Uncertainty-Responsive Safe MPC for Autonomous Driving in Dynamic Environments

Ying Shuai Quan[1], Paolo Falcone[1,2], Jonas Sjöberg[1]

***Abstract*— We present an uncertainty-responsive model predictive control framework designed to ensure the safe operation of autonomous vehicles (AVs) in environments like, e.g., urban traffic, where the predicted behavior of the surrounding road users (RUs) could be *highly uncertain*, thus leading to potential collisions between AV and RUs or an unacceptably over-conservative behavior of the AV. In our framework, the collision-avoidance constraints are adjusted on-line to adapt the AV's behavior to the varying uncertainty of the RUs' prediction model, such that safety is preserved. Simulations of highway driving scenarios, constructed upon real-world data, show that the proposed approach avoids collisions in presence of *unpredicted* behaviors of the surrounding RUs.**

INTRODUCTION

Model predictive control (MPC) is widely adopted in autonomous driving for its ability to balance control objectives, such as tracking performance, safety and comfort requirements, by integrating them into the objective function and constraints, respectively. Nevertheless, it is not easy to enforce a safe-by-design vehicle behavior, such that the safety constraints are satisfied at all times. While standard MPC formulations can be equipped with stability and recursive feasibility guarantees [1], extending these to MPC motion control and planning problems is an open challenge due to *a priori-unknown* safety constraints that arise, in real time, from interactions with human road users (RUs). [2].

Safe model predictive control (SMPC) frameworks have been developed to guarantee the satisfaction at all times of a priori-unknown safety constraints, provided that certain assumptions hold [3]. Nevertheless, their deployment in real-world driving scenarios might be complicated as frequently occurring unforeseen behaviors of RUs, such as those caused by sensor noise or faults, communication delays, unexpected jaywalkers or abrupt lane changes, can still lead to violations of the required assumptions.

Building on existing SMPC frameworks presented in [3], we propose an uncertainty-responsive SMPC algorithm that proactively adapts its driving mode in response to unpredicted RU behaviors in real time. By incorporating a novel constraint adaptation mechanism that dynamically adjusts acceleration limits, our controller enables the AV to navigate safely in uncertain environments with unforeseen events. We demonstrate the effectiveness of our approach through highway traffic scenarios, showcasing its potential for real-world deployment.

This work is funded by the Fordonsstrategisk Forskning och Innovation program of Vinnova under the grant 2018-05005.

[1] Ying Shuai Quan, Paolo Falcone and Jonas Sjöberg are with the Mechatronics group at the Department of Electrical Engineering, Chalmers University of Technology, Gothenburg, Sweden {quany,paolo.falcone,jonas.sjoberg}@chalmers.se

[2] Paolo Falcone is with the Dipartimento di Ingegneria "Enzo Ferrari" Università di Modena e Reggio Emilia, Italy falcone@unimore.it

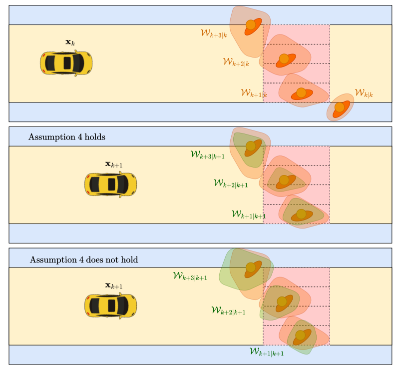

Fig. 1. First: initial prediction for an RU at time k. Second: prediction at time $k+1$ that satisfies Assumption 1. Third: prediction at time $k+1$ that does not satisfy Assumption 1.

METHODOLOGY

We frame vehicle motion planning as a constrained optimization problem solved in receding horizon. Let $\mathbf{x}_{k+1} = f(\mathbf{x}_k, \mathbf{u}_k)$ represent the vehicle dynamics, with $\mathbf{x}_k$ and $\mathbf{u}_k$ the state and input at time k, respectively, subject to *a-priori known* constraints $h(\mathbf{x}, \mathbf{u}) \leq 0$ and *a-priori unknown* constraints $g(\mathbf{x}, \mathbf{u}) \leq 0$. To ensure recursive feasibility, prior work [3] relies on the assumption of consistency:

Assumption 1: The a-priori unknown constraint functions satisfy

$$g_{n|k+1}(\mathbf{x}_{n|k}, \mathbf{u}_{n|k}) \leq g_{n|k}(\mathbf{x}_{n|k}, \mathbf{u}_{n|k}), \tag{1}$$

for all $n \geq k$.

Assumption 1 requires that the a-priori unknown constraints $g_{n|k}$ are *consistent*, meaning they do not become "more restrictive" as the system evolves. In autonomous driving, g introduces constraints that enforce trajectories that avoid collisions with other RUs. These constraints are built upon the RUs' positions, measured by the on-board sensors, and prediction tools relying on RU behavior models. Assumption 1 requires that the set $\mathcal{W}_{n|k}$ of RUs' positions at the future time n predicted based on the information available at time k must include the set $\mathcal{W}_{n|k+1}$ of position at the same time n predicted at time $k+1$, as shown in Fig. 1.

However, Assumption 1 may be overly conservative in practice and is often challenging to satisfy in real-world scenarios. As depicted in Fig. 1, this assumption can be readily

Algorithm 1: Uncertainty-Responsive SMPC

Input: Driving mode $j \in [1, N_d]$
Output: Updated driving mode
Initialize: Start with driving mode j
for *each time step* k **do**
  Obtain $\bar{g}^i_{n|k},\ i \in \mathbb{I}_1^{N_d}$
  for *next time step* $k+1$ **do**
    Obtain $g_{n|k+1}(\mathbf{x}_{n|k}, \mathbf{u}_{n|k})$
    if *(2) holds for* $i = j$ **then**
      Stay in mode j;
    else
      Switch to closest mode κ satisfyhing (2);
    Solve SMPC using current driving mode.

broken due to issues such as sensor noise, communication delays or unexpected jaywalkers. We then introduce a relaxed condition as an alternative to Assumption 1.

