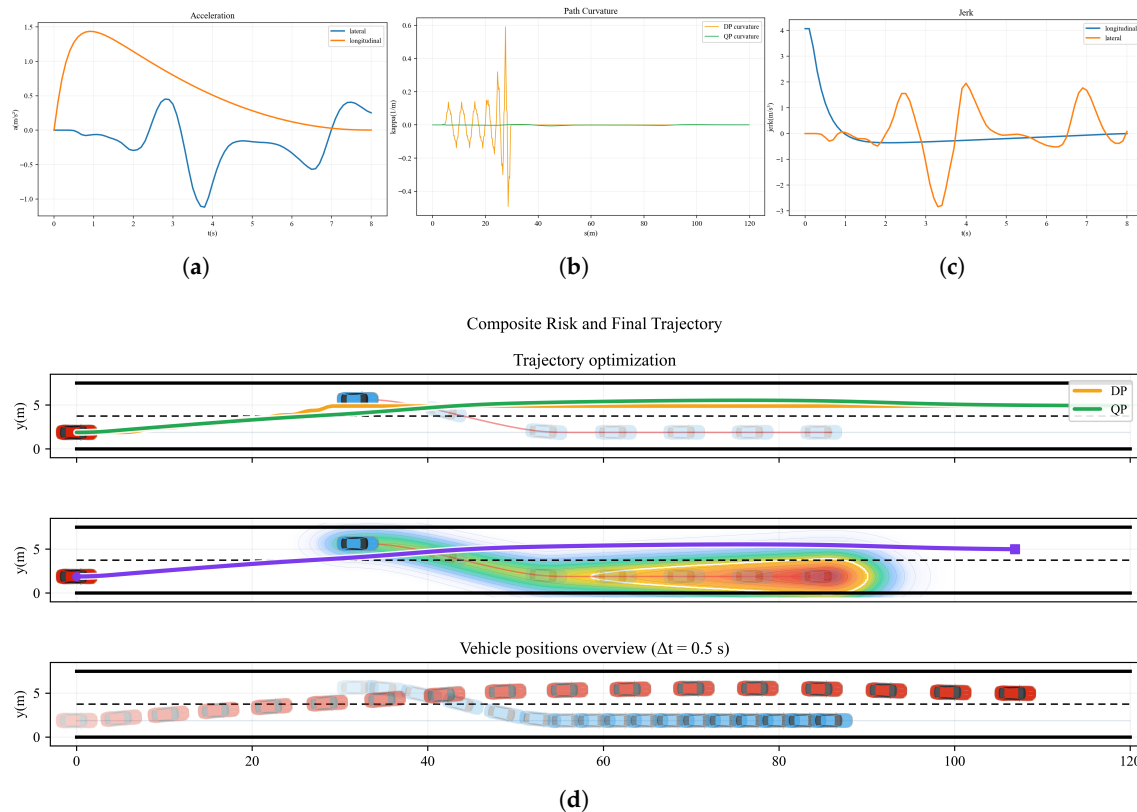


Figure 8. Adjacent-Vehicle Cut-In: (a) Lateral and longitudinal acceleration profiles; (b) Lateral and longitudinal path curvature; (c) Lateral and longitudinal jerk profiles; (d) Comparison of vehicle trajectory optimization results and schematic illustration of vehicle positions at 0.5 s intervals, where the orange line represents the DP result, the green line indicates the QP result, and the purple line denotes the final fused trajectory.

5.2.2. Non-Motorized Vehicle Crossing

This scenario considers a two-lane straight road segment in which the ego vehicle travels at 10 m/s, while a non-motorized vehicle crosses the roadway at 2 m/s from a position 45 m ahead. Because whether a genuine conflict arises depends on the temporal relationship between the two parties arriving at the intersection region, this scenario is primarily designed to verify whether the proposed method can identify effective temporal conflicts based on TTA, thereby avoiding overly conservative planning results caused by directly treating the entire predicted trajectory of the non-motor vehicle as a non-traversable region.

As shown in Figure 9c, when encountering the crossing non-motor vehicle, the ego vehicle neither brakes in advance nor performs an unnecessary lane change; instead, it maintains forward motion with only a slight lateral adjustment and ultimately passes through the conflict region smoothly. The risk region is concentrated only around the

locations where the trajectories of the two parties genuinely overlap in space and time, rather than forming a continuous blocking band along the entire predicted path of the non-motor vehicle, indicating that TTA filtering can effectively constrain the extent of potential conflict. When the non-motor vehicle has largely cleared the conflict region before the ego vehicle arrives, the ego vehicle is not required to decelerate in advance or execute a detour. Correspondingly, the longitudinal acceleration varies smoothly, the peak lateral acceleration remains small, and the trajectory curvature stays close to zero, demonstrating that the vehicle can pass safely with only minor lateral adjustment. These results verify that TTA filtering can reduce unnecessary deceleration and detouring caused by insufficient exploitation of temporal information.

