Final Project PCSML Abstract

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1 Abstract

Autonomous cars are growing in popularity, and with the rise of events such as Roborace and the Indy Autonomous Challenge, even more attention is being attracted to the field of autonomous racing. In these races, one or more fully autonomous racecars are deployed on a track and must maneuver around obstacles and other vehicles, at speeds of over 150 mph. In these situations, it is critical that the model and controls for the car are fast and accurate. If the system controlling the car is too slow to adapt to changes in the environment, or gives the wrong controlling commands for a situation, the car could potentially damage itself, other vehicles, and other obstacles on the course. Robust control mechanisms are integral to high-speed autonomous racing.

Model Predictive Control (MPC) is widely used to tackle the challenges associated with path following in a racing situation. As opposed to standard PID or LQR control which operate on single timeframes, Model Predictive Control (MPC) has predictive capabilities, thus providing an anticipation of future events for the vehicle while enforcing relevant constraints. Racecars need to operate at their performance limits in order to win races. Therefore, MPC optimization faces a tradeoff between computational speed and robustness of constraints (e.g. number of constraints).

Over the course of a race, as well as between races, the parameters and dynamics of this model must be updated to remain accurate. Sometimes these parameters are computed with a high degree of error, because better estimations are too computationally expensive for the high speed environment of the race. In order to tackle these two problems, our project will attempt two tasks: (1) estimate the true parameters using a learning-based approach to produce a more accurate model of the car, and (2) express the MPC model itself using scientific machine learning since nonlinear MPC optimization can be expensive to compute.

The basic vehicle model we are planning to use is based on a dynamic bicycle model with the relevant states

$$x = [X; Y; \phi; v_x; v_y; r; \delta; T] \tag{1}$$

where the physical state of the vehicle is described by position $[X; Y]$, heading angle ϕ, velocities $[v_x; v_y]$, and yaw rate r. The relevant parameters include constants related to the tires, rolling resistance, and drag.

We first plan to estimate the true parameters of the vehicle model, which could potentially later on be used to update the model used in MPC, in real time throughout the course of a race (as the parameters change). One approach, based on Kabzan et al and Kamthe and Deisenroth is to implement a probabilistic Gaussian Process transition model that describes the dynamics of the system, which is trained via machine learning [1, 2].

In our second task, we aim to potentially replace the entirety of both internal dynamic control as well as control input optimization in MPC with either a physics-informed neural network (PINN) or with a neural ODE (NODE) [3, 4]. In specific, each layer of the neural ODE ($\in \mathbb{R}^{n_p}$ where n_p is the number of parameters) would aim to capture each parameter-state update, with the number of layers corresponding to the number of discretization steps of the future time window. Hence the output of the NODE would either be the spatial prediction of the vehicle ($\in \mathbb{R}^2$) and/or the updated motor control inputs ($\in \mathbb{R}^{n_m}$) (where r_m is the number of control inputs). If PINNs are used to handle some of the more computationally intensive physical calculations where MPC constrained optimization is too slow, this could prove invaluable. This could improve MPC by both accounting for previously unidentified physical factors, and also by reducing computing complexity, allowing for more robust parameter prediction or vehicle positioning predictions further forward in time.

References

[1] Kabzan, J., Hewing, L., Liniger, A.,Zeilinger, M.N., *Learning-based Model Predictive Control for Autonomous Racing*. IEEE Robotics and Automation Letters. 2019. **4**(4).

[2] Kamthe, S., Deisenroth, M.P., *Data-Efficient Reinforcement Learning with Probabilistic Model Predictive Control*. In International Conference on Artificial Intelligence and Statistics (AISTATS), 2018.

[3] Raissi, M., Perdikaris, P., Karniadakis, G.E., *Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations*. Journal of Computational Physics, 2019.

[4] Chen, R.T.Q., Rubanoba, Y., Bettencourt, J., Duvenoud, D., *Neural Ordinary Differential Equations*. NeurIPS, 2018.