

A Parameter Estimator for a Model Based Adaptive Control Scheme for Longitudinal Control of Automated Vehicles

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Abstract: In order to improve the longitudinal control behavior of automated vehicles, a predictive control scheme with an adaptive vehicle state and parameter observer is proposed. The underlying nonlinear model of vehicle and powertrain dynamics makes use of the estimated torque signal which is calculated in the engine management system, as well as of vehicle speed and acceleration measurements. An Extended Kalman Filter is implemented to both estimate filtered vehicle states and the vehicle mass. Simulation results show good convergence of the parameter estimate. The contributions of this paper build the foundation to further examine the potential of improvement in fuel savings, planning accuracy and passenger comfort.

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1. INTRODUCTION

The general task of motion control of automated vehicles can be separated in three main parts: First, a motion planning instance is planning a path and speed profile or a trajectory. This instance needs to deal with the nonholonomic properties of the vehicle and plans several maneuvers to a goal. Second, a path following or trajectory controller calculates a steering angle command for lateral motion and a desired vehicle acceleration (or tire force in some implementations) for the longitudinal motion of the vehicle. Third, these commands are passed to actuator controllers which transform them into input commands for the actuators. In case of longitudinal control, this input command is the accelerator pedal, engine throttle or torque demand value (depending on the interface to the engine control unit) as well as a brake demand value. The controller also has to consider vehicle and powertrain dynamics or compensate for the resulting effects and other disturbances.

Precise trajectory following is essential for different reasons. For example, big deviations from the reference point on the trajectory do not allow to perform time critical scenarios. If for example a vehicle plans to enter an intersection just before an intersecting car and the vehicle lags behind its planned position, the risk to create unwanted traffic scenarios or even accidents increases significantly. Or, assuming that this effect is known to the engineers calibrating the planning algorithms, it has to be considered as uncertainty which leads to an overly defensive planning behavior. For the same reason, if longitudinal deviations are too high, vehicles trying to build a platoon need to keep larger safety distances up to a point where the fuel saving effect of forming the platoon is reduced drastically. Also in

regular automated operation, the efforts of the controller to compensate for deviations from the planned trajectory lead to overshoots in the torque demand to the engine, which has a negative effect on fuel consumption. There is big potential in fuel savings if smooth accelerations can be realized. Furthermore, speed and acceleration overshoots can be felt by passengers and hence have a negative effect on passenger comfort. High efforts have been done in recent years to optimize driveability for conventional vehicles working in open loop manual operation, where the driver sets the desired acceleration via the throttle pedal, but they mostly focus on reducing disturbances at high frequencies due to gearshifts or load changes.

Fully automated vehicles need to be able to cope with conditions appearing at steep hill climbing and parking a vehicle onto a target point at an accuracy of a few centimeters. These scenarios require a very accurate longitudinal actuator controller which is capable of compensating for road slope, friction and rolling resistances and takes into account changes in vehicle mass.

Available solutions for closed loop operation highly focus on cruise control or adaptive cruise control mode, scenarios in which vehicles are operating at higher speeds in areas where the influence of road gradients can be neglected.

To realize such a controller, it is necessary to take into account major effects of powertrain and longitudinal vehicle dynamics whilst keeping complexity low to reduce computational resource demand. This paper proposes an improved control scheme for longitudinal control of automated vehicles. The implementation of this control scheme consists of three parts. First, the derivation of a dynamical longitudinal vehicle model containing the effects of road slope, friction and rolling resistance. Second, the imple-

mentation of a state and parameter estimator which is able to quickly adopt for changes in vehicle mass. These two parts together with the definition of the control scheme are contributions of this paper, whereas the third part, the implementation of the model based controller is left to future work.

In the following, the remainder of the paper will give an overview over related work in Section 2, explain the planned controller structure in Section 3, derive the longitudinal vehicle dynamics in Section 4, before explaining the state and parameter estimator in Section 5. Simulation results are given in Section 6 before Section 7 gives a conclusion.

2. RELATED WORK

In several publications about autonomous vehicles one can find solutions for longitudinal controllers. Many publications appeared about the participants of the DARPA Urban Challenge during which many teams including the winning Tartan Racing Team (Urmson et al. (2008)) as well as Ben Franklin Racing Team (Bohren et al. (2009)) were using a solution directly actuating throttle and brake pedal via an electromechanical actuator instead of being able to use the torque interface. With such a solution, due to mechanical backlash effects it is very hard to accurately control vehicle acceleration. They further mention the use of a proportional-integral (PI) controller after linearization of throttle and brake dynamics.

