Long-Horizon Vehicle Motion Planning and Control Through Serially Cascaded Model Complexity

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Abstract

We propose the implementation and experimentation of a motion planning and control framework for autonomous vehicles based on nonlinear model-predictive control.The work is mainly based on [Laurense and Gerdes, 2022]. The code is available publicly at this GitHub repository.

Introduction

- Concepts of MPC
- Problem statement
- Literature review (?)
- Report outline

Model predictive control (MPC for short) is a control technique which, in closed-loop, computes the control inputs by means of an optimization algorithm, which uses a **model** of the system and measurements to **predict** future states and act accordingly by choosing the "best" control action.

$$\begin{aligned} & \min_{u_0,\dots,u_{N-1}} J(x,u) \\ \text{subject to} \quad & x_{k+1} = f(x_k, u_k) \\ & x_0 = x(t) \end{aligned} \tag{1}$$

We call $J(x)$ the **cost function** and $g(x)$ the **constraints**. In particular, the sequence of control actions is generated such that the cost function is minimized over the **prediction horizon** by solving a constrained optimization problem that depends on the evolution of the model over the horizon itself. Then, the controller applies just the first action: in this way the system has advanced one step, a new optimization problem with a new initial state is produced, and the process goes on. The advantages of MPC are many: it is a multivaribale controller, so it can control outputs by handling simultaneously all the interactions between system variables; it can handle constraints, so it allows to avoid possible undesired states; it predicts the future states, allowing to incorporate their information in the actual control. It is particulary useful for a real-time control that adapts to **changes in the environment**.

When dealing with nonlinear dynamics, a nonlinear MPC (or NMPC) can be used to capture more accurately the nonlinear behavior of a system. This entails a more robust manipulation of both nonlinearities and uncertainties in dynamics models and constraints. However, one of its highest problem is the computational power it can require, especially when dealing with highly nonlinear systems. This entails the need of a high-performance hardware to solve the optimization problem in an acceptable time, but sometimes this is not enough. Especially in a real environment, where the timeliness is fundamental to take a decision,

fast computations are of utmost importance.
The purpose of [Laurense and Gerdes, 2022] is to develop a novel approach for a real-time NMPC for an autonomous vehicle, which was tested in a race environment, where the objective was to complete a lap in the minimum possible time, while also enhancing computational efficiency. The architecture is a cascaded model composed by a detailed model of the car for the near term, and a less complex model used for a long horizon planning. This concept will be addressed more in detail.
In this report we tried to replicate the architecture of the paper, and we tested it in a simulation environment we created. Our purpose was to show the mean computation time for the cascaded model is lower than the mean computation time for a complete detailed model, with respect to the same length of the horizon.

Report outline

Related Work

Methodology

- Overview/Introduction
  - Concept of MPC for vehicle control
  - Concept of serially cascaded models
- Paper
  - Vehicle dynamic models
  - NLP

Implementation

- Tools and libraries
- Description of implementation process
- Modifications or adaptations wrt the paper

Experimental Setup

- Simulation setting (track etc.)
- Different configuration scenarios

Results

- Guess what

Conclusion

- Take-away message
- Pitfalls and future work

References

[Laurense and Gerdes, 2022] Laurense, V. A. and Gerdes, J. C. (2022). Long-horizon vehicle motion planning and control through serially cascaded model complexity. *IEEE Transactions on Control Systems Technology*.