Multi-Risk Assessment and Management in the Presence of Personal Light Electric Vehicles

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Keywords: Autonomous Vehicles, Autonomous Driving, Predictive Navigation, Risk Assessment and Risk Management, PLEVs, Multi-Modal Prediction, Multi-Risk.

Abstract: This paper presents an approach to autonomous vehicle navigation in urban environments with dynamic and multi-modal agents like Personal Light Electric Vehicles (PLEVs). The traditional Predictive Inter-Distance Profile (PIDP) risk assessment metric (Bellingard et al., 2023) is extended to handle multiple multi-modal motions using a fusion of PIDPs (F-PIDP). This approach accounts for the uncertainties in the various trajectories that PLEVs can follow on the road. A priority-based strategy is then developed to select the most dangerous agent. Then F-PIDP and Model Predictive Control (MPC) algorithm is employed for risk management, ensuring safe and reliable navigation. The efficiency of the proposed method is validated through several simulations.

1 INTRODUCTION

As Autonomous Vehicles (AV) become more integrated in real-world environments, there navigation among humans becomes increasingly critical. While research has focused on navigation among pedestrians, less attention has been given to Personal Light Electric Vehicles (PLEVs) such as electric bikes and scooters. AVs usually predict the motion of surrounding traffic agents to plan a safe trajectory. Most trajectory prediction algorithms predict a single most probable trajectory (Luo et al., 2018), (Lee et al., 2017). However, as opposed to walking pedestrians, PLEVs can exhibit varying speed profiles ranging from low to high speeds as much as five times that of pedestrians. This results in multiple possible predictions of the motion of the PLEV. Many multi-modal prediction algorithms have been developed in the literature to predict multiple future trajectories for such agents. For example, in (Jo et al., 2016) and (Lefkopoulos et al., 2020) a tracking algorithm that combines multiple models was proposed to predict the possible motions of traffic agents.

Once the future trajectories of the traffic agents or PLEVs are predicted, the AV needs to compute a safe trajectory towards its desired destination. Model Predictive Control (MPC) (Yu et al., 2021), (Saljanin et al., 2022) has emerged as a powerful and robust tool for controlling and optimizing the motion of AVs. Unlike traditional control algorithms, MPC uses the dynamic model of the system to predict future states and optimize the control actions of the system over specific time horizons. It can also handle various constraints, such as speed limits, and safety margins, ensuring feasible and safe control actions. Nevertheless, the presence of multiple trajectories for a single agent makes the computation of risk-free trajectories more challenging for autonomous driving systems.

This paper proposes to perform risk assessment using a fusion of PIDPs (F-PIDP) (Alao et al., 2024) to reduce the PIDPs to a single prediction. Multi-risk management is then performed using a priority-based target selection and F-PIDP+MPC method. Unlike the conservative MPC method that considers all the trajectories, the F-PIDP+MPC uses the F-PIDP as a safety reference.

Contributions. This work presents a method to perform risk assessment and management in the presence of multi-modal agents. We extend the approach proposed in (Alao et al., 2024) to handle multiple PLEVs. The method used in (Alao et al., 2024) handles un-

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Alao, E., Adouane, L. and Martinet, P.
Multi-Risk Assessment and Management in the Presence of Personal Light Electric Vehicles.
DOI: 10.5220/0013059500003822
Paper published under CC license (CC BY-NC-ND 4.0)
In *Proceedings of the 21st International Conference on Informatics in Control, Automation and Robotics (ICINCO 2024) - Volume 1*, pages 137-145
ISBN: 978-989-758-717-7; ISSN: 2184-2809
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certainties in the possible trajectories that a single agent can take. On the other hand, we describe in this study a priority-based collision avoidance method that also supports multiple agents. Additionally, an approach based on MPC was compared with the proposed method.

The structure of this paper is laid out as follows: Section 2 presents the related works. Section 3 introduces the preliminaries on PIDP, MPC, and motion prediction of traffic agents. Section 4 presents the proposed F-PIDP for multi-risk assessment of the future motion of multiple PLEVs. Section 5 then describes the proposed risk management strategy using F-PIDP+MPC and a priority-based collision avoidance strategy. Section 6 presents the results of various evaluations of the proposed method. Finally, Section 7 summarizes the paper's primary contributions and offers some prospects.

2 RELATED WORKS

Most criticality metrics for assessing and managing risk in traffic environments check for situations when or where safety is violated. For instance, the Time to Collision (TTC) (Westhofen et al., 2023) and Time to React (TTR) (Hillenbrand et al., 2006) risk metrics respectively check for the time when a collision occurs and the remaining time when the driver can perform a maneuver to avoid a collision. The Predictive Inter-Distance Profile (PIDP) (Bellingard et al., 2023) (Iberraken et al., 2018) (cf. Section 3.3), and the fusion of PIDPs (Alao et al., 2024) as the name implies computes the inter-distances between two or more agents and has been found to possess many features that can be harnessed to assess the risk of multiple agents. The main advantage of such methods lies in their low computational complexity, though they fail in dealing with situations with various uncertainties in the maneuvers of the agents.

Probability-based risk assessment and management methods have been developed to address these problems by modeling the uncertainty of the motion as a probability distribution. Therefore, probabilistic frameworks such as the Hidden Markov Model (HMM) (Laugier et al., 2011) and Dynamic Bayesian Network (DBN) (Li et al., 2019) & (Iberraken and Adouane, 2022) have been proposed to perform risk-aware navigation in the presence of uncertainties.

