Master Thesis

Overtaking assistant algorithm based on model predictive control

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Abstract

It is generally accepted that an anticipatory driving style can yield a substantial contribution to improve efficiency and safety of transport. However, such an anticipatory driving style requires high attention of the driver to assess the traffic situation accurately and presume the correct reactions. Considering country road traffic a high risk is present keeping in mind the high velocities as well as the oncoming traffic participants. This work focuses on overtaking maneuvers on country roads, and a stochastic model predictive control (MPC) algorithm is implemented to manage this task. The behavior of the surrounding vehicles is predicted stochastically by using Bayesian networks. Simulation results show that the control algorithm performs safe maneuvers for all the observed scenarios. Finally, the performance of the controller is compared to the human driver, with a study in a stochastic traffic environment. The results show that the control algorithm provides the safest trip in an acceptable travel time.

Control formulation

In order to use MPC a model of the system is required. Vehicles are highly nonlinear systems making the control objective a difficult task. There exist different models for vehicles e.g. the bicycle model. For control design the simple dynamics of a point mass is used to model the vehicle. Obviously this model is far too simple to describe vehicle dynamics correctly, but the simulations are carried out and validated in the high fidelity vehicle simulator IPG CarMaker. The state-space representation of the model is

$$\begin{bmatrix} \dot{x} \\ \dot{v}_x \\ \dot{y} \\ \dot{v}_y \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ v_x \\ y \\ v_y \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} a_x \\ a_y \end{bmatrix}. \tag{1}$$

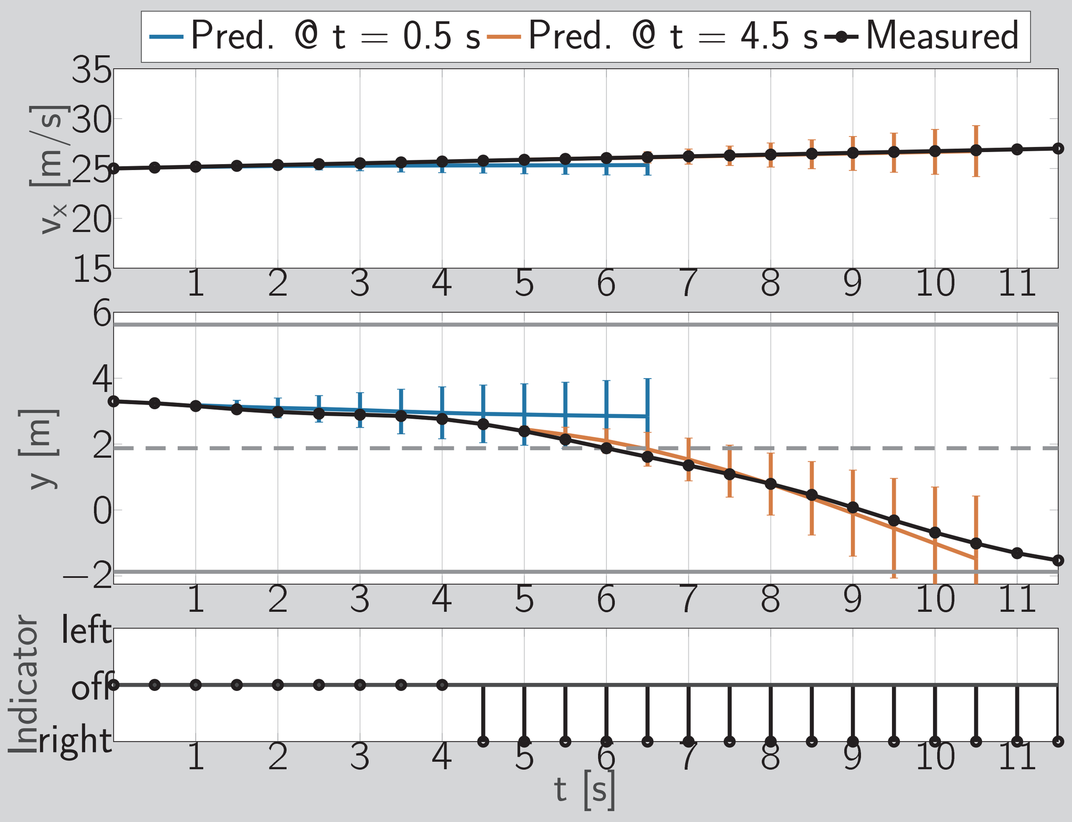
To be able to avoid the surrounding vehicles, a prediction is necessary. For the sake of simplicity often first principles like constant velocity or constant acceleration are used. Bearing in mind the behavior of humans, a deterministic prediction may not be sensible. Therefore, a stochastic prediction for the lateral position $y^{(S)}(k+i|k)$ and longitudinal velocity $v_x^{(S)}(k+i|k)$ is used, where S refers to the corresponding surrounding vehicle. The prediction model provides the mean values and the standard deviations of the aforementioned quantities at each prediction step. In order to assess the safety risk so-called time induced risk functions are considered. The used one is the time to collision (TTC). It is defined as the time for two vehicles to collide if they keep their current speeds. Furthermore, there exist constraints on the ego. The control formulation is shown in the following.