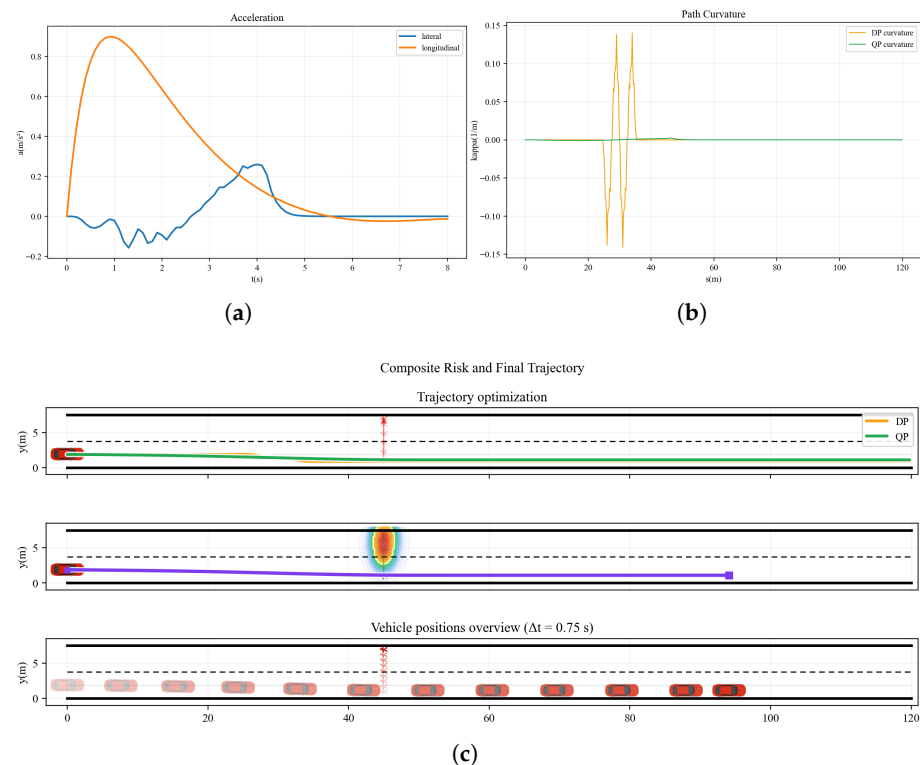


Figure 9. Non-motorized vehicles crossing: (a) Lateral and longitudinal acceleration profiles; (b) Lateral and longitudinal path curvature; (c) Comparison of vehicle trajectory optimization results and schematic illustration of vehicle positions at 0.5 s intervals, where the orange line represents the DP result, the green line denotes the QP optimization result, and the purple line indicates the final fused trajectory.

5.2.3. Mixed Interaction

This scenario considers a two-lane straight road segment with a total road length of 120 m, a lane width of 3.75 m, and a speed limit of 60 km/h. The ego vehicle starts at an initial speed of 8 m/s. The environment simultaneously includes a static obstacle, a decelerating lead vehicle traveling in the same direction, and a vehicle cutting in from the adjacent lane. Specifically, the static obstacle is located 65 m ahead; the lead vehicle is positioned 35 m ahead, with an initial speed of 10 m/s and a continuous deceleration of 2 m/s^2 ; and the adjacent-lane vehicle is located 28 m ahead, traveling at 12 m/s, and cuts into the ego lane while bypassing the obstacle. This scenario is designed to evaluate the local trajectory-planning capability and traffic efficiency of the proposed method under multiple concurrent constraints.

As shown in Figure 10e, under the combined influence of the static obstacle, the decelerating lead vehicle, and the adjacent-vehicle cut-in maneuver, the proposed method

is still able to maintain stable planning without exhibiting persistent car-following, abrupt braking, or repeated corrections. Before reaching the conflict region, the ego vehicle identifies the change in available traversable space and subsequently performs a single continuous lateral transition, bypassing both the slow-moving lead vehicle and the static obstacle via the adjacent lane, before returning to stable driving after passing through the conflict region. The risk is mainly concentrated in the vicinity of the static obstacle and in the localized interaction region formed by the cut-in vehicle and the lead vehicle, indicating that the proposed method can effectively compress the truly relevant conflict region under multi-source constraints and avoid overestimating the entire road segment as non-traversable.