Optimization methods have also been extended to compute safe control actions for autonomous vehicles while respecting constraints related to the vehicle and the traffic environment. Among them, the Model Predictive Control (MPC) (Kim and Kumar, 2014) method is a prominent solution in this domain, known for its capacity to predict future states and make real-time adjustments. MPC has been applied to solve problems in many fields of engineering as highlighted in (Mayne, 2014). Its performance is undeniable in autonomous driving systems due to constraints on vehicle actuators and physical limits that are not explicitly considered in several other methods, such as the PID controller and sliding mode controllers (Vu et al., 2021). In general, it is possible to perform both risk assessment and management using MPC, where risk assessment is formulated as collision constraints and risk management becomes the optimal control problem for the MPC algorithm to solve, as done in (Philippe et al., 2018) (Fiasché et al., 2023) (Nan et al., 2021) (Miao and Han, 2023). Nonetheless, considering collision risk is not sufficient for safe navigation since there exist multiple uncertainties in the traffic environment, such as the prediction uncertainties in the multiple maneuvers that PLEVs can perform in urban areas (Rudenko et al., 2020).

Learning-based methods have also been leveraged to compute safe trajectories for autonomous systems. For example, using Neural networks (Li et al., 2018) and (Kuderer et al., 2015) were able to learn from real driving scenarios. The authors in (Cimurs et al., 2021) presented a Deep Reinforcement Learning (DRL) based decision-making framework for automated exploration. In general, Learning-based methods can handle uncertainties implicitly, however, they require a large amount of data to generalize to multiple scenarios.

3 PRELIMINARIES

3.1 AV Motion Model

The motion of the ego-vehicle is considered a nonlinear motion model of the form:

$$\mathbf{x}_{t+1}^{AV} = f(\mathbf{x}_t^{AV}, \mathbf{u}_t^{AV}) \tag{1}$$

where at time step t, the state of the ego-vehicle is $x_t^{AV} \in \mathbb{R}^{n_x}$, $\mathbf{u}_t^{AV} \in \mathbb{R}^{n_u}$ denotes the control inputs, and the function $f : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \longrightarrow \mathbb{R}^{n_x}$, is the vehicle dynamic model. The control inputs to the AV, $\mathbf{u}_t^{AV} = [v, \delta]$ are the velocity v and steering angle δ of the AV with control limits $\mathbf{u}_{min} \leq \mathbf{u}^{AV} \leq \mathbf{u}_{max}$.

3.2 PLEVs Motion Model

Surrounding agents including PLEVs, are considered to be dynamic obstacles. Using suitable multi-modal motion prediction algorithms as in (Jo et al., 2016),

the possible future trajectories of the agents (cf. Figure 1) can be expressed as a linearized dynamic motion

$$\mathbf{x}_{j,t+1}^{PV} = A\mathbf{x}_{j,t}^{PV} + B\mathbf{u}_{j,t}^{PV} \tag{2}$$

where $\mathbf{x}_t^{PV} = \left[x_t^{PV}, y_t^{PV}, \theta_t^{PV}\right]^T$ are the longitudinal position, lateral position and orientation of the PLEV. The control action of the PLEV split into forward and angular velocity is denoted $\mathbf{u}_t^{PV} = [v_t^{PV}, w_t^{PV}]$ based on the unicycle motion model. The variable $j \in \{1, 2, \cdots, N_{traj}\}$ denotes a specific trajectory out of the multi-modal trajectories of the agent. Each trajectory is assumed to have a probability $Pr(j)$. A and B are linearized state and control matrices.

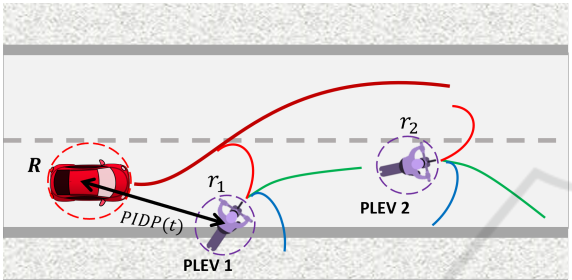

Figure 1: Urban traffic scenario with AV (in red) and multiple PLEVs (in purple): with multiple possible trajectories.

3.3 Predictive Inter-Distance Profile (PIDP)

The Predictive Inter-Distance Profile (PIDP) is a metric for assessing the risk of collision in traffic scenarios. It evaluates the potential for accidents by measuring the distance between the traffic agents, such as an autonomous vehicle and another road user, over a specified time horizon. Unlike other risk assessment methods, PIDP does not rely on the geometric shapes of the future trajectories of road users, making it versatile for various traffic situations. PIDP functions as a dual measure of risk, encompassing both spatial and temporal scales. As a spatial risk measure, PIDP shows the separation distance between traffic participants which is crucial for understanding the proximity of vehicles, pedestrians, or other road users. For example, when calculating the Euclidean distance between trajectories, PIDP considers the safety distance as a threshold. Let the radii of two interacting agents be R and r respectively, then the safety distance is defined as:

$$d_{safe} = R + r + d_{margin} \tag{3}$$

where d_{margin} is a safety margin which can be static or dynamic. If the minimum PIDP value ($minPIDP(t) \leq R + r$) falls below this threshold, it indicates a potential collision in the future (cf. Figure 2).

