Master's Thesis

Cost switching Lane-Change Adaptive Cruise Control (LC-ACC)

Author: Jakob Holzinger
Supervisor: Univ.-Prof. DI Dr. Luigi del Re
Dr. Pavlo Tkachenko
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Abstract

This thesis presents a novel approach to investigate traffic information for the development of better ACC systems. The goal is to incorporate this information into the control algorithm of an ACC to decrease conservativity and increase performance in certain traffic conditions.
At first, two generic performance indicators, namely fuel economy and comfort, are defined and used for traffic analysis. Data from naturalistic driving behavior are analyzed in order to find traffic situations which are more likely to offer optimization potential for one of the performance indicators. In a second step, regression analysis and machine learning are applied to describe these conditions mathematically and to find interesting clusters of traffic situations.
A two layer control structure for the high fidelity vehicle simulator IPG CarMaker is used to analyze the impact of different priorities of control objectives. The acceleration trajectories are computed by model predictive control (MPC) and translated into throttle, brake and steering inputs by lower level controllers. For collision avoidance, a stochastic traffic prediction model is introduced and trained with real world data.
Simulation of the ego car in an interesting traffic condition showed that indeed, it is more sensible to concentrate on improving comfort instead of fuel efficiency. A considerable advantage in comfort was possible while the increase in fuel consumption was comparatively low. However, several difficulties for validating such ACC systems have been identified and substantiated.

Performance Indicators and Data Analysis

Throughout this work, naturalistic driving data from the highD dataset is used to answer the question whether the performance of an ACC can be improved in certain conditions. Therefore, it is necessary to define performance indicators (KPIs). Comfort, described by quadratic jerk normalized in time (1), was chosen as first KPI because ACC was primarily developed to improve comfort. As second KPI, fuel consumption was chosen.

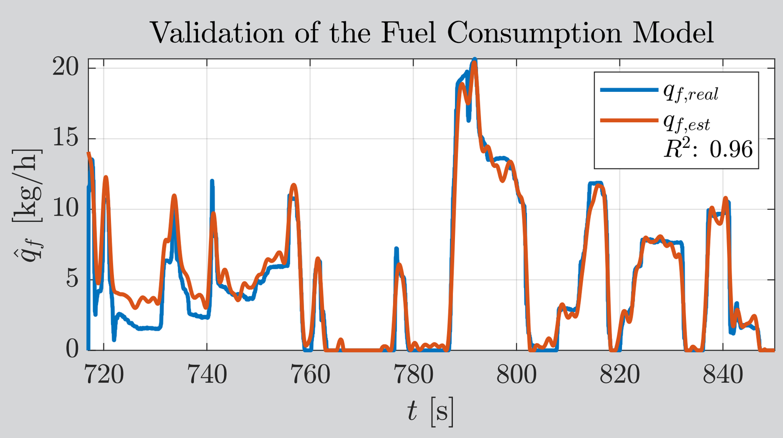
$$J = \frac{\dot{\mathbf{a}}^T\dot{\mathbf{a}}}{T_{car}} \quad (1)$$

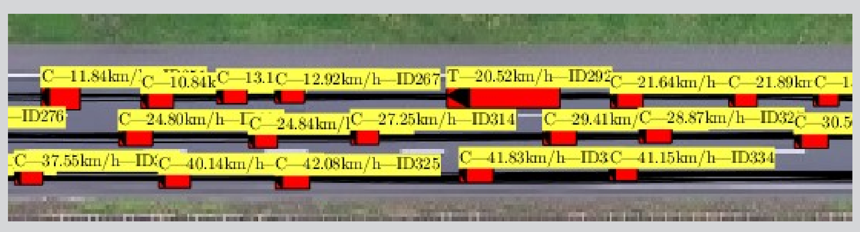
$$F_{\text{wheel},k} = \lambda \hat{m} a_k + c_w A \frac{\rho}{2} v_k^2 + c_{fr}\hat{m}g \quad (2a)$$

