Proactive Risk Mitigation and Reactive Control for Safe and Smooth Automated Driving

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***Abstract*—In addition to predictable static and dynamic objects on public roads, automated driving systems must also handle unpredictable hazards such as parked car doors opening, cyclists falling, or pedestrians stepping off curbs. One extreme approach would be to plan such that all hazards would come to pass, though this results in an uncomfortably conservative system. Another extreme approach would be to perform aggressive reactive maneuvers when hazards materialize, though this results in an uncomfortably reactive system. This paper proposes a robust approach that handles hazards through proactive planning and reactive control to achieve a smooth and safe automated driving (AD) while enabling the use of lower cost sensors.**

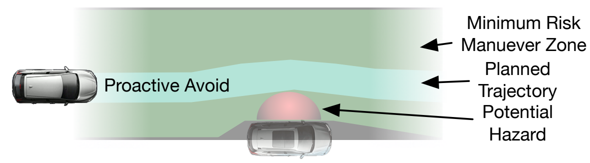
I. Introduction

In recent years, researchers have made remarkable headway in expanding automated driving (AD) capabilities [3, 9, 13]. In general, a top-down approach developing perception, prediction, decision making, and trajectory planning algorithms has led to a system that accommodates predictable objects and provides a smooth experience for passengers. Since even driving in predictable scenarios has proven itself to be exceptionally difficult, developers of AD systems have often omitted work on infrequent scenarios requiring reactive maneuvers [5, 7, 11]. As a result, safety drivers are still required to handle unpredictable events including, but not limited to, parked car doors opening, cyclists falling, or pedestrians stepping off curbs. One approach would be to plan conservatively assuming all hazards would materialize, though this results in an uncomfortably conservative system.

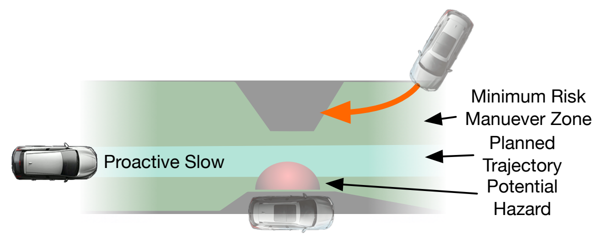
On the other hand, automotive companies have for decades been focused to develop bottom-up reactive systems such as Automatic Emergency Braking (AEB) and Automatic Emergency Steering (AES). In recent years, features such as Lane Keeping Assist (LKA) that can allow for hands-off driving on highways have even become both desirable and profitable endeavors [12]. Moreover, there has been significant academic research on reactive control [1, 2, 6, 10]. However, such Advanced Driver Assist Systems (ADAS) are a long ways from AD capabilities.

II. Approach

In this work, we propose a principled approach to fusion of state-of-the-art *smooth* proactive AD capabilities developed in research with proven and *safe* reactive driving capabilities developed for production vehicles (Fig. 1). We propose an approach which fuses industrial, *safe* reactive capabilities with state-of-the-art, *smooth* proactive AD capabilities (Fig. 2). The planner, based on AD research, is enhanced by proactively mitigating risks posed by commonly encountered road objects, allowing for smaller magnitude reactive maneuvers should a hazard materialize. The high frequency reactive control, based on development towards production ADAS, is modified to follow the proactive plan subject to the Minimum Risk Maneuver Zone (MRMZ) and raw perception.



(a) Scene allowing for proactive lateral maneuver.



(b) Scene requiring proactive speed maneuver.

Fig. 1: Our approach produces a principled and human-like fusion of proactive planning and reactive control.

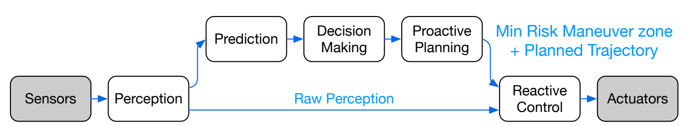


Fig. 2: Reactive control is tasked with following the proactive plan, subject to the MRMZ and raw perception.

A. Proactive Planning

The proactive planner solves a constrained optimization problem to compute a smooth, long-horizon (3-6 second) trajectory in anticipation of static and dynamic objects, and detected hazards. The goal is to find a sequence of control knots that optimizes the system's behavior over a prediction horizon of length K. Considering the current state, $\mathbf{q}_k$, the process model, and the state/control constraints, we define the following constrained optimization problem

$$[\mathbf{q}_{\mathrm{opt}}, \mathbf{u}_{\mathrm{opt}}] = \arg\min_{\mathbf{q},\mathbf{u}} J(\mathbf{q}, \mathbf{u}) = \mathbf{e}^T \, \mathbf{Q} \, \mathbf{e} + \mathbf{u}^T \, \mathbf{R} \, \mathbf{u} \tag{1}$$

$$\text{subject to}: \mathbf{q}_{k+i+1} = f(\mathbf{q}_{k+i}, \mathbf{u}_{k+i}), \; i \in 0..K-1 \tag{2}$$

$$h_{q,i}(\mathbf{q}) > 0, \; i \in 1...K \tag{3}$$

$$h_{u,i}(\mathbf{u}) > 0, \; i \in 1...m \tag{4}$$

where the equality constraints are used to enforce the process model, and the inequality constraints are used to enforce the MRMZ and control limits. The MRMZ (Fig. 1) represents where the reactive control module could take the vehicle in an emergency. The MRMZ is a subset of the area encapsulating a planned nominal trajectory (e.g. road), $\mathcal{Z}$, where the risk of collision at time i, $P(x, y, i)$, is less than c

$$\mathrm{MRMZ} = \{(x, y) : 1 \leq i \leq K, P(x, y, i) < c, (x, y, i) \in \mathcal{Z}\} \tag{5}$$

where x and y are longitudinal and lateral positions along the planned nominal trajectory, respectively.