As a temporal risk measure, PIDP considers how long it will take for the entities to reach a critical distance where a collision might occur. That is, PIDP provides insights into the urgency of potential collision scenarios. The time when safety is not respected (t_{SNR}) is the point when the safety distance is first violated, which can give an idea of the criticality of the situation (cf. Figure 2).

By combining spatial and time scales, PIDP delivers a comprehensive risk assessment that takes into account the urgency and physical proximity of potential collisions. While effective, PIDP assumes a unimodal motion prediction for each traffic participant, which is not sufficient for safe navigation in the presence of multi-modal agents like PLEVs. To address this problem, this paper proposes the Fusion of PIDPs (F-PIDP) to account for multi-modal motion.

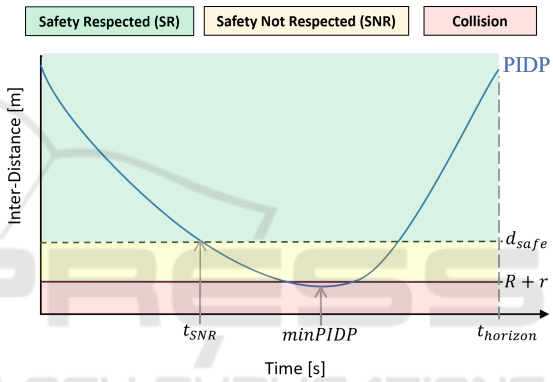

Figure 2: Predictive Inter-distance Profile (PIDP): showing the time when safety is not respected t_{SNR} and the minimum PIDP.

3.4 Model Predictive Control (MPC)

Model Predictive Control (MPC) is an optimization-based control method. It computes the system's future behavior over a finite prediction horizon and optimizes control inputs to minimize a cost function while satisfying desired constraints. The optimization problem is to minimize the objective function:

$$\min_U \sum_{t=0}^{N-1} \left(||\Delta\mathbf{x}_t^{AV}||_Q^2 + ||\mathbf{u}_t^{AV}||_R^2\right) + ||\Delta\mathbf{x}_N^{AV}||_S^2 \tag{4}$$

such that:

$$\mathbf{x}_{t+1}^{AV} = f(\mathbf{x}_t^{AV}, \mathbf{u}_t^{AV}), \quad t \in \mathbb{N}^N \tag{5}$$

$$\mathbf{x}_{t+1}^{PV} = f(\mathbf{x}_t^{PV}, \mathbf{u}_t^{PV}), \quad t \in \mathbb{N}^N \tag{6}$$

$$\mathbf{u}_t^{AV} \in \mathcal{U}_t, \quad t \in \mathbb{N}^N, \tag{7}$$

$$\mathbf{x}_{p,j,t}^{PV} \in \Xi_{safe}, p \in \mathbb{N}^{N_p} \times j \in \mathbb{N}^{N_{traj}} \times t \in \mathbb{N}^N \tag{8}$$

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where the control input to the AV is $U = (u_0, \ldots, u_{N-1})^T$ and $||x||_M^2 = x^T M x$. The cost to reach the reference state $\Delta \mathbf{x}_t^{AV} = \mathbf{x}_t^{AV} - \mathbf{x}_{t,ref}^{AV}$, with weighting matrices $Q, S \in \mathbb{R}^{3\times 3}$ and $R \in \mathbb{R}^{2\times 2}$, the prediction model of the AV is $f(\mathbf{x}_t^{AV}, \mathbf{u}_t^{AV})$. The constraints on the inputs and collision-safe states are $\mathcal{U}_t$ and Ξ_{safe}, respectively. Observe that the size of the state collision avoidance constraint is a product of the number of agents N_p, the number of predicted trajectories N_{traj}, and the size of the prediction steps N. This exponential increase in the constraint results in a conservative behavior, where the algorithm often fails to find a safe solution to the optimization problem.

4 MULTI-RISK ASSESSMENT USING FUSION OF PIDPs (F-PIDP)

The traditional PIDP method for risk assessment can not handle multi-modal motion prediction directly. This is because predicting multiple trajectories for a single agent makes it difficult to decide which of the PIDPs to consider for collision avoidance (cf. Figure 1 & 3). A trivial solution may be to avoid all the trajectories, but this usually leads to conservative behaviors, where the AV slow down to a stop or perform unsafe maneuvers to avoid the agent. Therefore, we propose to perform a fusion of PIDPs (F-PIDPs) as presented in (Alao et al., 2024). F-PIDP takes advantage of the information on the likelihood of each trajectory to combine the PIDPs from multiple predictions. The following subsections highlight the methods to compute the F-PIDP.

4.1 Multi-Modal PIDP

For each of the possible trajectories that the PLEV can execute $j \in \mathcal{P}$, we evaluate the inter-distance between the predicted motion of the AV and the PLEV, such that

$$PIDP_j(t) = \{d_j(t) | j \in \mathcal{P}, 0 \leq t \leq t_{horizon}\} \tag{9}$$

$$d_j(t) = \sqrt{(x^{AV}(t) - x^j(t)) + (y^{AV}(t) - y^j(t))} \tag{10}$$

where the predictive inter-distance between the AV and the jth trajectory of the PLEV is denoted $PIDP_j$. The variables (x^{AV}, y^{AV}) represent the position coordinates of the AV while (x^j, y^j) represent the position coordinates of the jth trajectory of a PLEV at time step t. $t_{horizon}$ is the specified time horizon of the prediction.