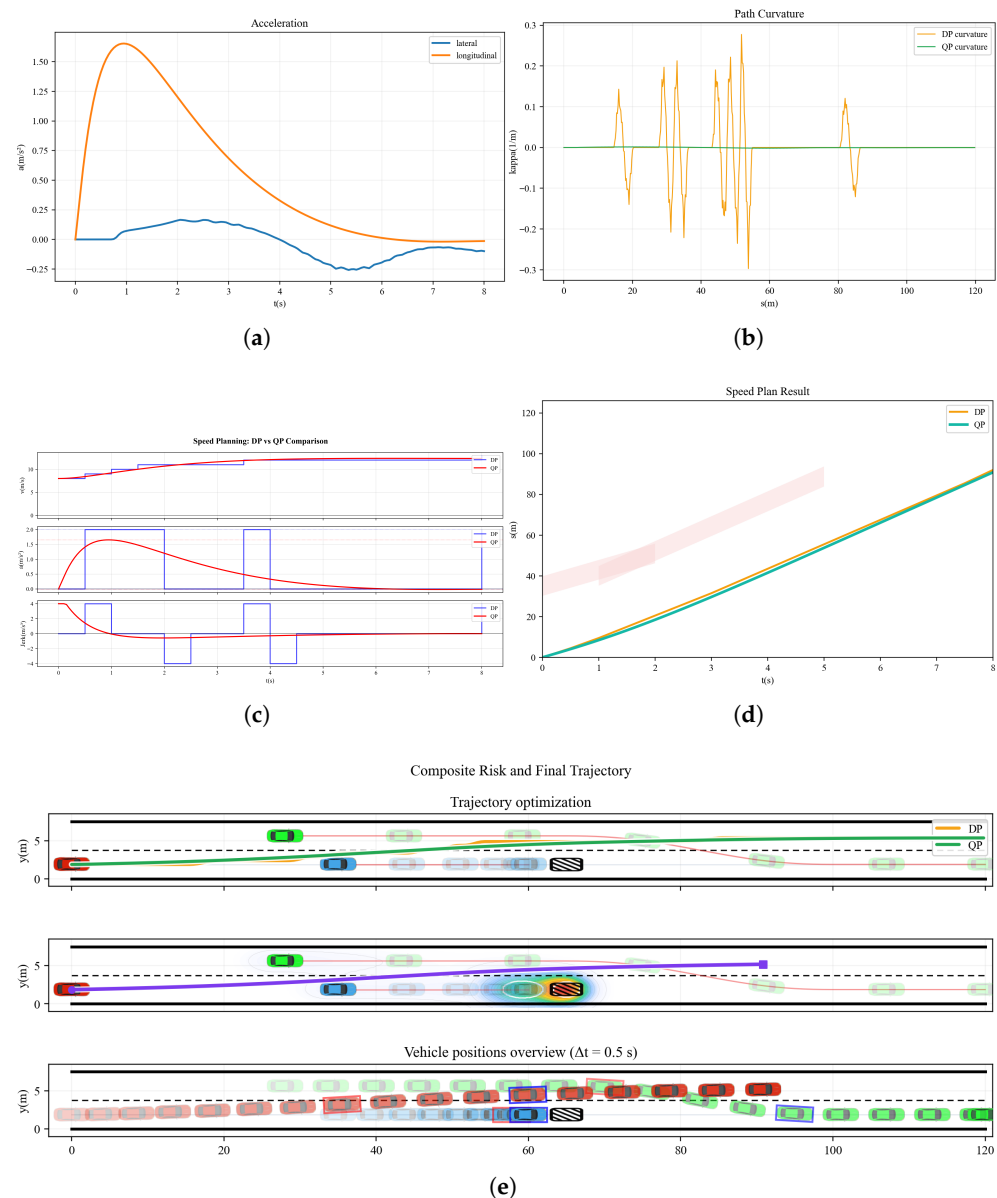


Figure 10. Mixed Interaction: (a) Lateral and longitudinal acceleration profiles; (b) Lateral and longitudinal path curvature; (c) Longitudinal DP and QP optimized speed profiles; (d) DP and QP S-T graph search results, where the pink area represents the non-traversable regions formed by the projection of dynamic obstacles; (e) Comparison of trajectory optimization results and schematic illustration of vehicle positions at 0.5 s intervals. The orange line indicates the DP result, the green line denotes the QP optimization, and the purple line represents the final fused trajectory. The red and blue boxes indicate the positions of traffic participants at 3.5 s and 5.5 s, respectively.

The speed-planning results further show that the DP-based speed profile exhibits pronounced discontinuities at discrete nodes, whereas the optimized speed curve is continuous and smooth. During the bypass maneuver, the ego vehicle accelerates gently and gradually converges to a stable speed, without showing any obvious stop or secondary abrupt deceleration. Correspondingly, the longitudinal acceleration remains smooth overall, the peaks in lateral acceleration occur mainly during lane-change initiation and recovery, and the longitudinal and lateral jerks exhibit only brief fluctuations during trajectory adjustment before decaying rapidly. These results demonstrate that the proposed method can effectively coordinate spatial bypassing and temporal speed regulation in mixed multi-obstacle interaction scenarios, while maintaining both trajectory continuity and smooth vehicle motion states under safe passage requirements.