With proactive risk mitigation (PRM), we further consider potential lateral lane intrusions by hazards. A hazard $\mathrm{d}x_{\mathrm{haz}}$ distance ahead is modeled using a lateral incursion rate, v_{haz},

$$t_{\mathrm{arrival}} = \mathrm{d}x_{\mathrm{haz}} / v_{\mathrm{AV}} \tag{6}$$

$$\mathrm{d}y_{\mathrm{haz}} = t_{\mathrm{arrival}} \cdot v_{\mathrm{haz}} \tag{7}$$

where $\mathrm{d}y_{\mathrm{haz}}$ is the extent of the potential lane incursion. However, rather than proactively mitigating the entire potential lane incursion, we model the reactive lateral capabilities of the ego-vehicle, $\mathrm{d}y_{\mathrm{reactMax}}$, using concatenated Dubins curves

$$\mathrm{d}y_{\mathrm{reactMax}} = \frac{2v_{\mathrm{AV}}^2}{a_{\max}} \left(1 - \sqrt{1 - \left(\frac{a_{\max} \mathrm{d}x_{\mathrm{haz}}}{2v_{\mathrm{AV}}^2} \right)^2} \right) \tag{8}$$

where $\mathrm{a}_{\max}$ is a conservative model of the maximum reactive lateral acceleration. We then proactively mitigate only part of the potential intrusion

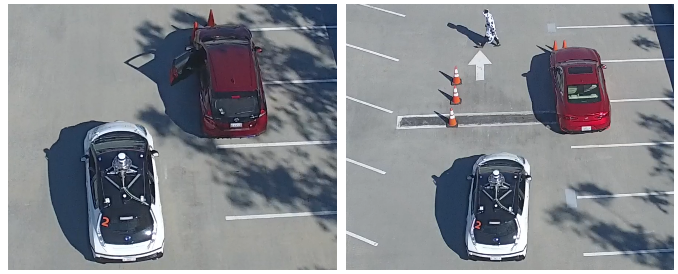
$$\mathrm{d}y_{\mathrm{proact}} = \max\left(0, \mathrm{d}y_{\mathrm{haz}} - \gamma \cdot \mathrm{d}y_{\mathrm{reactMax}}\right), 0 \leq \gamma \leq 1 \tag{9}$$

where the variable γ is used to control how reactive the vehicle is, with $\gamma = 0$ being completely proactive. By proactively executing part of the maneuver, we find a human-like approach to dealing with hazards. Moreover, this approach conservatively ensures that a reactive maneuver is successful.

The control constraints, $h_{u,i}(\mathbf{u})$, are narrow when used for PRM in the planner. This is to produce smooth driving behavior.

B. Reactive Control

The reactive controller solves a high-rate, constrained optimization problem with the goal of following the smooth, proactive plan while avoiding collisions within the MRMZ. Though the proactive plan is likely collision-free, the reactive controller provides safety by double-checking against raw perception and deviating from the proactive plan if necessary. It is based on the Adept obstacle avoidance system [4, 8] and



(a) Scene allowing for a proactive lateral maneuver. (b) Scene requiring a proactive speed maneuver.

Fig. 3: The overall architecture has been tested in a preliminary proof of concept with hazards arising from parked car doors and limitations to the MRMZ arising from static pylons.

is designed to be capable of operating at the vehicle grip limit. In contrast to the proactive planner, the reactive controller uses aggressive motion limits and torque vectoring to satisfy unpredictable and rapidly changing space constraints safely.

III. Results

The approach presented in this paper was tested on a Nissan LEAF AV platform in simple scenarios involving parked cars and the possibility of their doors opening. From our experiments, we noticed that in addition to being safe and smooth, this approach gave rise to human-like driving behavior in challenging scenes with narrow passages.

In the first example (Fig. 3(a)), the hazard is located in an open space where if the car door were to open, the reactive maneuver would be to move laterally. Recognizing this based on the MRMZ, the proactive planner uses only a proactive lateral motion without slowing down. As shown, the door did open and reactive control rapidly recognized this constraint through its connection to raw perception data. However, since the proactive planner had already anticipated this possibility, the reactive maneuver was limited and comfortable. If the door had not opened, passenger comfort would have still been maintained as the vehicle had not slowed down or moved all the way to avoid the hypothetical door.

In a second example (Fig. 3(b)), the hazard occurs in a constrained part of the road where if the door were to open, the reactive maneuver would be to stop. The resulting proactive plan is to move laterally if possible and slow down. In the event that the car door or an occluded pedestrian were to suddenly intrude into the lane, the reactive planner will rapidly recognize the additional constraint through its connection to raw perception data and begin braking. If the door had not opened, passenger comfort would have still been maintained as it was socially acceptable to slow down due to the conditions.

IV. Conclusion

While this approach is able to achieve a smooth and safe AD system in the scenarios we tested, this is still a work in progress and more research is required to find the right balance between proactive planning and reactive control for a wider variety of hazards under different conditions.

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