4.2 Extraction and Fusion of PIDP Features

From each of the PIDPs evaluated above we require certain features to perform the fusion of the PIDPs: (1) the start point of the trajectory $PIDP(t_0)$, (2) the minimum point of the $PIDP(t_{min})$, (3) and the endpoint of the trajectory $PIDP(t_{horizon})$.

Next, a weighted fusion of all the extracted features of the PIDP is calculated to obtain only three features that represent the information from all the trajectories. The fusion of the features is obtained by computing the probabilistic center of mass (pCOM) of all the PIDPs. The definition of the pCOM for each of the feature points is given by (11)

$$pCOM(t) = \sum_{j=1}^{N_{traj}} Pr(j) \times PIDP_j(t) \tag{11}$$

where $Pr(j)$ is the probability of maneuver j, $PIDP_j(t)$ represents the PIDP at any of the feature points $t \in \{t_0, t_{min}, t_{horizon}\}$ and $N_{traj} \in \mathbb{N}$ is the number of trajectories being considered. The pCOM gives a weighted average of the feature points based on the likelihood of the PLEV trajectory. Therefore, the resulting parameters for the F-PIDP are:

- $F_PIDP(t_0)$:= $pCOM(t_0)$ fusion of the start points $PIDP_j(t_0)$, the value is same for all trajectories of a PLEV
- $F_PIDP(t_{min})$:= $pCOM(t_{min})$ fusion of all the minimum points $PIDP_j(t_{min})$ of the possible trajectories
- $F_PIDP(t_{horizon})$:= $pCOM(t_{end})$ fusion of all the end points $PIDP_j(t_{horizon})$

4.3 Fusion of PIDP (F-PIDP) Curve

The aim of the fusion of PIDPs is to have a single PIDP curve that represents all the predicted inter-distance based on their likelihood. Assuming the motion of the AV follow a smooth trajectory, the PIDP can be approximated by a quadratic polynomial curve derived from the Euclidean distance of the agents. Hence, the F-PIDP is modeled as a single curve that fuses the features extracted from all the PIDPs of a particular PLEV.

The features from the previous section are employed to compute the variables of a quadratic curve that passes through the points. From the equation of a

quadratic curve

$$\begin{bmatrix} \text{F_PIDP}(t_0) \\ \vdots \\ \text{F_PIDP}(t_{horizon}) \end{bmatrix} = \begin{bmatrix} 1 & t_0 & t_0^2 \\ \vdots & \vdots & \vdots \\ 1 & t_{horizon} & t_{horizon}^2 \end{bmatrix} \cdot \begin{bmatrix} q_0 \\ q_1 \\ q_2 \end{bmatrix} \tag{12}$$

where the variables $[q_0, q_1, q_2]$ characterize the F-PIDP curve and are found by evaluating the matrix (or pseudo) inverse at $t \in [t_0, t_{min}, t_{horizon}]$ in order to solve the linear equation (12). The result is a singular F-PIDP curve that integrates the information from all PIDPs, as demonstrated in Figure 3.

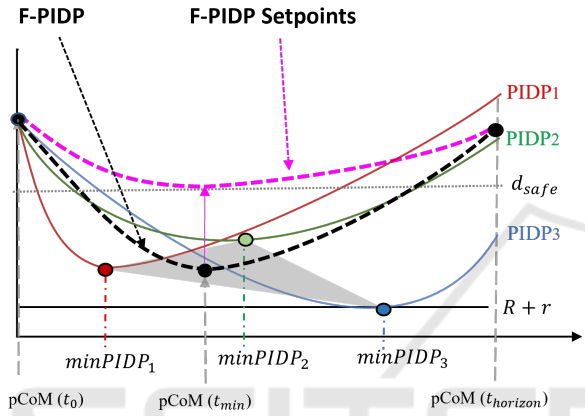

Figure 3: Fusion of PIDPs (F-PIDP) of an AV and multiple PLEVs with three (3) possible multi-modal trajectories.

4.4 F-PIDP Setpoint Determined by the Safety Distance

The Risk management algorithm requires the definition of an appropriate F-PIDP and a coherent setpoint to guarantee safety. However, one or more PIDPs may be below the safety distance and potentially in the collision zone (cf. Figures 2 and 3). This is usually propagated to the F-PIDP curve, depending on the likelihood of such PIDP. Therefore, a setpoint interpolation step is implemented, ensuring that the fused PIDP is always above the future safety distance. This is an interpolation step that translates the minimum of the F-PIDP curve to be above the established d_{safe} (Iberraken and Adouane, 2022).

$$F_PIDP(t_{min}) \triangleq max\{F_PIDP(t_{min}), d_{safe}\} \tag{13}$$

$$d_{safe} \triangleq R + r + v \times ETTC(1sec) \tag{14}$$

The safety distance, denoted as d_{safe}, is determined based on the AV's current linear velocity v and an extended time to collision ($ETTC$) (Iberraken et al., 2018) of 1 second.

The new curve termed as F-PIDP setpoint (cf. Figure 3) is then sent to the risk management algorithm to serve as a reference point (cf. Section 5). This step is therefore crucial for the proactive and preventive reduction of any risk of collision.