$$P_{\text{engine},k} = \frac{F_{\text{wheel},k} \cdot v_k}{\eta} \quad (2b)$$

$$\hat{q}_{f,k} = \max(0, P_{\text{engine},k} \cdot \text{BSFC}) \quad (2c)$$

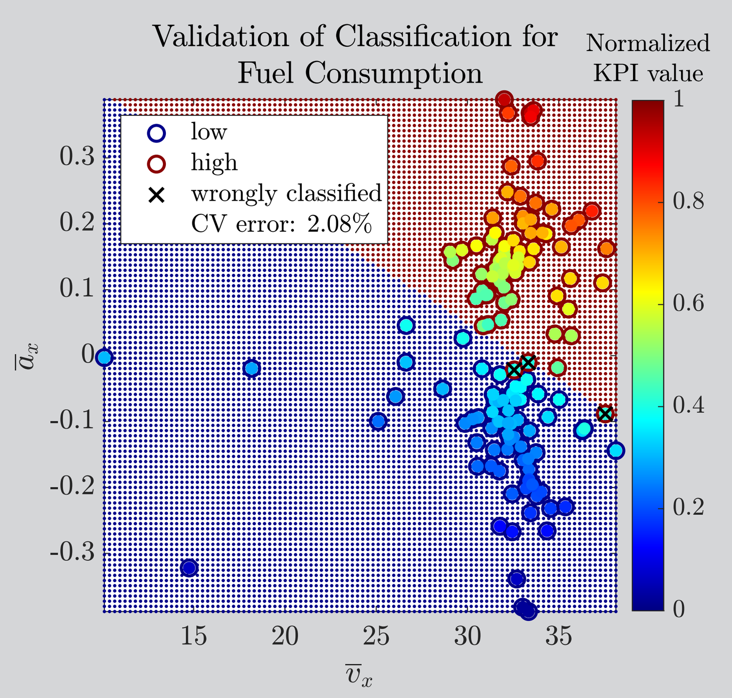
Naturally this is an important measure for the end user and can be easily interpreted. However, since there is no direct data of the vehicles fuel consumption available in the dataset, a fuel consumption model was introduced. At first, a cars weight is estimated with a regression model based on its footprint. In a second step, first order principles were applied to compute the current fuel consumption based on the dynamic data of the car (2). In order to describe a macroscopic traffic condition, coherent clusters of cars are introduced. Since there is no such thing as a KPI for a traffic condition, a reasonable way of describing it, is to use probability density functions (PDFs) derived from the KPIs of individual cars. Analyzing these PDFs, an interesting traffic condition (right picture) could be found that is probable to cause low low comfort and low fuel consumption and thus shows clear optimization potential for comfort.