5.3. Ablation Analysis

An ablation study was conducted in a mixed multi-obstacle interaction scenario to evaluate the roles of the key modules. The effects of the TTA filtering mechanism and the adaptive sampling strategy were examined separately by removing only the target module in each setting while keeping all other conditions unchanged. These two components were selected because they directly reflect the core contributions of the proposed method.

5.3.1. Ablation Study of the TTA Filtering Mechanism

To evaluate the effect of the TTA filtering mechanism on dynamic risk representation and planning performance, two settings were compared: the full method and the method without TTA filtering. In the full method, only the dynamic risks related to actual interactions are retained according to the TTA relationship between the ego vehicle and dynamic obstacles at potential conflict locations. In contrast, without TTA filtering, the risk field corresponding to the entire predicted trajectories of dynamic obstacles is directly projected into the planning space. The comparison focuses on the distribution of risk regions and the resulting trajectory patterns.

Figure 11 shows the comparison results of the two methods in the mixed interaction scenario. Without TTA filtering, the predicted trajectories of dynamic obstacles form a larger continuous high-risk region in the planning space, which shrinks the feasible region and makes the vehicle more likely to adopt conservative deceleration or even stopping strategies. With the full method, risk constraints are concentrated in regions associated with actual interactions, thereby preserving the effective feasible region and improving planning traversability. These results indicate that the TTA filtering mechanism can effectively suppress redundant risk propagation and reduce planning conservatism. As shown in Table 2, in the adjacent-vehicle cut-in scenario, removing TTA filtering increases the risk occupancy ratio from 4.65% to 19.47%, while reducing the average speed from 10.74 m/s to 9.13 m/s and increasing the planning time from 94 ms to 101 ms. By contrast, the minimum clearance remains nearly unchanged at 1.68 m and 1.69 m, respectively. These results indicate that TTA filtering effectively suppresses redundant high-risk occupancy and reduces unnecessary slowing-down behavior, while preserving a comparable safety margin. Therefore, the main contribution of TTA filtering lies in reducing conservatism in the risk representation rather than in reducing obstacle clearance aggressively.

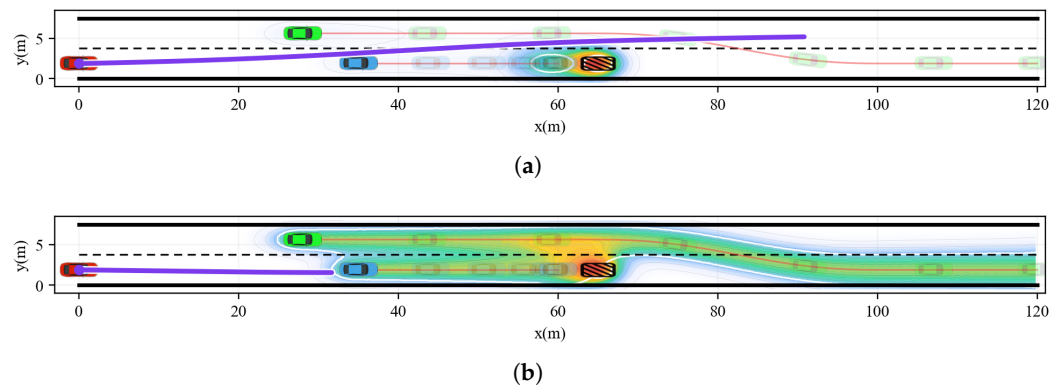


Figure 11. TTA Filtering Mechanism Ablation Results (a) Risk Field and Planning Results Without the TTA Filtering Mechanism. (b) Risk Field and Planning Results With the Full Method.

Table 2. Quantitative ablation results of TTA filtering and adaptive sampling.

Scenario	Method	Node Count	Risk Occupancy Ratio (%)	Min Clearance (m)	Avg. Speed (m/s)	Planning Time (ms)
Adjacent-vehicle cut-in	Proposed	615	4.65	1.68	10.74	94
Adjacent-vehicle cut-in	w/o TTA filtering	675	19.47	1.69	9.13	101
Mixed multi-obstacle interaction	Proposed	495	1.62	0.55	11.35	92
Mixed multi-obstacle interaction	Uniform sampling	915	1.62	0.61	11.46	132

5.3.2. Ablation Study of Adaptive Sampling

To evaluate the effect of the adaptive sampling strategy on the search efficiency of the path-planning layer, two settings, namely adaptive sampling and uniform sampling, were compared in a mixed multi-obstacle interaction scenario. Since Section 4.1 has already presented the adaptive sampling mechanism and the corresponding node distribution, this ablation study mainly adopts quantitative metrics for comparison. Table 2 summarizes the results of the two sampling strategies in terms of the number of search nodes, average planning time, and minimum safety distance.