5 F-PIDP + MPC FOR MULTI RISK MANAGEMENT WITH SAFETY GUARANTEE

We prioritize safety in the proposed approach through the addition of various constraints to the optimization problem. The constraints depend on the dimensions of the vehicles, the road, and the limits on the control inputs of the AV.

5.1 Road Boundary Constraint

The position of the AV is expected to stay within the lane of the road, such that the following constraint is satisfied,

$$y_{min}^{lane} \leq y_t^{AV} \leq y_{max}^{lane} \tag{15}$$

this ensures that the lateral position of the AV denoted y_t^{AV} at each time step t, is bounded by y_{min}^{lane} and y_{max}^{lane} based on the width of the road and the vehicle.

5.2 Control Input Constraint

The motion of the AV is also constrained by the physical limit on the velocity and acceleration of the wheels of the vehicle. These limits also have a direct influence on the comfort of the passengers. They are formulated as

$$\mathbf{u}_{min}^{AV} \leq \mathbf{u}_t^{AV} \leq \mathbf{u}_{max}^{AV} \tag{16}$$

where the vector $\mathbf{u}_{min}^{AV}$ and $\mathbf{u}_{max}^{AV}$ are respectively the bounds on the minimum and maximum values of the control inputs.

5.3 Priority-Based Collision Avoidance Strategy

Using MPC to compute the trajectory of multiple agents like PLEVs in urban roads is too conservative because of the narrow constraint of the road boundary as shown in the simulation Section 6. Therefore, a priority-based strategy is proposed to select a target agent to avoid, instead of trying to avoid collision with all the agents and their possible trajectories.

- **Step 1:** Compute the F-PIDP of all the agents,

- **Step 2:** Find P_{dmin}: the PLEV with the minimum inter-distance to the AV, and P_{tSNR}: the PLEV with the minimum t_{SNR},
- **Step 3:** If $P_{dmin} < d_{safe_{max}}$, that is, no collision predicted, then set the priority target PLEV P_T, to avoid collision with P_{dmin}, else set the priority target PLEV P_T as P_{tSNR}. P_T is considered to be the most dangerous agent.
- **Step 4:** Compute collision free trajectory between target PLEV and AV using F-PIDP+MPC, goto to **Step 1**.

Algorithm 1 summarizes the steps above.

```
while Goal not reached do
    Data: x^AV_[t,···,N], x^PV_[t,···,N]
    Compute F-PIDP of all the PLEVs;
    Compute P_dmin: the PLEV with the
      minimum inter-distance to the AV;
    Compute P_tSNR: the PLEV with the
      minimum t_SNR;
    if P_dmin < d_safe_max then
        P_T := P_dmin ;
    else
        P_T := P_tSNR ;
    end
    U^AV := F-PIDP+MPC(P_T);
end
```

Algorithm 1: Priority-based Target Selection Algorithm using F-PIDP.

5.4 F-PIDP+MPC Formulation

Considering the vehicle constraints, road constraints, and the priority-based target, the F-PIDP+MPC algorithm becomes:

$$\min_{U} \quad w_0 \cdot F_1 + (1 - w_0) \cdot F_2 \tag{17}$$

such that:

$$\mathbf{x}^{AV}_{t+1} = f(\mathbf{x}^{AV}_t, \mathbf{u}^{AV}_t), \quad t \in \mathbb{N}^N \tag{18}$$

$$\mathbf{x}^{PT}_{t+1} = f(\mathbf{x}^{PT}_t, \mathbf{u}^{PT}_t), \quad t \in \mathbb{N}^N \tag{19}$$

$$\mathbf{u}^{AV}_t \in \mathcal{U}_t, \quad t \in \mathbb{N}^N, \tag{20}$$

$$\mathbf{x}^{P_T}_t \in \Xi^{P_T}_{safe}, \quad t \in \mathbb{N}^N \tag{21}$$

where F_1 denotes the MPC objective costs defined in Section 3.4, augmented by the inter-distance cost function $F_2 \triangleq ||F_PIDP - d_j(t)||^2$. The inter-distance function $d_j(t)$ is given in (9) and w_0 is a weight that compensates for the influence of the F-PIDP on the motion of the AV. The safety constraint $\Xi^{P_T}_{safe}$, considers only the state $\mathbf{x}^{P_T}_t$ of the target PLEV P_T. All other parameters are defined in Section 3.4. This approach is less conservative since in (21), the size of the state collision avoidance constraint is simply the size of the prediction horizon N as compared to (8) using only MPC.

6 SIMULATION RESULTS

The proposed risk assessment and management method, F-PIDP+MPC, has been tested in MATLAB. The simulation environment consists of an AV and multiple PLEVs moving in a dual-lane traffic environment. We consider a challenging scenario (cf. Figure 4) with an AV (in red), a PLEV 1 (in yellow) with multi-modal predictions trying to overtake another PLEV 2 (in blue) with multi-modal predictions. For clarity, it is assumed that at each time step the PLEVs have three (3) possible trajectories they can follow: Left Turn (in Red), Forward (in Green), Right Turn (in blue) (cf. Figure 4).

(**cf. Video link** https://youtu.be/oH6yPuocRJk)

Therefore, two types of challenges arise: (1) the uncertainty on the true trajectory the agents are executing, and (2) the possibility of the PLEV changing its behavior (speed). The parameters of the agents are given in table 1, note that the speed of PLEV 1 can change from the initial 2 m/s to about 10 m/s. The agents are assumed to be enclosed by circles to simplify and reduce the computational complexity. However, a less conservative approach using multiple circumcircles may be employed as in (Bellingard et al., 2023).