$$\begin{aligned}
\min_{u^{(E)}(k+i|k)} \sum_{i=0}^{N} & \left(\mathbf{x}^{(E)}(k+i|k) - \mathbf{x}_{\text{ref}}^{(E)}\right)^T Q \left(\mathbf{x}^{(E)}(k+i|k) - \mathbf{x}_{\text{ref}}^{(E)}\right) + \\
& + \left(\mathbf{u}^{(E)}(k+i|k)\right)^T R\mathbf{u}^{(E)}(k+i|k) + \\
& + \left(\Delta\mathbf{u}^{(E)}(k+i|k)\right)^T R_{\Delta u}\Delta\mathbf{u}^{(E)}(k+i|k) \\
& \text{s.t.}
\end{aligned}$$

$$\begin{aligned}
\mathbf{x}^{(E)}(k+i+1|k) &= A\mathbf{x}^{(E)}(k+i|k) + B\mathbf{u}^{(E)}(k+i|k) \\
\mathbf{x}^{(E)}(k+i|k) &\in \left[\underline{\mathbf{x}}^{(E)}, \overline{\mathbf{x}}^{(E)}\right], \mathbf{u}^{(E)}(k+i|k) \in \left[\underline{\mathbf{u}}^{(E)}, \overline{\mathbf{u}}^{(E)}\right] \\
v_y^{(E)}(k+i|k) &\in [-\tan(\beta), \tan(\beta)] v_x^{(E)}(k+i|k) \\
-x^{(E)}(k+i|k) &\leq -\overline{x}^{(S)}(k+i|k) - cL \\
&\quad - \text{TC}_{\min}\left|\overline{v}_x^{(S)}(k+i-1|k) - c v_x^{(E)}(k+i-1|k)\right| + M\left(\beta_1^{(S)} + \beta_2^{(S)}\right) \\
x^{(E)}(k+i|k) &\leq \underline{x}^{(S)}(k+i|k) - cL \\
&\quad - \text{TC}_{\min}\left|v_x^{(E)}(k+i-1|k) - c \underline{v}_x^{(S)}(k+i-1|k)\right| + M\left(1 - \beta_1^{(S)} + \beta_2^{(S)}\right) \\
-y^{(E)}(k+i|k) &\leq -\overline{y}^{(S)}(k+i|k) - l + M\left(1 + \beta_1^{(S)} - \beta_2^{(S)}\right) \\
y^{(E)}(k+i|k) &\leq \underline{y}^{(S)}(k+i|k) - l + M\left(2 - \beta_1^{(S)} - \beta_2^{(S)}\right) \\
\beta_1^{(S)}, \beta_2^{(S)} &\in \{0, 1\}
\end{aligned}$$