As shown in Table 2, in the mixed multi-obstacle interaction scenario, adaptive sampling reduces the planning time from 132 ms to 92 ms compared with uniform sampling. Meanwhile, the average speed changes only slightly from 11.46 m/s to 11.35 m/s, and the minimum clearance changes from 0.61 m to 0.55 m. These results indicate that the main benefit of adaptive sampling lies in improving computational efficiency by reducing the path-search burden, while maintaining broadly comparable driving efficiency and safety margin.

On the basis of the above comparison between uniform sampling and adaptive sampling, an additional sensitivity analysis was conducted to further examine the influence of key parameters in the adaptive sampling strategy. Specifically, the density-shaping coefficient γ and the Gaussian smoothing parameter σ_g were analyzed. The effect of γ was evaluated with $\sigma_g = 3$ fixed, while the effect of σ_g was evaluated with $\gamma = 1$ fixed. The number of search nodes, average planning time, and minimum safety distance were still adopted as evaluation metrics.

As shown in Table 3, with increasing γ , the number of search nodes decreases and the planning time is reduced. Meanwhile, a larger γ strengthens the response of the sampling

density to the risk distribution, causing sampling nodes to concentrate more strongly in high-risk regions and thereby reducing redundant search effort.

Table 3. Sensitivity analysis with respect to the density-shaping coefficient γ ($\sigma_g = 3$).

γ	Node Count	Planning Time (ms)	Min. Safety Distance (m)
0.5	555	98	0.56
0.8	510	94	0.53
1.0	495	92	0.55
1.2	480	91	0.61
1.5	480	91	0.55

As shown in Table 4, with increasing σ_g , both the number of search nodes and the planning time increase, while paths with larger minimum safety distance are more likely to be found. A larger σ_g enlarges the longitudinal influence range of local risk peaks, causing wider dense-sampling regions to be allocated around obstacle neighborhoods. This improves the safety margin, but also increases the computational cost.

Table 4. Sensitivity analysis with respect to the Gaussian smoothing parameter σ_g ($\gamma = 1$).

σ_g	Node Count	Planning Time (ms)	Min. Safety Distance (m)
1	480	91	0.52
2	495	92	0.54
3	495	92	0.55
4	510	94	0.59
5	525	95	0.62

Taken together, the results indicate that γ mainly affects the response strength of the sampling density to the risk distribution, whereas σ_g mainly affects the longitudinal spread of the risk. The two parameters jointly determine the trade-off between efficiency and conservatism in adaptive sampling. Overall, the proposed strategy remains stable within a reasonable parameter range.

5.3.3. Computational Stress Test of the S–L Path-Planning Layer

To further examine the computational behavior of the path-planning layer in crowded spatial scenes, an additional stress test was conducted under increasing static-obstacle density. Static obstacles were used in this test because they directly contribute to the spatial risk field and are not reduced by the TTA filtering mechanism, thereby making it possible to densely populate the risk distribution in the S–L space and directly stress the adaptive-sampling-based DP search.

As shown in Table 5, the number of adaptive S–L sampling nodes increases from 465 to 795 as the number of static obstacles increases from 2 to 10. Correspondingly, the S–L DP runtime increases from 40.5 ms to 58.6 ms, while the total planning time increases from 90.3 ms to 113.8 ms. By contrast, the risk-field construction time increases only slightly, from 1.4 ms to 2.4 ms. These results indicate that the dominant runtime growth mainly comes from the increase in adaptive S–L sampling nodes and the associated DP path-search burden.

Moreover, as the obstacle density increases, the total runtime gradually approaches the minimum-spacing uniform-sampling baseline, whose runtime varies from 128.3 ms to 131.2 ms in the same test. This suggests that the worst-case tendency of the path-planning layer remains close to the minimum-spacing uniform-sampling baseline rather than growing without bound.

Table 5. Path-planning runtime under increasing static-obstacle density.

Case	Obs.	S–L Nodes	Risk (ms)	DP (ms)	Total (ms)	Uniform (ms)
Low	2	465	1.4	40.5	90.3	128.3
Medium	5	585	1.8	47.2	98.1	129.4
High	8	720	2.2	53.4	106.9	130.1
Extreme	10	795	2.4	58.6	113.8	131.2

5.4. Comparison with a Representative Hybrid Planner

In order to further evaluate the proposed framework, the proposed framework is compared with the representative hybrid trajectory planner of Wang et al. [10] under two dynamic interaction scenarios, namely adjacent-vehicle cut-in and mixed multi-obstacle interaction. These two scenarios are selected because they are representative of the temporal-risk filtering problem and the multi-obstacle coordination problem addressed in this work. The comparison is focused on minimum clearance, average speed, RMS jerk, and planning time, which together reflect safety margin, driving efficiency, comfort, and computational performance, as shown in Table 6.

Table 6. Comparison with the Wang baseline under dynamic interaction scenarios.

