Safe Autonomous Navigation under Uncertainty: A Multi-Risk Control Optimization Framework

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***Abstract*— Autonomous Vehicles (AVs) operating around vulnerable road users must handle uncertainties arising from the multimodal trajectories of these agents, which complicates navigation planning. This work introduces a multi-level optimization framework that integrates sampling-based and direct optimization methods to enhance safety and trajectory smoothness. In the first stage, a sampling-based strategy employing the Fusion of stochastic Predictive Inter-Distance Profile (F-sPIDP) identifies safe candidate trajectories by modeling multimodal traffic dynamics and uncertainty. The optimal reference trajectory and F-sPIDP setpoints are then selected under strict safety and smoothness constraints. A secondary local optimization refines this trajectory to satisfy AV kinematic and dynamic limits while accounting for quantified uncertainties. Simulation results demonstrate the method's robustness under varying uncertainty levels.**

I. INTRODUCTION

Recent motion prediction models [1], [2] predict distributions of multimodal trajectories rather than single paths (cf. Fig. 1), enabling better handling of perception noise and abrupt behaviors, such as sudden velocity changes by Personal Light Electric Vehicles (PLEVs). However, two main challenges persist: (1) uncertainty in the predicted states of surrounding agents and (2) difficulty in managing multimodal motion predictions without excessive conservatism. Conventional methods [3], [4] and Model Predictive Control (MPC) [5] struggle with these issues, while Stochastic MPC (SMPC) [6], [7] is often overly conservative. Direct optimization approaches tend to find only local optima in nonlinear systems [8], and sampling-based planners [9], [10] usually neglect agent dynamics to reduce computation.

To address these limitations, this paper proposes a multi-level motion optimization framework combining sampling-based planning with local control refinement for safe and smooth navigation under uncertainty. Key contributions include:

- A multi-level architecture integrating sampling-based and direct optimization for robust decision-making and control.

- Incorporation of the Fusion of stochastic Predictive Inter-Distance Profile (F-sPIDP) [11], that extends the PIDP framework [12], [13], [14] to represent multimodal behaviors and stochastic uncertainties.

- Development of a sampling-based planner using F-sPIDP-derived safety constraints, followed by local control optimization ensuring dynamic feasibility and consistency with uncertainty profiles.

Simulation results demonstrate improved safety, robustness, and trajectory smoothness across varying uncertainty conditions.

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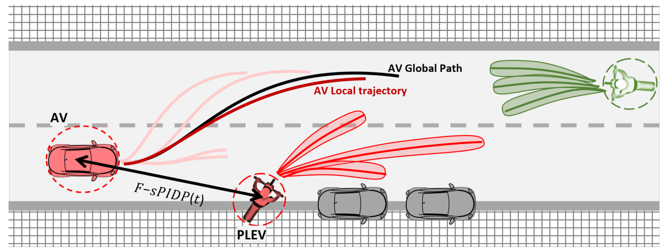

Fig. 1. A scenario showing the evolution of the uncertainty of multiple PLEVs with multimodal motion uncertainties, the candidate trajectories of the AV, the selected global safe trajectory, and the local control trajectory

II. FRAMEWORK OVERVIEW

The proposed AV control architecture (cf. Fig. 2) relies on perception and localization inputs (block P) to obtain the states of surrounding agents and the environment. The multi-level motion optimization framework comprises five key modules. The Multimodal Prediction Module (block 1) uses perception data to predict multiple probable trajectories of surrounding agents ($\{\mathbf{x}_i(t)\}_{j=1}^{N_{traj}}$, where $\mathbf{x}_i(t) = (x_i(t), y_i(t), \theta_i(t))$ represents the position and orientation over time t for the j-th mode of the i-th agent), with associated probabilities $Pr(j)$ and uncertainties $\mathbb{V}[x_i, y_i, \theta_i]$, following [15], [16]. In parallel, the Vehicle Candidate Trajectories Generation Module (block 2) computes lane-disciplined trajectories $\mathbf{x}_{traj} \in \mathcal{X}_{traj}$ in the Frenet frame [17], ensuring compliance with lane-keeping and lane-change behaviors.