Team AnnieWAY as well as Daimler's Bertha Drive Vehicle described in Ziegler et al. (2013) mention to use the integral anti-windup feedback controller from Geiger et al. (2012) to reactively compensate for disturbances like aerodynamic drag and road slope, but do not actively consider the resulting forces in their controller.

The vehicle described in Aeberhard et al. (2015) about BMW Group's Highly Automated Driving Project uses a combination of controllers published in Werling (2010) and Bartono (2004). Werling (2010) mentions to calculate the desired tire force in the trajectory controller part and uses a separate controller with a simple anti windup integrator to compensate for wind drag, road slope and vehicle mass changes. It does not make use of the torque interface but mentions to directly calculate the desired throttle angle out of a map with desired longitudinal force and engine speed as inputs. This map together with a speed dependent compensation term needs to be calibrated in vehicle experiments with much effort.

Bartono (2004) uses an inverse powertrain model to calculate the desired engine torque out of the desired vehicle acceleration. To reduce modeling effort, the model does not directly take into account road slope, wind- or rolling resistance nor the effect of changing vehicle mass. The sum of all these effects are modeled as a resulting disturbing acceleration which is estimated in a disturbance observer. Since the work focuses on the special case of following a lead vehicle in Adaptive Cruise Control (ACC) and Stop & Go scenarios, this disturbance observer is implemented using the distance information to the lead vehicle and hence cannot be used in scenarios without a lead vehicle.

Gehrling (2000) focuses on control schemes for vehicle platoons and presents a control loop for acceleration control using feed forward control to linearize the nonlinear vehicle dynamics. Throttle angle is used as input variable to the engine, probably lacking the existence of a modern torque based engine control management. The relation of acceleration, speed and throttle angle is approximated in an experimentally derived map. The influence of vehicle mass, road grade is not considered in this approach, except that resulting disturbances are compensated by a PID controller.

Sauter and Flad (2014) designs an ADAS which decreases the drivers pedal position value in order to realize savings in fuel consumption. A Model Predictive Controller (MPC) scheme is used to determine this accelerator pedal value difference, although the paper also states the difficulty of this approach due to missing predictions of the drivers future pedal values. Since the accelerator pedal is used as an input variable to realize torque, a lookup table is used to map the engine torque prediction depending on engine speed and accelerator pedal, an approach which is not as accurate as using the more complex model inside of an engine control unit. In the vehicle model, road slope and friction is considered, whereas vehicle mass is modeled as a constant value.

André et al. (2015) converts accelerator pedal value into half shaft torque, which is considered proportional to acceleration but neglecting resistance. This approach is considered good enough for a more or less exact interpretation of the pedal value as the drivers acceleration demand but not suitable for achieving an exact acceleration value in automated trajectory control. Vehicle mass is estimated in a Kalman filter but the paper does not take into account aerodynamic drag or road resistance.

As seen in this section, todays longitudinal controllers for highly automated vehicle operation have the following drawbacks: First, none of the controllers actively take into account the effects of changing vehicle mass or changes in road slope but treat them as disturbances. This leaves compensation to the feedback controller in a reactive way, which is less effective than proactively take countermeasures before deviations from the desired trajectory occur. Second, although the planning module calculates trajectories containing future demand values, none of the control schemes make use of this information but only use the current acceleration or longitudinal force demand value to command an actual torque demand value to the engine (or brake in case of deceleration). With the knowledge of future demand values in the case of automated driving in contradiction to the case of manual operation, where no information about the future plans of the driver is available but has to be predicted, one can make use of this information throughout the whole controller chain.

Different theoretical foundations exist for designing stabilizing nonlinear MPCs (see de Nicolao et al. (1998), Wan and Kothare (2003), Magni and Scattolini (2006)). Another difficulty for nonlinear MPC is the real time implementation on an embedded platform. Here recent advances have been made to create solutions with reduced computational load. For example, many advances have been made on solving the involved optimal control problem

efficiently (see Biral et al. (2016) for an overview). Further, Explicit NMPC (Johansen (2004), Alessio and Bemporad (2009)) can be used to solve the optimal control problem offline and store the solutions to reduce the online computational load to that of a (highly dimensional) look-up table search.