PLEV 1 accelerate its speed in the simulation setup after about 1 second. Five speed levels are considered $v \in \{2, 4, 6, 8, 10\} m/s$. The first speed level assumes that PLEV 1 maintains its initial speed of 2 m/s throughout the motion, while other speed levels indicate a sudden acceleration. The simulation time is set to run for 7.5 s, where at each time step, $\Delta t = 0.05$ the prediction horizon $t_{horizon} = \Delta t \times N = 2s$.

6.1 Result Using MPC

First, we analyse the results of the simulation using MPC. The results for the first two speed levels of 2 m/s and 4 m/s show that the MPC can handle small changes in the speed of the agents without violating the collision constraints (cf. Figure 4). The PIDP is above d_{safe} which implies safe navigation over the prediction horizon. This can be observed in the inter-distance plot between the AV and the two PLEVs at

Table 1: Agents Parameters and initial states.

AV Parameters	Value	Unit
radius	2	m
initial position	[0, -6]	m
initial velocity	[8, 0]	m/s
$\mathbf{u}^{AV}_{max}$	[8, 35]	[m/s, °]
$\mathbf{u}^{AV}_{min}$	[0, -35]	[m/s, °]
PLEV 1 Parameters	**Value**	**Unit**
radius	0.5	m
initial position	[10, -9]	m
initial velocity	[2, 0]	m/s
v_{max}	10	m/s
PLEV 2 Parameters	**Value**	**Unit**
radius	0.5	m
initial position	[16, -6]	m
initial velocity	[2, 0]	m/s
v_{max}	2	m/s

time $t \leq 1s$ (cf. Figure 6 (a) & (c)).

However, MPC is very conservative because it slows down to almost a stop due to the possibility of collision with PLEV 2. This is because the PIDP of a possible Left turn trajectory (cf. Figure 6 (d), in red) by PLEV 2 may lead to a collision. Therefore, the MPC algorithm tries to minimize the risk by maintaining some distance behind PLEV 2, instead of overtaking it. This is why even at the end of the simulation $t = 7.5$, the AV is far from the reference position of $X_{ref} = [-2, 60]m$ (cf. Figure 4 (b)).

Furthermore, at high speeds of 6 m/s and above, the MPC algorithm could not find a solution that satisfies all the safety constraints. Most especially, as seen in (cf. Figure 5), the AV violates the road boundary constraint to avoid collision with the other agents after the sudden acceleration of the PLEV.

6.2 Result Using Priority-Based F-PIDP+MPC

The proposed method using F-PIDP+MPC performs better than MPC for all speed changes considered. Here, the weight $w_0 = 0.2$ in (17) penalises the deviations from the F-PIDP setpoints, whereas setting $w_0 = 1.0$ using the previous MPC method ignores the setpoints. By employing the F-PIDP as a risk measure and focusing on the target PLEV deemed the most dangerous, the AV can find a less conservative trajectory that satisfies the safety constraints. For instance, at $t = 1s$, the priority target P_T is PLEV 1 (cf. Figure 7 (a)). After the fusion of the PIDPs, the F-PIDP setpoint suggests that the AV should create more distance between itself and PLEV 1 to avoid possible collision (cf. Figure 8 (a)). And since the focus is only on the priority target, PLEV 1, the proposed solution from the F-PIDP+MPC algorithm is to safely overtake PLEV 1. Then at $t = 5s$, PLEV 2 became the priority target that the AV overtook after PLEV 1 (cf. Figure 7 (b)).

This priority-based behavior enables the AV to quickly leave the dangerous region instead of considering all the multi-modal agents simultaneously leading to conservative behaviors. Hence, the AV can cover more distance in less time as compared to the MPC method that remains beside PLEV 2, after 7.5 s (cf. Figure 7 (b)). Overall, the PIDPs of all the agents during the simulation are always above the safety distance using the proposed method (cf. Figure 8). This approach applies to both PLEVs and other road vehicles.

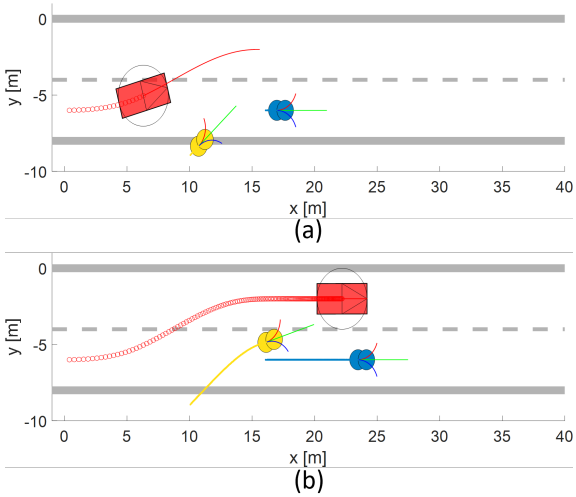

Figure 4: A scenario using MPC showing an AV (in red) and multi-modal PLEVs (1 in Yellow & 2 in Blue): (a) At t = 1 s, the actual speed of both PLEVs is 2 m/s (b) At t = 7.5 s, AV overtakes PLEV 1 but stays beside PLEV 2 to avoid a possible collision with a possible Left turn trajectory of PLEV 2.

