Master Thesis

Stochastic Model Predictive Control applied to Cooperative Adaptive Cruise Control

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Abstract

Modern cars feature a variety of different driving assistance systems, which aim to improve driving comfort and safety as well as fuel consumption. Recent developments in the field of intelligent transport systems and the increasing possibilities to establish communication between traffic participants allow the consideration of surrounding traffic's actions and motivations for a variety of driving assistance and safety function. The presented cooperative adaptive cruise control (CACC) approach deals with an urban traffic environment and utilizes V2V and V2I information. The basic goals of CACC are to ensure safety and reduce the risk of crashes in a vehicle following scenario. Besides, the control actions that are necessary for this goals are chosen in a way that the fuel consumption is minimized. For this reason the predecessor's velocity is predicted and incorporated into different stochastic model predictive control (MPC) algorithms. A conditional Gaussian model is used to estimate the probability distribution of the upcoming velocity of the preceding vehicle based on current measurements and upcoming traffic light signals. Finally, the stochastic control algorithms are evaluated in a virtual traffic simulation and compared against deterministic approaches.

Cooperative Adaptive Cruise Control

- Expansion of ordinary adaptive cruise control in an urban, vehicle-following traffic scenario
  - improve safety and driving comfort while relieving the driver
  - reduce fuel consumption through anticipatory driving
- Take advantage of information provided by Intelligent Transport Systems
  - increasingly networking between traffic participants and environment
  - CACC utilizes vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communication systems for driver behavior prediction
- Exploitation of a variable spacing policy to conserve kinetic energy
  - inter-vehicle distance is variable and constrained: $d_{min} \le \Delta x \le d_{max}$
  - theoretical fuel saving potential of 7-20% in urban traffic

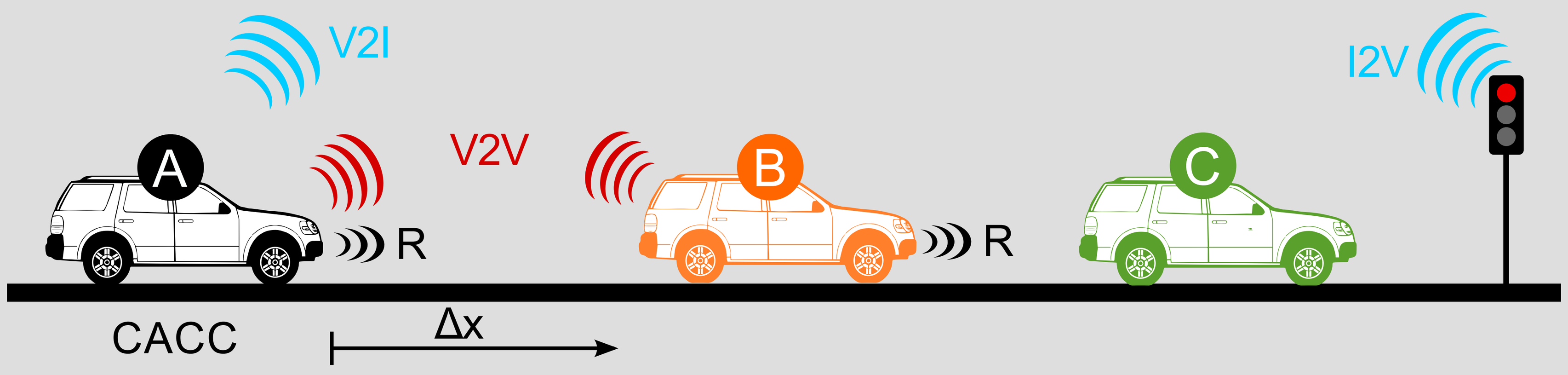


Illustration of communication between vehicles (V2V) and infrastructure (V2I). Vehicle A is the controlled vehicle that follows vehicle B while exploiting variable spacing policy.

Stochastic velocity prediction of a vehicle

- Prediction of the predecessor's velocity v_B up to $h_P = 15$s is necessary for planning fuel optimal control actions for brake or accelerator pedal
  - inclusion of driver's reaction on traffic participants and traffic light signals
  - covering the non-deterministic driving characteristics of humans through predicting distribution function of future velocity