3. PROPOSED CONTROLLER STRUCTURE

Therefore, we propose the following controller structure (see Figure 1): A motion planner creates trajectories, meaning desired values of vehicle position and speed at each time step for a certain look ahead into the future. State of the art trajectory controllers transform this information into desired values for steering and acceleration (or longitudinal force) at the current time step, without passing the information about desired values in the future to the lower level controller.

Our proposal is to calculate trajectories of speed (by nature containing future values) and using them in the lower level longitudinal controller. This naturally leads to a MPC scheme which calculates the torque demand value for the powertrain or engine control unit. The benefit of this approach should be explained in an example: Let us examine the case that due to controller errors one of the state variables, for example vehicle acceleration, is too big compared to the desired value. A conventional controller, lacking information about desired values in the future, will tend to reduce the acceleration much more, than a predictive controller which has knowledge about that in the next time steps, the desired acceleration and hence the torque demand value will increase.

Ideally, the powertrain or engine controller is also capable of using future trajectory information, but we focus on the longitudinal control unit and leave the other out of the scope of this work. We only require to get an estimated value of the current engine and brake torque back from the powertrain control unit and measurement values for vehicle speed and acceleration from the vehicle. To filter these noisy measurements and estimate the most influential parameter in the equation, namely the vehicle mass, an adaptive state and parameter observer is proposed, which updates parameter values in the model used in the model predictive controller. This allows to improve the reference tracking capability of the controller and as a side effect makes the controller more robust to model errors and badly estimated parameters. Further, constraints which might be occurring in the realization of the demanded vehicle acceleration (for example the maximum torque created by the engine might be suddenly limited due to failure mode operation of a combustion engine and resulting cylinder cut off) should be detected by the longitudinal controller and communicated to the higher level control and planning modules. This enables the planning algorithm to adopt for future maneuvers.

3.1 Torque Structure of Engine Management System

Modern Engine Management Systems (EMS) have integrated torque models which calculate the engines indicated torque and torque losses as a multidimensional function of various engine parameters. Depending on the type of

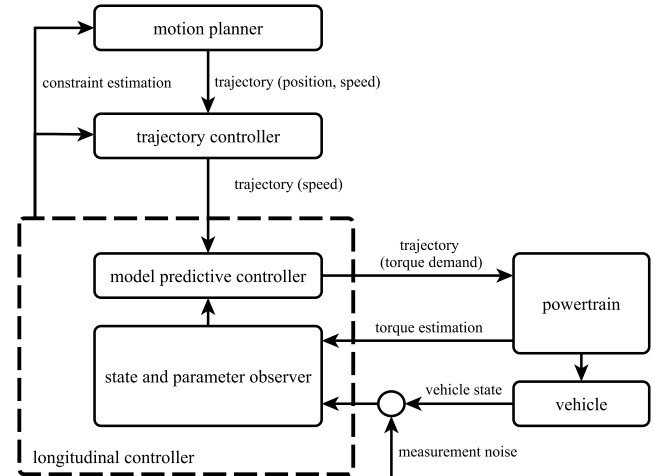


Fig. 1. Proposed controller structure for longitudinal vehicle control

engine, these parameters could be relative load, air/fuel ratio, spark advance, intake and exhaust valve timings, valve lift and number of active cylinders for SI engines. In diesel engines, the resulting torque is mainly determined by the injection quantity and start of combustion, which is given by the injection pattern of many pre-, main- and post injections. These parametric torque models are calibrated for each engine with high effort on a stationary engine test bed, collecting measurement data in the whole variation space over weeks. Since both the engines indicated torque and torque losses are available on the Controller Area Network (CAN) we propose to use these values in the absence of expensive torque measurement devices. From the authors experience in torque structure calibration it is known that the typical accuracy achieved by an EMS torque structure is around 5-10% of the real torque measured on an engine test bed.

In the case of electric engines, the indicated torque is proportional to the measured electrical current and hence a torque estimation is also available in vehicles with electric or hybrid powertrains. This makes the proposed structure compliant with all common types of vehicles, although for the rest of the paper, special emphasis is put on a passenger car with a conventional powertrain driven by an IC engine, with automatic gearbox and torque converter.