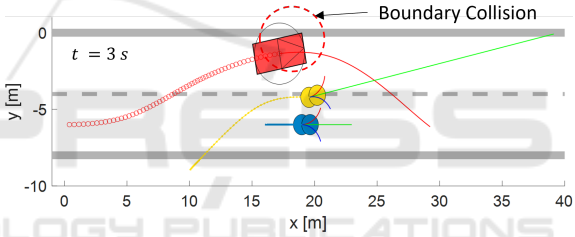

Figure 5: At t = 3 s, MPC violates the boundary constraint due to the sudden change in speed of PLEV 2.

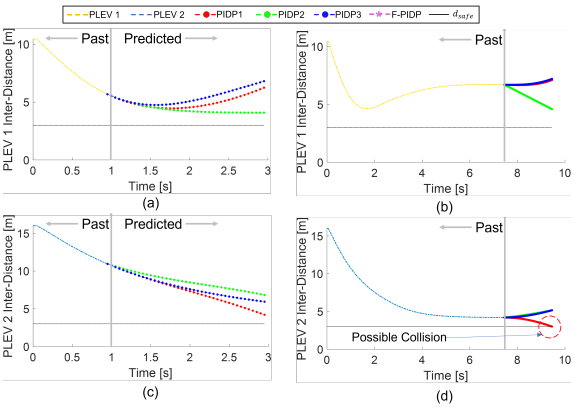

Figure 6: Inter-Distance plot between the AV and the PLEVs using MPC: (a) & (c) At t = 1 s, all PIDPs (red, blue, green) of PLEV 1 & 2 are above safety distance d_{safe}, (b) & (d) At t = 7.5 s, the PIDPs of PLEV 1 are above d_{safe} while a PIDP of PLEV 2 may lead to collision.

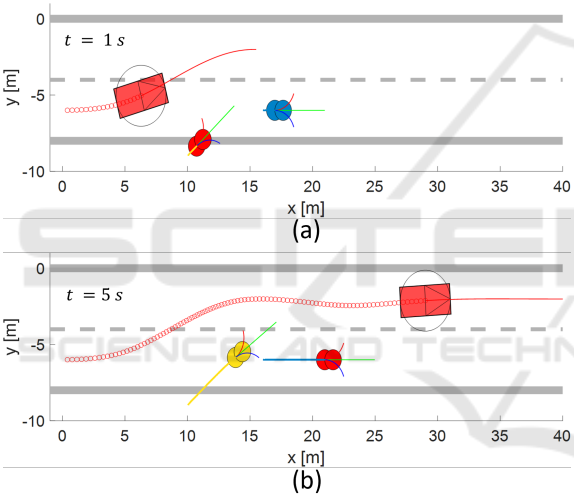

Figure 7: A scenario using the proposed method: (a) At t = 1 s, AV overtakes the priority target PLEV 1 (in red) (b) then at t = 5 s, AV overtakes the new priority target PLEV 2 (in red).

7 CONCLUSION

We propose in this paper a method for risk assessment and management for autonomous navigation among Personal Light Electric Vehicles (PLEVs). The proposed method hinges on modeling the behavior of PLEVs as multi-modal predictions. Then the Predictive Inter-Distance Profiles (PIDPs) of the PLEVs' predictions are fused using a Fusion of PIDPs (F-PIDP). This method reduces the complexity of the problem from multiple predictions to a single F-PIDP for each agent. A priority-based strategy is developed to choose a target agent considered to be the most dangerous. Safe control actions are then computed using F-PIDP+MPC.

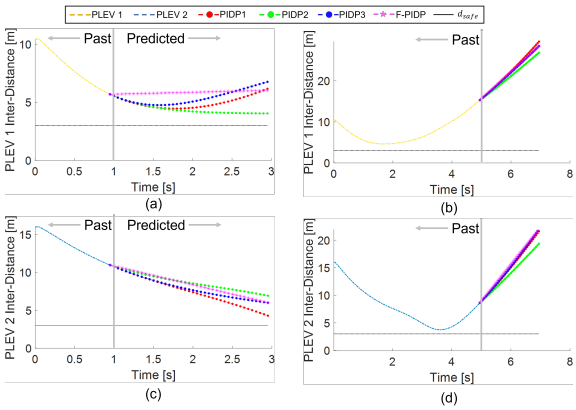

Figure 8: Inter-Distance plot between the AV and the PLEVs using proposed method: (a) At t = 1 s, F-PIDP suggest creating more distance between AV and PLEV 1 (b),(c), & (d) All PIDPs are above d_{safe}.

Results from various simulations obtained from varying the behavior of the agents show that the proposed method is efficient for risk assessment and management. A comparison with the traditional MPC method shows that the proposed method is less conservative. Future works will focus on considering disturbances in the predicted states of the agents and to further optimizing the method for real-time experimentation.

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ACKNOWLEDGEMENTS

This research is part of the ANNAPOLIS project (https://project.inria.fr/annapolis/), funded by the French National Research Agency (ANR-21-CE22-0014).

REFERENCES

Alao, E., Adouane, L., and Martinet, P. (2024). Reliable risk assessment and management using probabilistic fusion of predictive inter-distance profile for urban autonomous driving. In *European Control Conference (ECC)*.