Assumption 2: The a-priori unknown constraint functions satisfy

$$g_{n|k+1}(\mathbf{x}_{n|k}, \mathbf{u}_{n|k}) \leq \bar{g}_{n|k}, \tag{2}$$

for all $n \geq k+1$.

Here, $\bar{g}_{n|k}$ is computed by solving an extra optimization problem under a-priori known constraints $h(\mathbf{x}, \mathbf{u})$. Evaluating $\bar{g}_{n|k}$ enables assessing the future feasibility of the SMPC problem and guides switching between predefined driving modes. We consider N_d driving modes, each with a distinct constraint set $h^i(\mathbf{x}, \mathbf{u}), i \in \mathbb{I}_1^{N_d}$, reflecting varying levels of control authority (e.g., comfort, moderate, and aggressive driving modes), characterized by different acceleration and braking limits. Each mode yields a different $\bar{g}^i_{n|k}$, indicating the level of environmental uncertainty it can tolerate. The updated value of $\bar{g}^i_{n|k}$ can then be used to guide mode selection, allowing the controller to dynamically adapt the a priori-known constraint settings (specifically, the selection and application of driving modes) to ensure that Assumption 2 is consistently met. The proposed uncertainty-responsive SMPC is organized in Algorithm 1.

Results

We evaluated the proposed uncertainty-responsive SMPC in a highway scenario involving an emergency lane change by a surrounding car, using real-world data from the ZOD dataset [4]. We consider three driving modes, ranging from comfort to aggressive driving. At $t = 5.6\,\text{s}$, a vehicle in the left lane begins an unexpected lane change to the right, violating Assumption 1. As shown in Fig. 2, the predicted RU set $\mathcal{W}_{n|k}$ (orange shaded region) does not include the set $\mathcal{W}_{n|k+1}$ (green shaded region), indicating that Assumption 1 does not hold anymore. Fig. 4 displays $\bar{g}^i_{k+m|k}, i \in \mathbb{I}_1^{N_d}$ and $g_{k+m|k+1}$ with m a prediction step at which g is active. In this case, Assumption 2 is not satisfied under driving mode 1, meaning that an admissible solution can no longer be guaranteed. To restore feasibility in response to the unexpected change, the controller switches to mode 2, which allows a more aggressive behavior where Assumption 2 holds. This adaptation reflects a trade-off: the system compromises on comfort only when necessary to ensure continued safety in response to rare and unforeseen events.

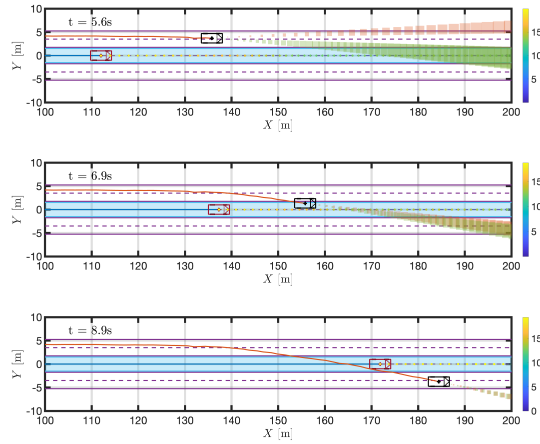

Fig. 2. Three time instances of the simulation environment.

Conclusion

We proposed an uncertainty-responsive SMPC framework that enables safe and adaptable autonomous driving in dynamic, uncertain environments. By relaxing a conservative assumptions and incorporating a real-time mode-switching mechanism, the controller maintains safety and performance even in the presence of unpredictable RU behaviors.

References

[1] F. Borrelli, A. Bemporad, and M. Morari, *Predictive control for linear and hybrid systems.* Cambridge University Press, 2017.

[2] I. Batkovic, A. Gupta, M. Zanon, and P. Falcone, "Experimental validation of safe mpc for autonomous driving in uncertain environments," *IEEE Transactions on Control Systems Technology*, 2023.

[3] I. Batkovic, M. Ali, P. Falcone, and M. Zanon, "Safe trajectory tracking in uncertain environments," *IEEE Transactions on Automatic Control*, 2022.

[4] M. Alibeigi, W. Ljungbergh, A. Tonderski, G. Hess, A. Lilja, C. Lindström, D. Motorniuk, J. Fu, J. Widahl, and C. Petersson, "Zenseact open dataset: A large-scale and diverse multimodal dataset for autonomous driving," in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2023, pp. 20 178–20 188.

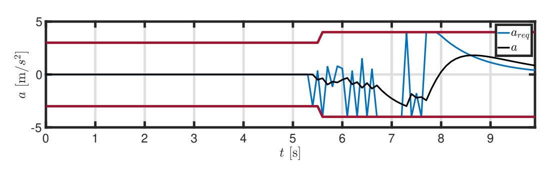

Fig. 3. Closed-loop trajectories for AV.

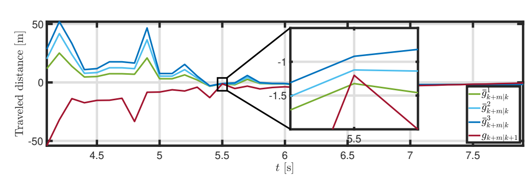

Fig. 4. Time evolution of $g_{n|k+1}$ and $\bar{g}_{n|k}$ for $n = k + m$.