Scenario	Method	Clearance (m)	Speed (m/s)	RMS Jerk (m/s ³)	Time (ms) (Mean ± Std)
Adjacent-vehicle cut-in	Proposed	1.68	10.74	2.56	94.1 ± 3.9
Adjacent-vehicle cut-in	Wang et al.	1.53	9.40	13.23	74.3 ± 2.3
Mixed multi-obstacle interaction	Proposed	0.55	11.35	1.83	92.3 ± 4.2
Mixed multi-obstacle interaction	Wang et al.	0.89	6.79	44.13	76.6 ± 2.7

The results show that in the mixed multi-obstacle interaction scenario, the Wang baseline preserves a slightly larger clearance, whereas the proposed method achieves substantially higher average speed and markedly lower RMS jerk, which suggests a better balance between safety, efficiency, and comfort in dense interactive situations.

Overall, the results suggest that the proposed framework improves driving efficiency and comfort in representative dynamic interaction scenarios while preserving safe obstacle clearance and practical real-time performance.

6. Conclusions

This paper presented a hierarchical hybrid trajectory-planning method with a TTA-driven dynamic risk-filtering mechanism for dynamic road scenarios. Using the Frenet coordinate system as a unified representation framework, the method maps road boundaries, ego-vehicle states, static obstacles, and predicted trajectories of dynamic obstacles into the planning space, constructs an S–L fused risk field and an S–T spatiotemporal interaction graph, and filters dynamic risks unrelated to actual interactions through TTA relationships. On this basis, the path-planning layer integrates risk-guided adaptive sampling, dynamic programming, and quadratic programming, whereas the speed-planning layer performs non-uniform spatiotemporal discretization, safe-corridor extraction, and speed-profile optimization to generate a continuous and executable local trajectory.

Simulation results show that the proposed method improves coarse-path quality in static-obstacle avoidance scenarios and reduces unnecessary deceleration and lane changes

in adjacent-vehicle cut-in scenarios and non-motorized-vehicle crossing scenarios by restricting conflict regions to temporally relevant interactions. In mixed multi-obstacle interaction scenarios, the method maintains stable planning performance and avoids persistent car-following, abrupt braking, and repeated corrections. Ablation results further show that TTA filtering suppresses redundant risk propagation and reduces planning conservatism. In addition, adaptive sampling reduces the number of search nodes from 915 to 495 and the average planning time from 132 ms to 92 ms, while maintaining a broadly comparable minimum safety distance. Overall, the proposed method improves traversability, smoothness, and motion continuity while maintaining computational feasibility. It should be noted, however, that the present conclusions are drawn primarily from simulations under representative scenarios. Although the receding-horizon formulation continuously updates obstacle predictions and the corresponding TTA-based risk filtering results, substantial prediction uncertainty or pronounced multi-modal behaviors may still lead to insufficient representation of certain potentially relevant risks. Future work will therefore consider multi-modal prediction integration, uncertainty-aware risk fusion, more complex traffic flows, and closed-loop validation on real vehicles.

Author Contributions: Methodology, L.H.; Software, T.H.; Validation, T.H. and J.H.; Formal analysis, J.H.; Resources, L.H. and H.D.; Data curation, H.D.; Writing—original draft, T.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Science Fund for Distinguished Young Scholars grant number 52325211, Major Scientific Research Instrument of the NSFC grant number 52527815, National Natural Science Foundation of China grant number 52472428, 52372348 and the Innovative Research Group Project of Hunan Province grant number 2025JJ10006.

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.