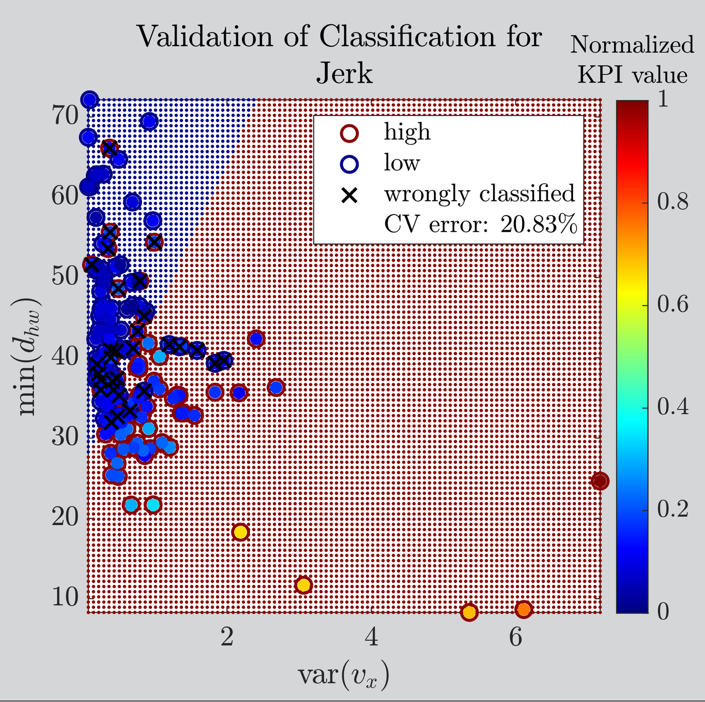




Description and Classification of Traffic Conditions

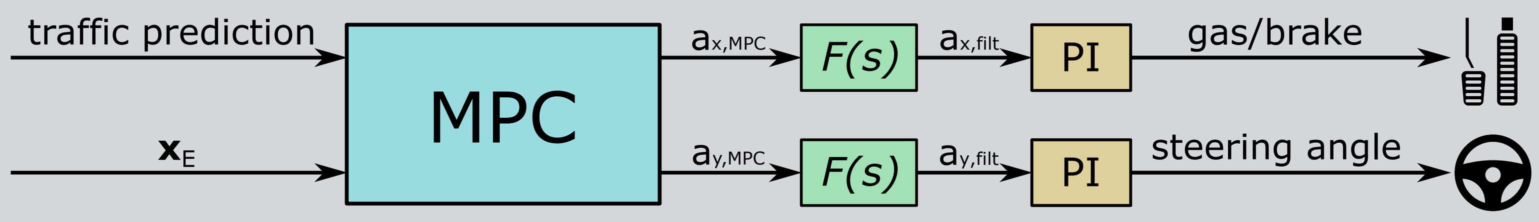
Macroscopic features like $\overline{v}_x$, var(a_x), var(v_x), min(TTC) or number of lane changes per car are introduced to mathematically describe traffic conditions. Classification was then used to find interesting clusters of traffic conditions that cause high or low KPIs. For that reason, the traffic conditions are labeled into causing high or low KPIs and a feature selection method was applied to find pairs of two features that are best suited to describe the KPIs.





Controller Design

A hierarchical control structure using high level model predictive control (MPC), low level PI controllers and fast low pass filters $F(s)$ is used to compute desired acceleration trajectories and to compensate for nonlinearities, respectively. The virtual steering and pedal inputs are then applied to the high fidelity IPG CarMaker model of a BMW sedan.



The optimal control problem (3) is solved for the prediction horizon at every time instant k. Collision avoidance was implemented by a stochastic MPC due to the meaningful treatment of uncertainty. For that reason, second order Markov chains were trained with real world data to predict the motion of cars in the near future.

$$\min_{\mathbf{u}_{(k+i|k)}} J_{\text{obj},k} \quad (3a)$$

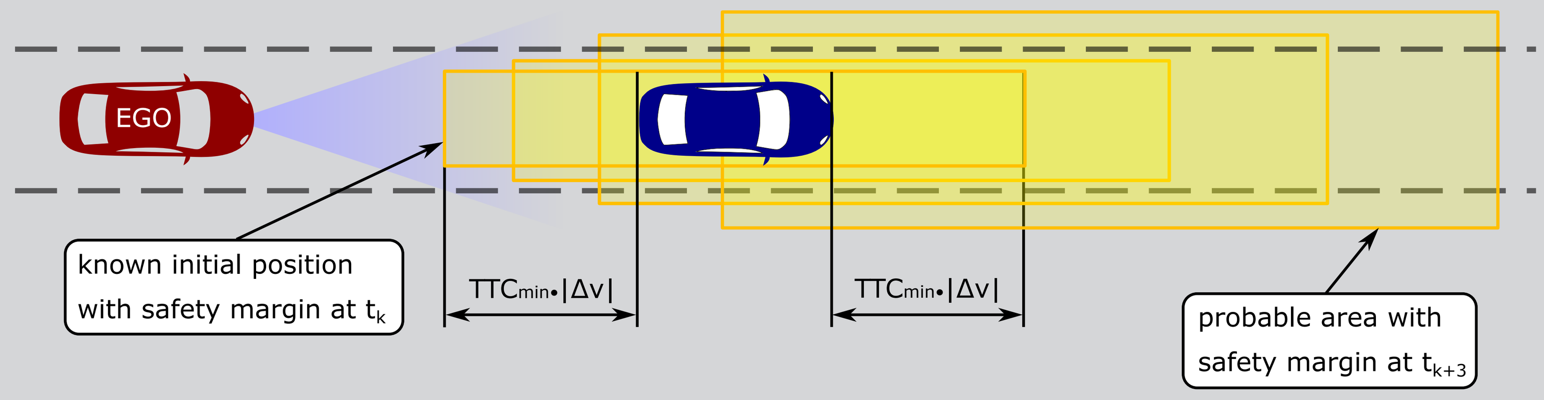
$$\text{s.t.} \quad \mathbf{x}_{(k+i+1|k)} = \mathbf{A}_d \mathbf{x}_{(k+i|k)} + \mathbf{B}_d \mathbf{u}_{(k+i|k)} \quad (3b)$$