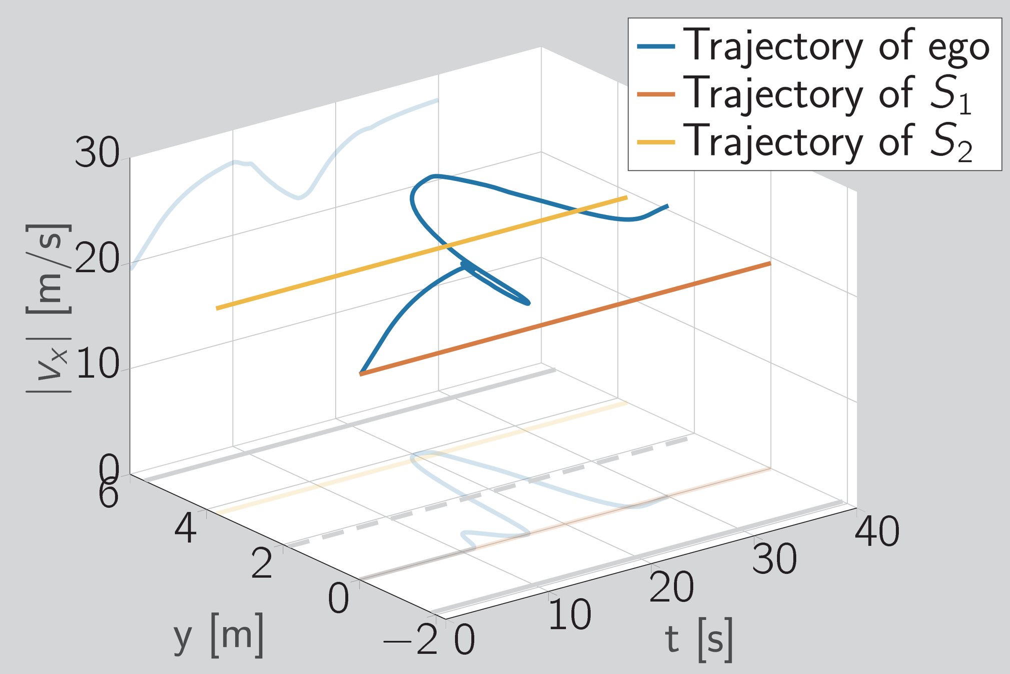
Prediction Model

The prediction model allows to predict the longitudinal velocity and the lateral position with a Gaussian distribution. The figure shows a real trajectory and the predictions of the stochastic model. It can be seen that the velocity is predicted almost perfectly, while also the prediction of the position shows satisfactory results. For the second prediction the blinker is set, which evidently affects the prediction and allows for a good prediction of the real trajectory.



Simulations results

One of the scenarios which is observed describes the simplest possible country road scenario. There exists one preceding vehicle on the same lane and one vehicle on the adjacent lane moving in the other direction. Considering the human behavior when overtaking on a country road, either it is done in one maneuver if the oncoming vehicle is far away or there is no oncoming vehicle at all, or the vehicle is moved slightly to the line marking and then the situation is evaluated. A similar behavior as the last one can be observed from the controller trajectory. The results for this scenario are shown in the figure below.



Furthermore, the controller is evaluated in a stochastic traffic environment that automatically generates traffic scenarios of different complexity. The controller is compared to that of real human drivers on the same route. The results of this evaluation are presented in the table below. Looking at the mean value of the final time, it is visible that the control algorithm performs better than the drivers. It must not be neglected that the velocity plays a major role on the final time, thus the speed limit violations are of interest in that context. One can see that except for one student the speed limits are violated significantly. Hence, it is obvious that a smaller final time is achievable. Considering the accidents, it is shown that the control algorithm drives safer compared to the human test drivers. Finally, the executed overtakings are studied. It can be seen that the controller outperforms the drivers except for one student. This explains why the final times are similar even though the human drivers highly violate the allowed speed limit.

	t_f [s]	accidents	$t\,(v > v_{\text{ref}})$ [s]	overtakings
Controller	226.29	0/1	0.5	12
Student 1	223.27	0/1	87.1	9
Student 2	224.88	0/2	10	12
Student 3	236.86	0/2	60.4	9
Student 4	243.18	1/2	74.2	8
Student 5	220.63	0/3	61.6	10
Mean	229.78	-	58.66	9.6

Conclusion

This work shows an implementation for autonomous overtaking on country roads by using collision avoidance constraints in an MPC formulation. Furthermore, a prediction of the movement of surrounding traffic participants is introduced. In order to cope with the stochasticity of usual traffic situations, a stochastic prediction model based on real country road measurements is used. The functionality of the algorithm is shown for different scenarios with varying complexity. Finally, the proposed control algorithm is compared to the driving behavior of humans in a dedicted study scenario.