4. VEHICLE AND POWERTRAIN DYNAMICS

A derivation of the vehicle and powertrain equations can be found in Rajamani (2011), with the difference that there the final equations do not contain the terms from resulting forces due to road grade and rolling resistance. Therefore these equations are derived in this section for vehicle dynamics equations which contain the most important effects on longitudinal motion but remain as simple as possible to reduce both computational complexity and complexity in controller design. The following assumptions are made for modeling longitudinal vehicle and powertrain dynamics:

The acceleration signal (corrected for bias, but noisy) and the road slope is assumed to be known from measurement input from a gyroscope, which we presume to be available in a highly automated vehicle from an integrated IMU/INS accelerometer. An estimation of the engine torque is available the engine control unit (see Section 3.1). The influence of powertrain elasticity and backlash effects is small and can be neglected. The effects of tire slip are neglected, since they are small during normal operation, where the planning module will plan trajectories far away from the physical limits. It is assumed that the effect of power losses during gear shifts is compensated by a powertrain control unit and therefore only the case of a transmission in steady state is considered.

For a future implementation of the MPC for the whole operating range of the vehicle, the nonlinear behavior of the torque converter needs to be taken into account. The static model of Kotwicki (1982) is proposed for this task. For the derivation of the vehicle mass estimator in Section 5 it is sufficient to investigate the special case of a locked torque converter, because the estimation process can be reduced to phases of a drive cycle where the converter is locked.

4.1 Vehicle Equations

Applying Newton's law and building the dynamic equilibrium of forces, one will get:

$$m \cdot \dot{v} = F_{tire} - F_{pitch} - F_{aero} - F_{rr} \quad (1)$$

F_{tire} is the longitudinal tire force from all tires (see Section 4.2). $F_{pitch} = m \cdot g \cdot \sin \varphi$ is the resulting gravity force on the vehicle due to changing road slope φ , the gravity constant g , F_{aero} the aerodynamic drag force :

$$F_{aero} = c_x \cdot A \cdot \frac{p_u}{2 \cdot \bar{R} \cdot T} \cdot (v + v_{wind})^2 \quad (2)$$

with A is the frontal area of the vehicle, p_u is the ambient pressure, the ideal gas constant \bar{R} , T is the ambient temperature and c_x is the aerodynamic drag coefficient. The simplification $C_{aero} = c_x \cdot A \cdot \frac{p_u}{2 \cdot \bar{R} \cdot T}$ is used in future.

The rolling resistance $F_{rr} = C_{rr} \cdot m \cdot g \cdot \cos \varphi$ is approximated by a linear correlation between the rolling resistance coefficient C_{rr} and the vertical tire force. Hence, the resulting vehicle dynamics can be described as:

$$m \cdot \dot{v} = F_{tire} - m \cdot g \cdot (\sin \varphi + C_{rr} \cdot \cos \varphi) - C_{aero} \cdot (v + v_{wind})^2 \quad (3)$$

4.2 Powertrain Equations

Assuming the torque converter is fully locked, the torque at the gearbox T_g works directly against the engine net torque T_e and therefore the engine dynamics can be written as $I_e \cdot \dot{\omega}_e = T_e - T_g$ with the engine inertia I_e , the engine speed ω_e , and the wheel dynamics as:

$$I_w \cdot \dot{\omega}_w = T_w - T_{br} - r \cdot F_{tire} \quad (4)$$

with the inertia of all wheels I_w , the wheel speed ω_w , the wheel torque induced by the engine $T_{e,w}$, the braking torque T_{br} , the effective wheel radius r and $\dot{\omega}_w = \frac{1}{r} \dot{v}$ further

$$F_{tire} = \frac{1}{r} \cdot T_{e,w} - \frac{1}{r} \cdot T_{br} - \frac{I_w}{r^2} \cdot \dot{v} \quad (5)$$

So, with the total powertrain ratio R and the powertrain efficiency η_{pwt} and $T_{e,w} = \eta_{pwt} \cdot R \cdot T_g$ and $\omega_e = R \cdot \omega_w$ it can be written:

$$F_{tire} = \frac{\eta_{pwt} \cdot R \cdot T_e - T_{br}}{r} - \frac{(R^2 \cdot I_e + \frac{1}{R} \cdot I_w)}{r^2} \cdot \dot{v} \quad (6)$$

4.3 Resulting vehicle dynamics and discussion

Inserting (6) in Equation (3), and simplifying

$I_{res} = \frac{(R^2 \cdot I_e + \frac{1}{R} \cdot I_w)}{r^2}$ the resulting vehicle equation can be written as:

$$(m + I_{res}) \cdot \dot{v} = \frac{\eta_{pwt} \cdot R \cdot T_e - T_{br}}{r} - m \cdot g \cdot (\sin \varphi + C_{rr} \cdot \cos \varphi) - C_{aero} \cdot (v + v_{wind})^2 \quad (7)$$

The effective wheel radius r in Equation 7 dynamically changes at high rotational speeds, but can be modeled as static for low vehicle speeds. It is assumed that the effective wheel radius can be obtained using an approach similar to Carlson and Gerdes (2005) and is available on the CAN Bus. Nevertheless, for simplification in the dynamic equations, it is treated as time invariant.