Next, the F-sPIDP [11] Collision Check Module (block 3) filters unsafe trajectories by evaluating collision risks under multimodal uncertainty, producing a safe trajectory set $\mathcal{X}_{safe}$. The Optimal Trajectory Selection Module (block 4) then selects the smoothest trajectory $\mathbf{x}_{ref} \in \mathcal{X}_{safe}$. Finally, the Local Control Optimization Module (block 5) refines control inputs $\mathbf{u}(t)$ to track $\mathbf{x}_{ref}$ while respecting vehicle dynamics and F-sPIDP uncertainty constraints.

III. SIMULATION RESULTS AND DISCUSSIONS

A. Implementation Details

The proposed method was implemented in MATLAB leveraging built-in functions for the sampling-based reference trajectory computation, while the direct optimization

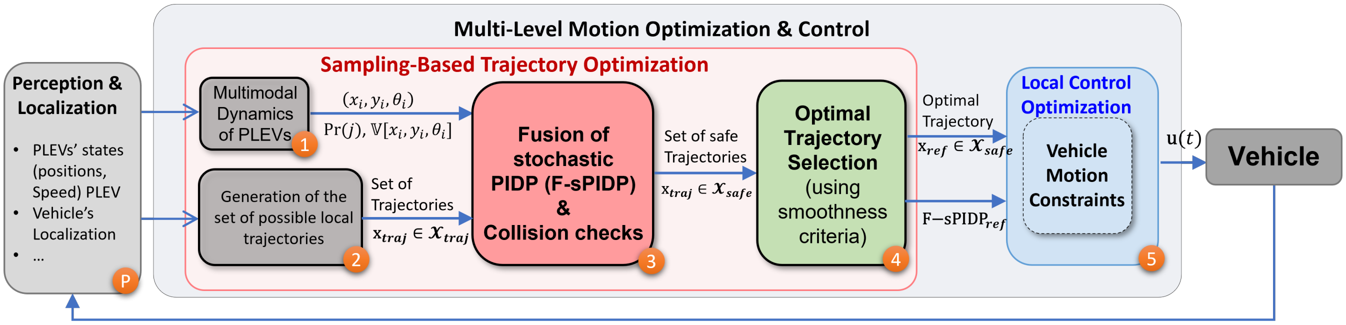

Fig. 2. The multi-level motion optimization architecture showing the inputs and outputs of each module. Red shows the sampling-based trajectory selection procedure, and blue shows the local control optimization step

problem was solved using the CasADi optimization framework [18]. At each time step $\Delta t = 0.1$, we predict the motion of the traffic agents over a time horizon, t_{hor}. (**cf. video shown through this link** `https://youtu.be/S4uAOAuYsGU`)

B. Comparative Analysis of Proposed Method

A cut-in scenario was simulated where a PLEV rapidly enters the lane to overtake another vehicle (cf. Fig. 3), representing a realistic challenge involving abrupt, uncertain maneuvers by vulnerable road users. The PLEV's motion incorporates multi-object detection and tracking errors typical of LiDAR- and camera-based systems, with translation noise up to $\Sigma_T = 1.0$ m [19]. The sampling stage averaged 75 ms per computation, while local control refinement required 20 ms, both suitable for real-time operation and further accelerable via GPU parallelization.

Trajectory Performance: The proposed multi-level optimization with F-sPIDP was benchmarked against the Chance-Constrained Optimization (CC-Opt) baseline [6]. While both avoided collisions, CC-Opt produced reactive trajectories with oscillations and poor lane discipline due to sensitivity to PLEV uncertainty (cf. Fig. 3 (a)). In contrast, the proposed method generated smoother, collision-free trajectories by integrating stochastic uncertainty within F-sPIDP and refining them through local optimization. The resulting AV motion exhibited stable lane behavior and improved comfort despite the sudden cut-in (cf. Fig. 3 (b)).