References

1. Huang, H.; Liu, Y.; Liu, J.; Yang, Q.; Wang, J.; Abbink, D.; Zgonnikov, A. General optimal trajectory planning: Enabling autonomous vehicles with the principle of least action. *Engineering* **2024**, *33*, 63–76. [\[CrossRef\]](#)
2. Zheng, H.; Li, Y.; Zheng, L.; Hashemi, E. Safe motion planning and control framework for automated vehicles with zonotopic TRMPC. *Engineering* **2024**, *33*, 146–159. [\[CrossRef\]](#)
3. Huang, J.; Peng, Y.; Hu, L. A multilayer stacking method base on RFE-SHAP feature selection strategy for recognition of driver's mental load and emotional state. *Expert Syst. Appl.* **2024**, *238*, 121729. [\[CrossRef\]](#)
4. Huang, J.; Deng, X.; Hu, L. Enhanced grey wolf optimizer with hybrid strategies for efficient feature selection in high-dimensional data. *Inf. Sci.* **2025**, *705*, 121958. [\[CrossRef\]](#)
5. Li, B.; Ouyang, Y.; Li, L.; Zhang, Y. Autonomous driving on curvy roads without reliance on frenet frame: A cartesian-based trajectory planning method. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 15729–15741. [\[CrossRef\]](#)
6. Liu, F.; Zhao, X.; Su, W.; Wen, Y. Dynamic path-speed planning algorithm for autonomous driving on structured roads. *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.* **2024**, *238*, 3172–3193. [\[CrossRef\]](#)
7. Lin, X.; Wang, T.; Zeng, S.; Chen, Z.; Xie, L. Autonomous vehicles lane-changing trajectory planning based on hierarchical decoupling. *IEEE Trans. Intell. Transp. Syst.* **2024**, *25*, 20741–20752. [\[CrossRef\]](#)
8. Shi, X.; Li, X. Trajectory planning for an autonomous vehicle with conflicting moving objects along a fixed path—An exact solution method. *Transp. Res. Part B Methodol.* **2023**, *173*, 228–246. [\[CrossRef\]](#)
9. Guo, Y.; Yao, D.; Li, B.; He, Z.; Gao, H.; Li, L. Trajectory planning for an autonomous vehicle in spatially constrained environments. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 18326–18336. [\[CrossRef\]](#)
10. Wang, M.; Zhang, L.; Zhang, Z.; Wang, Z. A hybrid trajectory planning strategy for intelligent vehicles in on-road dynamic scenarios. *IEEE Trans. Veh. Technol.* **2022**, *72*, 2832–2847. [\[CrossRef\]](#)
11. Feng, Z.; Song, W.; Fu, M.; Yang, Y.; Wang, M. Decision-making and path planning for highway autonomous driving based on spatio-temporal lane-change gaps. *IEEE Syst. J.* **2021**, *16*, 3249–3259. [\[CrossRef\]](#)