The value of the resulting powertrain inertia I_{res} can be obtained using a method described in Van Karsen et al. (2007).

The total powertrain ratio R is assumed to be known from the gear manufacturer.

The rolling resistance coefficient C_{rr} and the aerodynamic drag coefficient C_{aero} can be obtained by performing coast down tests for which the vehicle speed trajectory is measured after letting a vehicle roll with detached powertrain until it stops, usually in two directions on a plane surface to compensate for wind forces and road slope disturbances. Methodologies are described in Hamabe et al. (1985) or Djordjevic et al. (2009). Typical values for C_{rr} are around 0.015 for passenger cars according to Wang et al. (2004).

Since the gross vehicle mass m is the sum of the net vehicle mass plus vehicle load plus fuel mass, it can be considered as slowly varying parameter due to fuel consumption, assuming that the vehicle load remains constant during one trip. The effect of changing vehicle mass should be considered in the powertrain model and therefore a method for online estimation is proposed in the next section.

5. STATE AND PARAMETER ESTIMATION

Since the correct knowledge of the vehicle mass has a very high impact on the quality of vehicle longitudinal

control, it should be estimated online while driving. Further, it is desirable not to use noisy measurement signals of acceleration and speed directly in a controller but to provide filtered estimates instead. A time discrete Extended Kalman Filter (EKF) as can be found in Simon (2006) can be used to perform both tasks in parallel. To implement the EKF, Equation 7 is further simplified with the assumption that wind speed needs to be neglected lacking a proper estimate. Remember that the equation includes the assumption of a locked torque converter, which is valid since it is possible to use the observer as a parameter estimator only in locked torque converter mode by introducing gain switching of the artificial process noise covariance on the vehicle mass prohibit adaptation in modes where the torque converter is in regular operation. In order to estimate the vehicle mass parameter, it is treated as an additional state which leads to the state vector $\mathbf{x} = [v \ a \ m]^T$. Euler discretization with time step T_s further leads to the time discrete state space equations for the nonlinear state dynamics:

$$\begin{bmatrix} v_k \\ a_k \\ m_k \end{bmatrix} = \begin{bmatrix} v_{k-1} + T_s \cdot a_{k-1} \\ f_a(u_{k-1}, \varphi_{k-1}, v_{k-1}) \\ m_{k-1} + \omega_m \end{bmatrix} \quad (8a)$$

with

$$f_a = \frac{1}{\tilde{m}_{k-1}} \cdot (u_{k-1} - m \cdot g \cdot (\sin \varphi + C_{rr} \cdot \cos \varphi) - C_{aero} \cdot v_{k-1}^2) \quad (8b)$$

where $\tilde{m} = m + I_{res}$ and the input $u_k = \frac{\eta_{pwt} \cdot R \cdot T_{ek} - T_{brk}}{r}$. The vehicle mass m is considered as constant. Adding artificial (white) process noise ω_m is a trick to allow the EKF to adapt to the true value. The measurement equations can be written as $v_k = v_{mk} + v_v$ and $a_k = a_{mk} + v_a$ with (white) measurement noise v_v and v_a for speed and acceleration measurements. So the state space equations can be written as:

$$\begin{aligned} \mathbf{x}_k &= f(\mathbf{x}_{k-1}, u_{k-1}, \boldsymbol{\omega}_{k-1}) \\ \mathbf{y}_k &= h(\mathbf{x}_k) + \mathbf{v}_k \end{aligned} \quad (9)$$

and therefore with the Jacobians

$$\begin{aligned} \mathbf{F}_{k-1} &= \left. \frac{\partial f}{\partial \mathbf{x}} \right|_{\hat{\mathbf{x}}_{k-1}, u_{k-1}} = \begin{bmatrix} 1 & T_s & 0 \\ -\frac{2}{\tilde{m}_0} \cdot C_{aero} \cdot v_0 & 0 & \frac{\partial f_a}{\partial m} \\ 0 & 0 & 1 \end{bmatrix} \\ \mathbf{H}_k &= \left. \frac{\partial h}{\partial \mathbf{x}} \right|_{\hat{\mathbf{x}}_k} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \end{aligned} \quad (10)$$

with

$$\frac{\partial f_a}{\partial m} = -\frac{1}{\tilde{m}_0^2} \cdot (u_{k-1} + C_{aero} \cdot v_0^2) - \frac{g}{\tilde{m}_0} \cdot (\sin \varphi + C_{rr} \cdot \cos \varphi).$$