Bellingard, K., Adouane, L., and Peyrin, F. (2023). Risk assessment and management based on neuro-fuzzy system for safe and flexible navigation in unsignalized intersection. In *IEEE Intelligent Vehicles Symposium (IV)*, pages 1–7.

Cimurs, R., Suh, I. H., and Lee, J. H. (2021). Goal-driven autonomous exploration through deep reinforcement learning. *IEEE Robotics and Automation Letters*, 7(2):730–737.

Fiasché, E., Martinet, P., and Malis, E. (2023). Towards autonomous robot navigation in human populated environments using an universal sfm and parametrized mpc. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*.

Hillenbrand, J., Spieker, A. M., and Kroschel, K. (2006). A multilevel collision mitigation approach—its situation assessment, decision making, and performance tradeoffs. *IEEE Transactions on Intelligent Transportation Systems*, 7(4):528–540.

Iberraken, D. and Adouane, L. (2022). Safe navigation and evasive maneuvers based on probabilistic multi-controller architecture. *IEEE Transactions on Intelligent Transportation Systems*, 23(9).

Iberraken, D., Adouane, L., and Denis, D. (2018). Multi-level bayesian decision-making for safe and flexible autonomous navigation in highway environment. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 3984–3990.

Jo, K., Lee, M., Kim, J., and Sunwoo, M. (2016). Tracking and behavior reasoning of moving vehicles based on roadway geometry constraints. *IEEE transactions on intelligent transportation systems*, 18(2):460–476.

Kim, K.-D. and Kumar, P. R. (2014). An mpc-based approach to provable system-wide safety and liveness of autonomous ground traffic. *IEEE Transactions on Automatic Control*, 59(12):3341–3356.

Kuderer, M., Gulati, S., and Burgard, W. (2015). Learning driving styles for autonomous vehicles from demonstration. In *2015 IEEE international conference on robotics and automation (ICRA)*, pages 2641–2646. IEEE.

Laugier, C., Paromtchik, I. E., Perrollaz, M., Yong, M., Yoder, J.-D., Tay, C., Mekhnacha, K., and Nègre, A. (2011). Probabilistic analysis of dynamic scenes and collision risks assessment to improve driving safety. *IEEE Intelligent Transportation Systems Magazine*, 3(4):4–19.

Lee, N., Choi, W., Vernaza, P., Choy, C. B., Torr, P. H., and Chandraker, M. (2017). Desire: Distant future prediction in dynamic scenes with interacting agents. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 336–345.

Lefkopoulos, V., Menner, M., Domahidi, A., and Zeilinger, M. N. (2020). Interaction-aware motion prediction for autonomous driving: A multiple model kalman filtering scheme. *IEEE Robotics and Automation Letters*, 6(1):80–87.

Li, J., Dai, B., Li, X., Xu, X., and Liu, D. (2019). A dynamic bayesian network for vehicle maneuver prediction in highway driving scenarios: Framework and verification. *Electronics*, 8(1):40.

Li, L., Ota, K., and Dong, M. (2018). Humanlike driving: Empirical decision-making system for autonomous vehicles. *IEEE Transactions on Vehicular Technology*, 67(8):6814–6823.

Luo, W., Yang, B., and Urtasun, R. (2018). Fast and furious: Real time end-to-end 3d detection, tracking and motion forecasting with a single convolutional net. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 3569–3577.

Mayne, D. Q. (2014). Model predictive control: Recent developments and future promise. *Automatica*, 50(12):2967–2986.

Miao, B. and Han, C. (2023). Intelligent vehicle obstacle avoidance path-tracking control based on adaptive model predictive control. *Mechanical Sciences*, 14(1):247–258.

Nan, J., Shang, B., Deng, W., Ren, B., and Liu, Y. (2021). Mpc-based path tracking control with forward compensation for autonomous driving. *IFAC-PapersOnLine*, 54(10):443–448.

Philippe, C., Adouane, L., Thuilot, B., Tsourdos, A., and Shin, H.-S. (2018). Safe and online mpc for managing safety and comfort of autonomous vehicles in urban environment. In *21st International Conference on Intelligent Transportation Systems (ITSC)*, pages 300–306.

Rudenko, A., Palmieri, L., Herman, M., Kitani, K. M., Gavrila, D. M., and Arras, K. O. (2020). Human motion trajectory prediction: A survey. *The International Journal of Robotics Research*, 39(8):895–935.

Saljanin, M., Müller, S., Kiebler, J., Neubeck, J., and Wagner, A. (2022). A model predictive control approach for highly automated vehicles in urban environments. *Automotive and Engine Technology*, 7(1):105–113.

Vu, T. M., Moezzi, R., Cyrus, J., and Hlava, J. (2021). Model predictive control for autonomous driving vehicles. *Electronics*, 10(21):2593.

Westhofen, L., Neurohr, C., Koopmann, T., Butz, M., Schütt, B., Utesch, F., Neurohr, B., Gutenkunst, C., and Böde, E. (2023). Criticality metrics for automated driving: A review and suitability analysis of the state of the art. *Archives of Computational Methods in Engineering*, 30(1):1–35.

Yu, S., Hirche, M., Huang, Y., Chen, H., and Allgöwer, F. (2021). Model predictive control for autonomous ground vehicles: a review. *Autonomous Intelligent Systems*, 1:1–17.