12. Li, S.; Wei, C.; Wang, Y. Combining decision making and trajectory planning for lane changing using deep reinforcement learning. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 16110–16136. [\[CrossRef\]](#)
13. Li, Z.; Hu, J.; Leng, B.; Xiong, L.; Fu, Z. An integrated of decision making and motion planning framework for enhanced oscillation-free capability. *IEEE Trans. Intell. Transp. Syst.* **2023**, *25*, 5718–5732. [\[CrossRef\]](#)
14. Zhang, D.; Jiao, X.; Zhang, T. Lane-changing and overtaking trajectory planning for autonomous vehicles with multi-performance optimization considering static and dynamic obstacles. *Robot. Auton. Syst.* **2024**, *182*, 104797. [\[CrossRef\]](#)
15. Zhang, X.; Zang, Z.; Chen, X.; Lu, Y.; Qi, J.; Gong, J. Optimization-based trajectory planning for autonomous vehicles in scenarios with multiple reference lines. *Control Eng. Pract.* **2025**, *163*, 106407. [\[CrossRef\]](#)
16. Song, J.; Wang, T.; Sun, Y.; Zhang, X.; Zang, Z.; Ji, X. Vehicle dynamics oriented motion planning methodology for autonomous vehicles using iterative linear quadratic regulator. *Adv. Eng. Inform.* **2025**, *68*, 103789. [\[CrossRef\]](#)
17. Lin, Z.; Wu, K.; Shen, R.; Yu, X.; Huang, S. An efficient and accurate A-star algorithm for autonomous vehicle path planning. *IEEE Trans. Veh. Technol.* **2023**, *73*, 9003–9008. [\[CrossRef\]](#)
18. Yu, J.; Chen, C.; Arab, A.; Yi, J.; Pei, X.; Guo, X. RDT-RRT: Real-time double-tree rapidly-exploring random tree path planning for autonomous vehicles. *Expert Syst. Appl.* **2024**, *240*, 122510. [\[CrossRef\]](#)
19. Wang, D.; Deng, W.; Hu, L.; Huang, Z.; Lu, Y.; Zhang, H. Safety assessment of intelligent vehicles considering drivers' risk perception information under interval 2-tuple q-rung orthopair fuzzy sets. *Appl. Soft Comput.* **2025**, *175*, 112919. [\[CrossRef\]](#)
20. Xia, T.; Chen, H.; Yang, J.; Guo, Z. Geometric field model of driver's perceived risk for safe and human-like trajectory planning. *Transp. Res. Part C Emerg. Technol.* **2024**, *159*, 104470. [\[CrossRef\]](#)
21. Han, J.; Zhao, J.; Zhu, B.; Song, D. Spatial-temporal risk field for intelligent connected vehicle in dynamic traffic and application in trajectory planning. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 2963–2975. [\[CrossRef\]](#)
22. Wang, Z.; Shi, B.; Zhang, J.; Zhu, X.; Zhou, J.; Xu, B.; Li, B. A data-driven spatio-temporal driving risk field mechanism for path planning. *Expert Syst. Appl.* **2025**, *298*, 129834. [\[CrossRef\]](#)
23. Liu, K.; Wang, H.; Fu, Y.; Wen, G.; Wang, B. A dynamic path-planning method for obstacle avoidance based on the driving safety field. *Sensors* **2023**, *23*, 9180. [\[CrossRef\]](#)
24. Ji, Y.; Ni, L.; Zhao, C.; Lei, C.; Du, Y.; Wang, W. TriPField: A 3D potential field model and its applications to local path planning of autonomous vehicles. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 3541–3554. [\[CrossRef\]](#)
25. Zhao, J.; Yan, X.; Zhou, Z.; Zhang, Z. Rule-adaptive lane-changing trajectory planning method for autonomous vehicles driven by dynamic risk information. *Sci. Rep.* **2025**, *15*, 31514. [\[CrossRef\]](#) [\[PubMed\]](#)
26. Zhu, L.; Zhang, Z.; Yu, J.; Zhang, Y.; Fu, J. A real-time synthesized driving risk quantification model based on driver risk perception-response mechanism. *Transp. Res. Part C Emerg. Technol.* **2025**, *174*, 105073. [\[CrossRef\]](#)
27. Jiang, L.; Zhang, C.; Hu, Z.; He, R.; Xiao, H.; Xu, W.; Meng, J. Safe path planning for autonomous vehicles with real-time observation based localization uncertainty prediction. *Expert Syst. Appl.* **2025**, *281*, 127596. [\[CrossRef\]](#)
28. Liu, X.; Wang, Y.; Jiang, K.; Zhou, Z.; Nam, K.; Yin, C. Interactive trajectory prediction using a driving risk map-integrated deep learning method for surrounding vehicles on highways. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 19076–19087. [\[CrossRef\]](#)
29. Chen, B.; He, G.; Hu, L.; Li, H.; Wang, M.; Zhang, R.; Gao, K. Energy management of electric vehicles based on improved long short term memory network and data-enabled predictive control. *Appl. Energy* **2025**, *384*, 125456. [\[CrossRef\]](#)
30. Zhang, E.; Zhang, R.; Masoud, N. Predictive trajectory planning for autonomous vehicles at intersections using reinforcement learning. *Transp. Res. Part C Emerg. Technol.* **2023**, *149*, 104063. [\[CrossRef\]](#)
31. Zhang, T.; Song, W.; Fu, M.; Yang, Y.; Tian, X.; Wang, M. A unified framework integrating decision making and trajectory planning based on spatio-temporal voxels for highway autonomous driving. *IEEE Trans. Intell. Transp. Syst.* **2021**, *23*, 10365–10379. [\[CrossRef\]](#)
32. Chen, Y.; Cheng, J.; Gan, L.; Wang, S.; Liu, H.; Mei, X.; Liu, M. Ir-stp: Enhancing autonomous driving with interaction reasoning in spatio-temporal planning. *IEEE Trans. Intell. Transp. Syst.* **2024**, *25*, 10331–10343. [\[CrossRef\]](#)
33. Ding, W.; Zhang, L.; Chen, J.; Shen, S. Epsilon: An efficient planning system for automated vehicles in highly interactive environments. *IEEE Trans. Robot.* **2021**, *38*, 1118–1138. [\[CrossRef\]](#)
34. Zhang, X.; Wang, B.; Lu, Y.; Liu, H.; Gong, J.; Chen, H. A hierarchical multi-vehicle coordinated motion planning method based on interactive spatio-temporal corridors. *IEEE Trans. Intell. Veh.* **2023**, *9*, 2675–2687. [\[CrossRef\]](#)
35. He, G.; Yu, H.; Li, G.; Li, K. Trajectory Planning for Autonomous Driving in Transportation Systems Based on Deep Reinforcement Learning and Spatio-Temporal Voxels. *IEEE Trans. Intell. Transp. Syst.* **2025**, *27*, 742–758. [\[CrossRef\]](#)
36. Han, Z.; Wu, Y.; Li, T.; Zhang, L.; Pei, L.; Xu, L.; Li, C.; Ma, C.; Xu, C.; Shen, S.; et al. An efficient spatial-temporal trajectory planner for autonomous vehicles in unstructured environments. *IEEE Trans. Intell. Transp. Syst.* **2023**, *25*, 1797–1814. [\[CrossRef\]](#)
37. Guo, J.; Xie, Z.; Liu, M.; Dai, Z.; Jiang, Y.; Guo, J.; Xie, D. Spatio-temporal joint optimization-based trajectory planning method for autonomous vehicles in complex urban environments. *Sensors* **2024**, *24*, 4685. [\[CrossRef\]](#)

38. Gao, K.; Li, Q.; Hu, L.; Huang, J.; Li, H.; Wu, Y. Physical informed neural network for SOH estimation of lithium-ion battery with electrochemical mechanism. *Energy* **2025**, *342*, 139753. [[CrossRef](#)]
39. Li, Q.; He, H.; Hu, M.; Wang, Y. Spatio-temporal joint trajectory planning for autonomous vehicles based on improved constrained iterative lqr. *Sensors* **2025**, *25*, 512. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.