Velocity Profile: Similar behavior is observed in the AV's velocity profile (cf. Fig. 4 (a–b)). Both methods initially decelerate sharply in response to the parked vehicle and the PLEV's entry, indicating prompt collision avoidance. However, the baseline method performs repeated deceleration to accommodate the evolving multimodal PLEV trajectories, resulting in a jerky and overly conservative velocity profile that reduces ride comfort and energy efficiency.

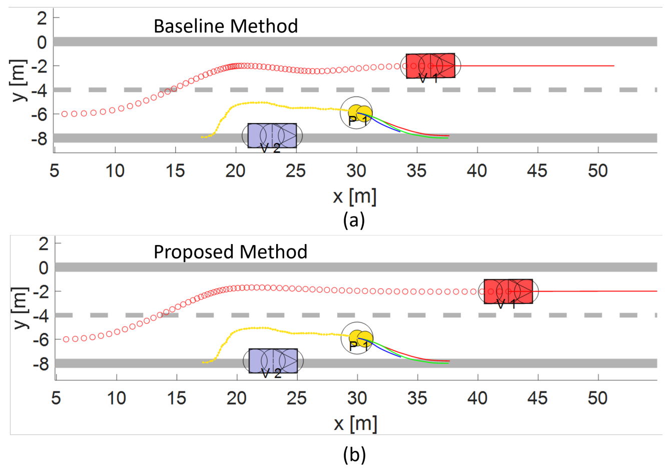

Fig. 3. Comparison of the trajectory performance: (a) Baseline (CC-Opt) results in oscillatory AV motion, excessively influenced by the PLEVs' uncertain behavior, (b) Proposed method shows little oscillation by generating collision-free trajectories that respect desired lane-changing and lane-keeping maneuvers while accounting for uncertainties in the PLEV motion

IV. CONCLUSION

This work introduces an autonomous navigation algorithm that ensures safe and efficient motion around dynamic entities, such as Personal Light Electric Vehicles (PLEVs), under uncertainty. The proposed multi-level framework combines sampling-based and local control optimization, using the Fusion of stochastic Predictive Inter-Distance Profile (F-sPIDP) to model multimodal behaviors and uncertainties of surrounding agents. Safe candidate trajectories are generated and refined to satisfy dynamic constraints while maintaining probabilistic safety margins. By embedding uncertainty into the global planning stage, the method demonstrates improved results compared to conventional reactive approaches. Future work will focus on accelerating computation through GPU parallelization for real-time implementation.

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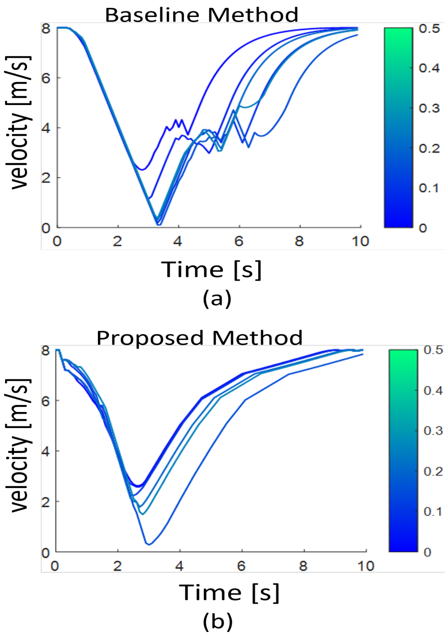

Fig. 4. Velocity profile over time for varying level of uncertainty $\Sigma_T = [0, 0.5]m$: (a) Baseline (CC-Opt) approach showing multiple pronounced decelerations, (b) Proposed method with a single deceleration upon PLEV detection

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