$$\mathbf{u}_{(k+i|k)} \in [\underline{\mathbf{u}}, \overline{\mathbf{u}}] \quad (3c)$$

$$\mathbf{x}_{(k+i|k)} \in [\underline{\mathbf{x}}, \overline{\mathbf{x}}] \quad (3d)$$

$$v_{y(k+i|k)} \in [-\tan(\beta), \tan(\beta)] v_{x(k+i|k)} \quad (3e)$$

$$\text{collision avoidance (figure below)} \quad (3f)$$



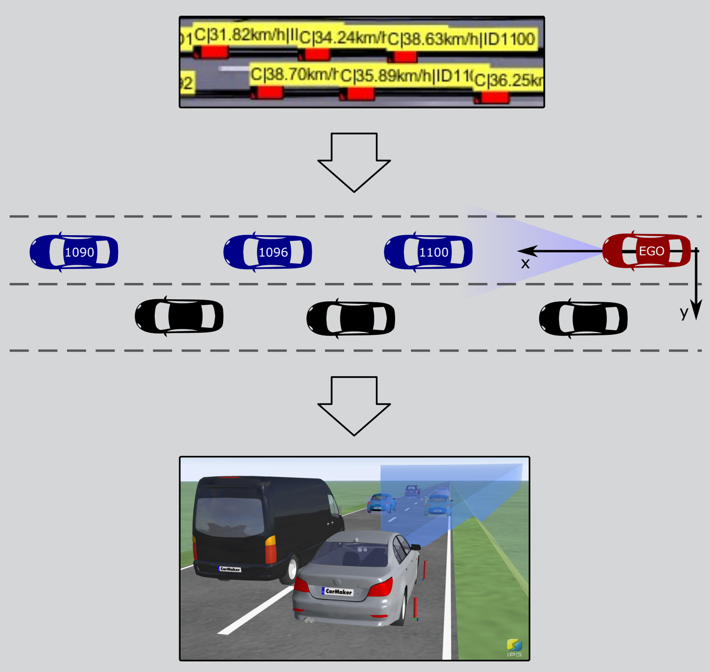
The cost function (4) has been designed so that one can shift the focus between the secondary objectives economy and comfort with a parameter $\lambda \in [0, 1]$.

$$J_{\text{obj},k} = J_{\text{track},k} + (1-\lambda) J_{\text{eco},k} + \lambda J_{\text{comfort},k} \quad (4)$$

