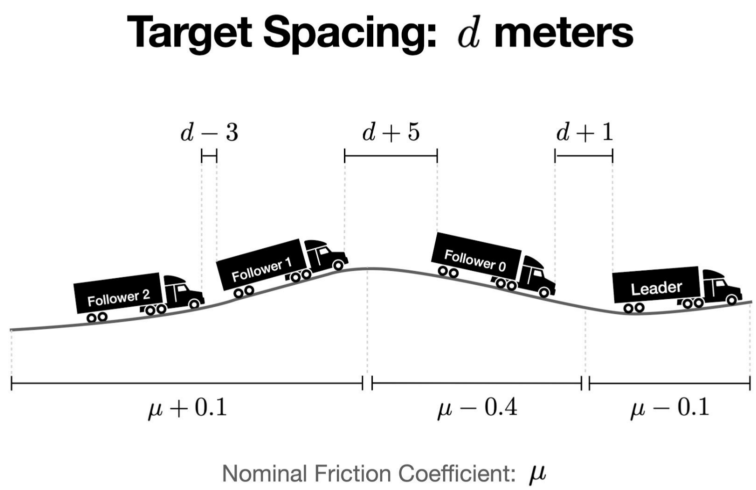
Trajectory Optimization for Vehicle Platoons Using Learning-based Model Predictive Control

Background



Platooning has been identified as one of the key strategies towards a more efficient and sustainable transportation system. A fleet of vehicles are platooning when they are driving close together as a single unit. In ideal conditions, by driving close together, the vehicles are able to reduce their air drag and save fuel. In addition to the fuel savings earned by driving together in ideal conditions, platooning offers several other opportunities: a reduction of needed drivers, improved safety for trucks and nearby road vehicles, etc.

While great progress has been made in recent years, platooning still has some issues that need to be addressed. One issue is disturbance in the road condition. These disturbances can include phenomena such as change in road grade or change in road friction. While there are approaches for handling change in road grade [3], these approaches require hard-to-acquire data on the road topography. Moreover, there are newly developed learning-based model predictive controllers that have the potential to handle these disturbances using data [1][2].

Project Description

This thesis project will evaluate the potential of learning-based model predictive control for maintaining efficient and safe vehicle platoon distances under road condition-related disturbances, such as change in road grade and road friction.

Based on the trajectory optimization proposed in [1], the control problem of platooning will be formulated in the framework of Learning Model Predictive Control. This requires a decomposition of the inter-vehicle distance constraint into local constraints for the individual vehicles. Using data from previous trajectories, the local terminal safe set and the local terminal cost functions for the local MPC problems will be learned and iteratively improved.

The algorithm will be extended to cope with uncertainties in the model and disturbances w.r.t. road conditions for example. A further extension of the algorithm will be in terms of task decomposition, where data from previously driven trajectories can be used on other parts of the road.

Experimental evaluation will be on a fleet of the Small Vehicles for Autonomy (SVEA) platform in the Smart Mobility Lab.

Eligibility

The student should have experience with model predictive control and a familiarity with data-driven techniques. The student should have experience working with robotics projects (experienced with ROS, Python, Ubuntu, Git).

Supervisors

Yvonne Stürz (y.stuerz@berkeley.edu)
Frank Jiang (frankji@kth.se)

References

[1] Zhu, E. L., Stürz, Y. R., Rosolia, U., & Borrelli, F. (2020). Trajectory Optimization for Nonlinear Multi-Agent Systems using Decentralized Learning Model Predictive Control. *ArXiv Preprint ArXiv:2004.01298*.

[2] Stürz, Y. R., Zhu, E. L., Rosolia, U., Johansson, K. H., & Borrelli, F. (2020). Distributed Learning Model Predictive Control for Linear Systems. *ArXiv Preprint ArXiv:2006.13406*.

[3] Turri, V., Flärdh, O., Mårtenssont, J., & Johansson, K. H. (2018). Fuel-optimal look-ahead adaptive cruise control for heavy-duty vehicles. In *2018 Annual American Control Conference (ACC)* (pp. 1841–1848). https://doi.org/10.23919/ACC.2018.8431494