

Self-Driving Car Nanodegree

P5: Model Predictive Controller

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1. Introduction

The purpose of this project was to develop a nonlinear model predictive controller to drive a car around a simulated track. During the simulation the controller based on received information about the car position, speed, heading and waypoints computes optimal car trajectory to secure staying the car on the track. In this project it could be possible to drive safely with the speed 100mph.

2. The Model

In order to provide simplicity of the project the car was modelled as a bicycle with controllable front wheel. Other simplification was applied to physical model where only the kinematics of the vehicle is considered. The dynamics of the car is not considered (forces, frictions, torques and inertias). Kinematic model of the modelled vehicle can be described by following non-linear (depending on time) equations:

$$\begin{aligned}x_{t+1} &= x_t + v_t * \cos(\varphi_t) * \Delta t \\y_{t+1} &= y_t + v_t * \sin(\varphi_t) * \Delta t \\ \varphi_{t+1} &= \varphi_t + \frac{v_t}{L_f} * \delta_t * \Delta t \\v_{t+1} &= v_t + a_t * \Delta t\end{aligned}$$

where, x, y, ϕ and v is a respectively the position, heading and velocity of the car. L_f is the distance between the center of mass of the vehicle and the front wheels and affects the maneuverability.

3. Timestep Length and Elapsed Duration (N & dt)

The parameters timestep length and elapsed duration defines the prediction horizon computed by solver which generates the optimal control signal in respect to defined cost function. Generally, the longer prediction horizon is taken into account, the smoother control of the vehicle is. More timesteps affects the solver response, which needs more time to compute optimal command. It influences the increase of latency, which in real time system should be as low as possible. On the other hand, the shorter prediction horizon decreases the latency but negatively influences on optimal control signal. In this time, the considerable car position overshoots exist.

In order to approach optimal solution the balance between latency and overshoot level had to be elaborated. Several setups of the N and dt were investigated. Finally, successful optimal parameters in this project were figured out and can be presented as follows : N=10, $\Delta t=0.1$.

4. Polynomial Fitting and MPC Preprocessing

In this project the MPC controller first performs a preprocessing of the received data, which by shifting the origin and rotation to align the heading direction is transferred to vehicle coordinate system.

Polynomial fitting is applied to waypoints. Third order of polynomial is used to compute the reference trajectory.

Applied transformation is given by following equations:

$$\begin{aligned} shift_x &= ptsx[i] - px \\ shift_y &= ptsy[i] - py \\ ptsx[i] &= (shift_x * \cos(0 - \varphi) - shift_y * \sin(0 - \varphi)) \\ ptsy[i] &= (shift_x * \sin(0 - \varphi) + shift_y * \cos(0 - \varphi)) \end{aligned}$$

5. Model Predictive Control with Latency

In order to compensate the latency of the controller it is necessary to predict the next state before calling the MPC solver. Due to the lack of dynamic model of the vehicle the next state is computed in use of kinematic model:

$$\begin{aligned} state[0] &= v * \cos(0) * latency \\ state[1] &= v * \sin(0) * latency \\ state[2] &= -v * steeringangle * \frac{latency}{L_f} \\ state[3] &= v + throttle_value * latency \\ state[4] &= cte + v * \sin(epsi) * latency \\ state[5] &= epsi - v * steer_value * (latency/Lf) \end{aligned}$$