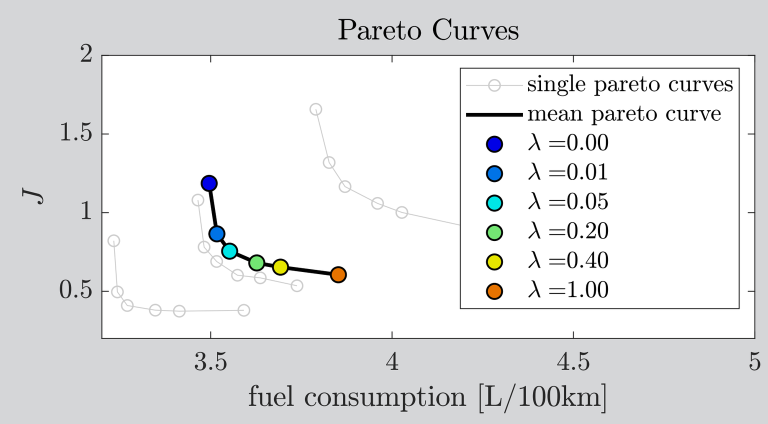
Simulations

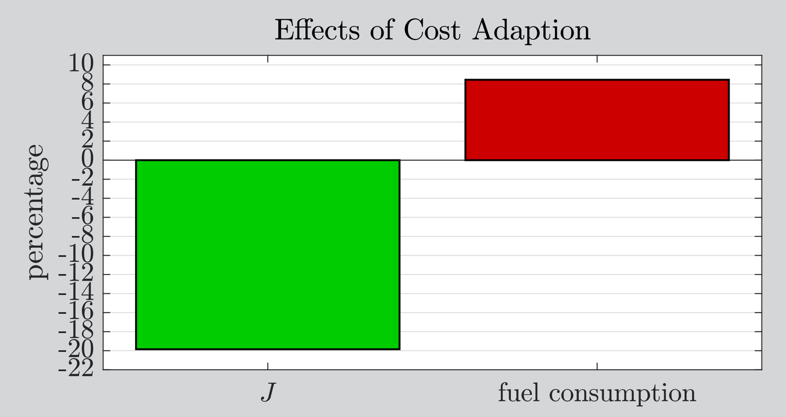
An example convoy from the interesting dense traffic condition was chosen to be simulated. Three cars from the highD dataset, whose driving behavior could be clearly classified as low comfort and low fuel consumption, are used as preceding cars for the controlled ego vehicle. The goal of the simulation is to investigate the trade-off between fuel consumption and comfort. Therefore, a λ-vector

$$\boldsymbol{\lambda} = [0,\ 0.01,\ 0.05,\ 0.2,\ 0.4,\ 1] \quad (5)$$



is introduced to gradually shift the focus of the optimization problem (3). After simulation, the KPIs can be directly calculated from the simulated data. The results are three gray trade-off curves for the three simulated positions of the ego car and the mean pareto curve in black. The effect of a suggested cost adaption from a reasonable base setup $\lambda_{\text{base}} = 0.05$ to the most comfortable setting $\lambda_{\text{adapted}} = 1$ is shown in the lower right figure. It has been possible to achieve a considerably higher comfort at the price of a reasonable small trade-off in fuel consumption.





Conclusion and Outlook

Other than the title indicates, no cost switching law could be derived due to different factors. The dataset and the controller simply were not suitable to simulate overall traffic conditions, rather than a scenario. Most of the highD dataset's trajectories offer too low simulation run times in order to derive meaningful differences in fuel consumption or jerk. However, due to traffic analysis we learned that there are indeed conditions that offer potential for optimization. In conclusion, the thesis can be seen as pre-studies which helped to gain insights in traffic analysis and it pointed out some difficulties which can be considered in future work.
Traffic analysis itself is an interesting approach that opens new possibilities for advanced driver assistance systems (ADAS). Other datasets could be investigated and new traffic features like curvature or light conditions could be introduced. For example, different weather conditions or daytimes might lead to interesting changes in driver behavior. Most importantly, however, a flexible simulation environment is needed to validate the performance of adaptive control algorithms and to make use of overtaking. In addition, the control structure must be refined for natural lane changes in multi lane environments. Regarding KPIs, one could try to define other ones (e.g. travel time or emissions) that make it easier to derive a cost switching law.