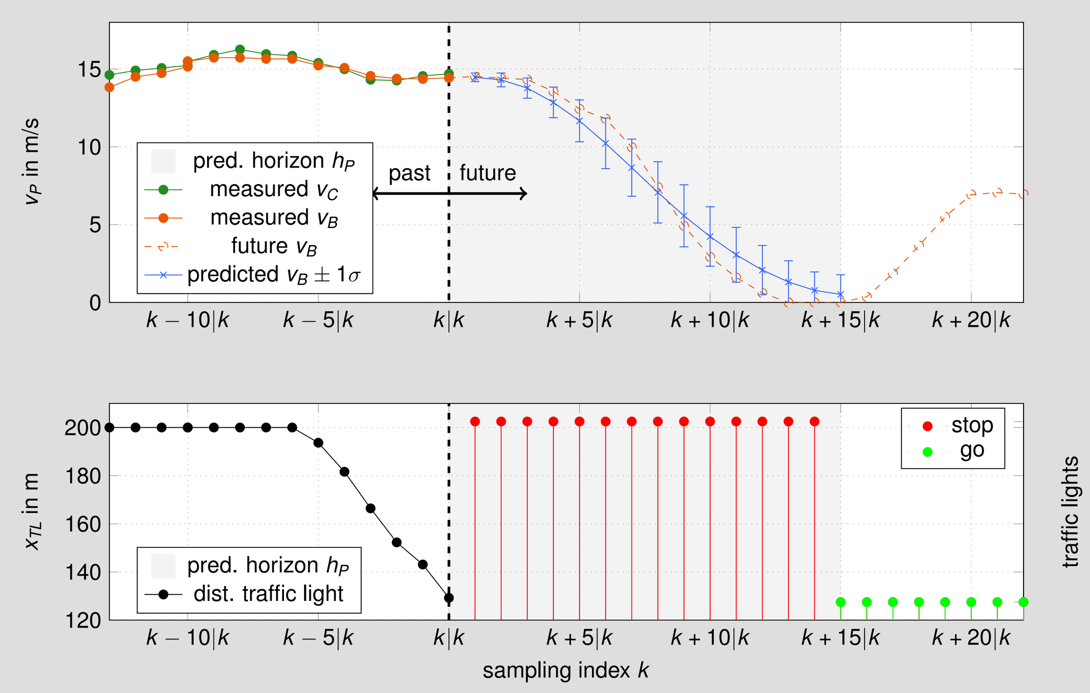


Illustration of model inputs at time instance k: based on the distance to the next red traffic light x_{TL}, the future traffic light signals δ_{TL}, current and past velocity values of vehicles B and C, the distribution function of the velocity v_B is estimated for a prediction horizon $h_P = 15$s

Stochastic MPC – optimal decisions under uncertainty

- Minimization of the fuel consumption q_f in a receding horizon manner
  - non-linear function depended on velocity v, acceleration a and engaged gear g
  - uncertain future disturbance input v_B modelled by a conditional Gauss distribution

$$\min_{a_k, g_k} \sum_{i=0}^{h_P-1} q_f(v_k, a_k, g_k)$$

- Improving safety by constraining the violation probability α of a constraint

$$\mathbb{P}\left[\Delta x_{k+i+1} \le d_{min} + h\bar{v}_{k+i+1}\right] \ge \alpha_i \quad i \in [0, 1, \dots, h_P]$$

- Comparison of deterministic (D-MPC), chance constrained (CC-MPC) and randomized (R-MPC) model predictive control approaches
  - D-MPC: neglects the uncertain velocity prediction by using exclusive the mean value
  - CC-MPC: constraint tightening using inverse cumulative Gauss function $\Phi^{-1}(\cdot)$

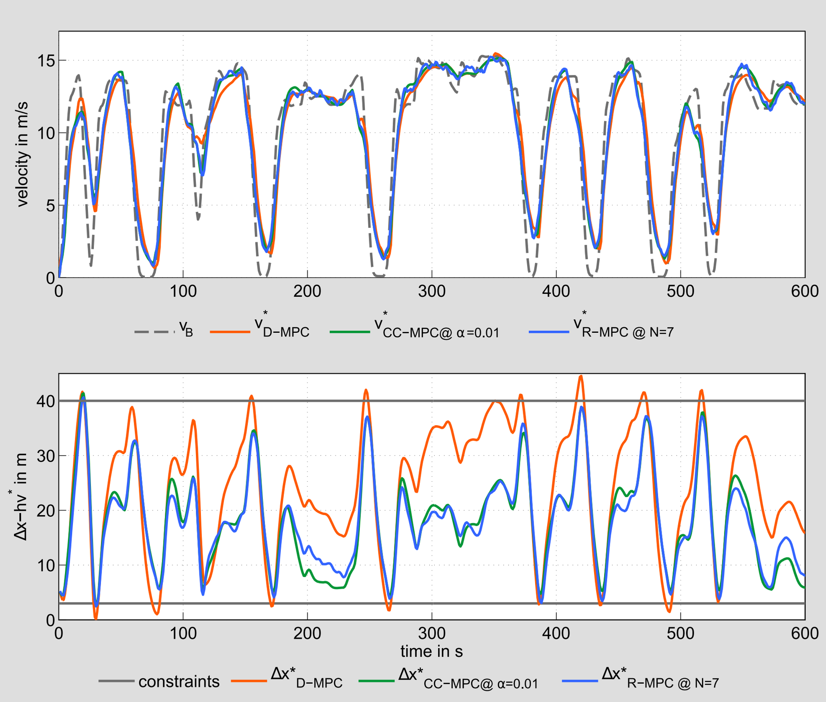
$$\overline{\Delta x}_{k+i+1} \ge d_{min} + h\bar{v}_{k+i+1} + \Phi^{-1}(1-\alpha)\Sigma^{1/2}_{\Delta x_{k+i+1}} \quad i \in [0, 1, \dots, h_P]$$

