The subtle art of testing algorithms in an autonomous vehicle

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Description

As the reality of autonomous vehicles come closer it becomes more and more important to understand how the "theoretical algorithms" have to take into account the actual problems encountered in a real vehicle, both regarding implementation problems and errors from sensor measurements, noise and robustness. To acquire this knowledge, a project was started which aims to take a "theoretical" overtaking algorithm all the way from the theoretical work to real-life implementation.

Background & Motivation

The motivation of this project is twofold. The first is to get some real data from running tests in a real vehicle which can be analyzed and published. The second part is to understand what is needed of new algorithms in order for them to actually be useful in practice, i.e. when implemented in an autonomous vehicle and not just run in simulation. The resources available for doing the testing (which is scheduled in march) is the ReVeRe lab at Chalmers, Lindholmen which has both an autonomous truck and an autonomous car. The actual testing will be performed at the Asta Zero test track.

Methods & Preliminary Results

The main focus of the project is the trajectory planner. There are several different ways of implementing this planner as an optimization problem. The most obvious way is to sample in time. However, this will yield not only a non-convex but a mixed integer problem. The integer constraints (and the non-convexity) occurs when modelling the leading vehicles critical zone (see Figure 1). The critical zone can in fact be modeled as a convex constraint if one sample in space instead of time. Except for the critical zone constraints there are also bounds on the vehicle states (such as longitudinal and lateral velocity and slip) and control signals (such as lateral acceleration). Here, only the space formulation and its results are presented. As can be seen this problem is also non-convex (since we divide by the longitudinal velocity \(\dot{x}\)). But this is not an integer problem and can thus be linearized using standard methods.

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\begin{align*}
\min & \quad J(\tilde{x}(\tilde{x}), \tilde{u}(\tilde{x})) \\
\text{subject to} & \quad \dot{\tilde{x}}(\tilde{x}) = A\tilde{x}(\tilde{x}) + B\tilde{u}(\tilde{x}) \\
& \quad \tilde{x}(\tilde{x}) \in [\tilde{x}_{\min}(\tilde{x}), \tilde{x}_{\max}(\tilde{x})] \\
& \quad \tilde{u}(\tilde{x}) \in [\tilde{u}_{\min}(\tilde{x}), \tilde{u}_{\max}(\tilde{x})] \\
& \quad \tilde{y}(\tilde{x}) \in [\tilde{y}_{\min}(\tilde{x}), \tilde{y}_{\max}(\tilde{x})] \\
& \quad \tilde{x}(0) = \tilde{x}_0
\end{align*}
\]

Roadmap & Milestones

As can be seen in the roadmap below there are essentially five milestones. The first four are done in simulation on PC and the last one is done in a real vehicle. The goal of the different milestones are 1) to generate safe and comfortable overtaking trajectories, 2) To successfully use the trajectory planner in a model predictive control (MPC) scheme, 3) To implement controllers which can follow trajectories generated in steps 1-4. To include this controller into the MPC model, 4) To implement the environment resulting from steps 1-4 in a real vehicle.

Bibliography