Master’s Thesis

Learning-based Hybrid Control in Autonomous Driving

Autonomous driving systems require both robust motion planners [1, 2, 3] and reliable controllers [4]. Our chair’s open-source project CommonRoad [5], the motion planning and benchmarking suite, has become a widely recognized and used framework over the years.

Figure 1: Our research vehicle EDGAR.

We are in the process of enriching our open-source project with CommonRoad-Control[1], a toolbox that implements several state-of-the-art controllers. Few open-source projects offer a comprehensive, closed-loop perspective between motion planning and control, so we are the first to close this gap from a practical coding perspective. We have designed a modular architecture for developing control algorithms, integrating them with different dynamic models and closing the loop with state-of-the-art motion planners.

Now, we want to investigate different strategies for automatically configuring, tuning and evaluating the controllers. In this project, you’ll research, develop, implement and evaluate advanced methods tackling these tasks.

Description

This thesis unites a deep knowledge in control with an interest in open-source software development and the application of learning techniques. Good skills and understanding in control and reasonable knowledge in practical learning are prerequisites. With this thesis, you have the chance to learn how to write code that can actually be released as a pipy package. We are planning to (officially) release the toolbox at the end of the thesis.

High-level, we want you to develop a two-facetted approach that (1) uses learning methods to automatically learn / tune relevant parameters of the controller and the dynamics model based on feedback from their execution; and (2) uses a compatible and scalable method to automatically generate reference trajectories for the learning task.

We already have a concept based on dynamic models for the second part. For the first part, promising methods include reinforcement learning [6, 7, 8, 9] and genetic algorithms [10, 11]. However, a deep dive in literature and your interests might expand this list. Note that we use the term learning loosely here, so not only deep learning and reinforcement learning are options.

Tasks

- Familiarization with the current state of the art in motion planning and control.

1 https://optimal-control-ad-personal-repos-bb7de67c51e7f51ec3bda98b62f32.pages.gitlab.lrz.de/introduction/concept/

- Literature deep dive into (learning-based) methods for automatic parameter identification and tuning
- Selection, implementation, training and evaluation of the most promising method(s)
- Implementation and evaluation of our method for creating reference trajectories without scenarios.
- Evaluation of the overall concept of automatically tuning our controllers and dynamic models.

Application

If you are interested in the topic, please send an email to the contact information provided on the right and attach a short CV, your current grade report, and your Bachelor grade report.

Required skills

- Good understanding in control,
- Good Python3 coding skills, practical knowledge in using Ubuntu,
- Interest in applying novel learning algorithms and practical deep learning.

References

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