  - R-MPC: N samples of future disturbance realization are drawn according to its probability distribution, then the optimal solution is determined by solving

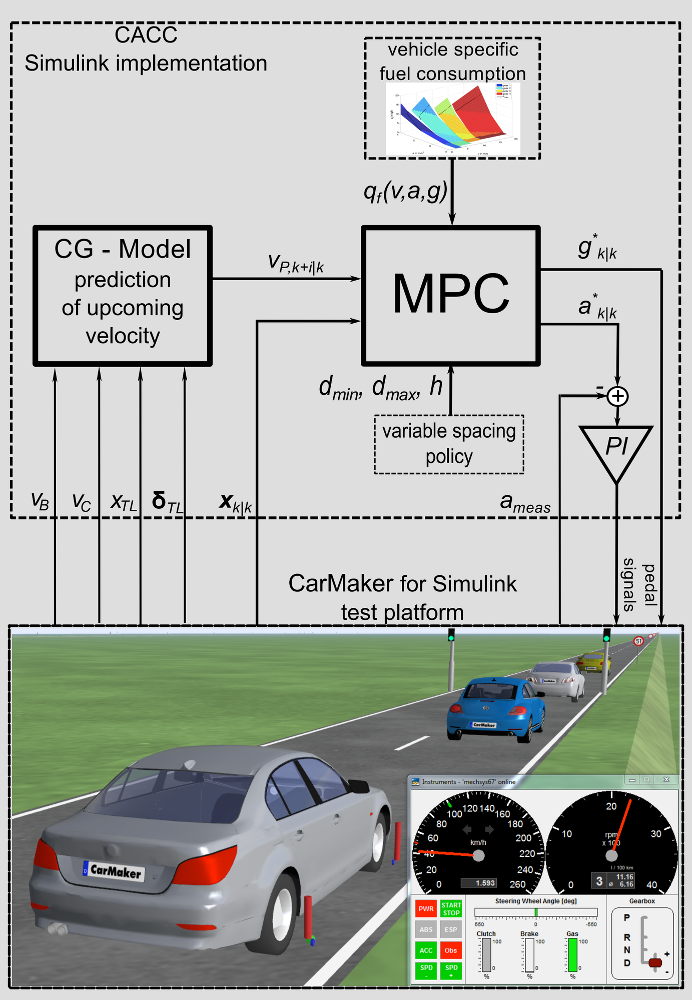
$$\min_{a_k, g_k} \left[\max_{v_B^{(n)} \in \mathcal{V}_{B,\epsilon}} \sum_{i=0}^{h_P-1} \hat{q}^{(n)}_{f,k+i|k} \right] \quad n \in [1, \dots, N]$$

Evaluation with a virtual traffic simulation

- Evaluation in a 600s long cycle with 9 differently timed sets of traffic lights
- Vehicle B and C are autonomous driving



Velocity trajectories and inter-vehicle distance for D-MPC, CC-MPC and R-MPC



Simulation structure

Performance: fuel consumption vs. constraint violation

- CC-MPC outperforms D-MPC and R-MPC by achieving
  - a lower number of constraint violations n_{LB} and n_{UB}
  - a lower fuel consumption Q_f

	preced. vehicle	CACC MPC			
		D-MPC [1]	D-MPC	CC-MPC	R-MPC
n_{LB}	—	0	22	3	2
n_{UB}	—	1	29	3	2
$Q_{f,rel}$	100%	82.3%	87.2%	84.6%	90.5%

[1] perfect prediction

Conclusion & Outlook

- Achievable fuel savings of up to 15.4% using the prediction model and the CC-MPC
- Potential expansions and enhancements of the presented CACC approach
  - incorporation of an optimal gear selection with optional declutching
  - expansion to hybrid power trains and start-stop system
  - consideration of additional traffic scenarios (e.g. overland, stop and go)
- Evaluation of the controllers in a real urban traffic situation