The a priori (denoted by $-$) EKF equations can be written for the predictions of the state $\hat{\mathbf{x}}^-$ and covariance matrix \mathbf{P}^- :

$$\begin{aligned} \hat{\mathbf{x}}_k^- &= f(\hat{\mathbf{x}}_{k-1}, u_{k-1}) \\ \mathbf{P}_k^- &= \mathbf{F}_{k-1} \mathbf{P}_{k-1} \mathbf{F}_{k-1}^T + \mathbf{L} \mathbf{Q} \mathbf{L}^T \end{aligned} \quad (11)$$

and the innovations for the a posteriori (denoted by $+$) estimates as

$$\begin{aligned} \hat{\mathbf{x}}_k^+ &= \hat{\mathbf{x}}_k^- + \mathbf{K}_k (\mathbf{y}_k - \mathbf{H} \hat{\mathbf{x}}_k^-) \\ \mathbf{P}_k^+ &= (\mathbf{I} - \mathbf{K}_k \mathbf{H}) \mathbf{P}_k^- (\mathbf{I} - \mathbf{K}_k \mathbf{H})^T + \mathbf{K}_k \mathbf{R} \mathbf{K}_k^T \end{aligned} \quad (12)$$

with the Kalman Gain \mathbf{K}

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}^T (\mathbf{H} \mathbf{P}_k^- \mathbf{H}^T + \mathbf{M} \mathbf{R} \mathbf{M}^T)^{-1} \quad (13)$$

where \mathbf{Q} is the process noise covariance matrix and \mathbf{R} is the measurement noise covariance matrix, and the matrices \mathbf{L} and \mathbf{M} are the Jacobians:

$$\mathbf{L} = \left. \frac{\partial f}{\partial \boldsymbol{\omega}} \right|_{\hat{\mathbf{x}}_{k-1}, u_{k-1}} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix} \quad (14)$$

$$\mathbf{M} = \left. \frac{\partial h}{\partial \mathbf{v}} \right|_{\hat{\mathbf{x}}_k} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (15)$$

6. SIMULATION RESULTS

Vehicle dynamics Equation (7) was used to simulate the longitudinal behavior of the vehicle. To make the simulation more realistic, colored noise was added on vehicle speed and acceleration. Additionally, to simulate a more realistic engine behavior, first order dynamics with a time constant of 0.2 was used to delay engine torque demand to the actual engine torque applied to the vehicle equation. Figure 2 shows the simulation results, in which repeated speed profiles were simulated in closed loop to demonstrate the capabilities of the EKF to filter the acceleration and speed signals (upper two subplots, with a zoom into a detail on the right hand side in Figure 2) and to estimate the vehicle mass \hat{m} online. One can see that \hat{m} converges to the true value of 1200 kg after a few seconds (center subplot). The state estimate errors $e_a = a - \hat{a}$ for the vehicle acceleration and $e_v = v - \hat{v}$ for vehicle speed show that the estimates are slightly biased during the first seconds before the vehicle mass estimate is closer to the true value, and are very accurate after the estimation has converged (lower subplots).

7. CONCLUSION AND OUTLOOK

The main contributions presented in this paper are (a) the proposition of a novel model based controller scheme for longitudinal low level control of automated vehicles, including (b) the algebraic model equations and (c) a state and parameter observer for online estimation of the vehicle mass. The main difference to state-of-the art solutions is that the information about future demand values is used throughout all controller components, whereas other solutions typically do not make use of this information. The model equations as basis for further implementation of this model based controller could be derived. As first step, a state and parameter observer based on an Extended Kalman Filter was implemented and validated through simulation. As future steps, vehicle tests are planned, before implementing and testing the model based control scheme in closed loop. Investigations on the performance of the longitudinal controller in automated mode are planned. The contributions of this paper build the foundation to further examine the potential of improvement in fuel savings, planning accuracy and passenger comfort.

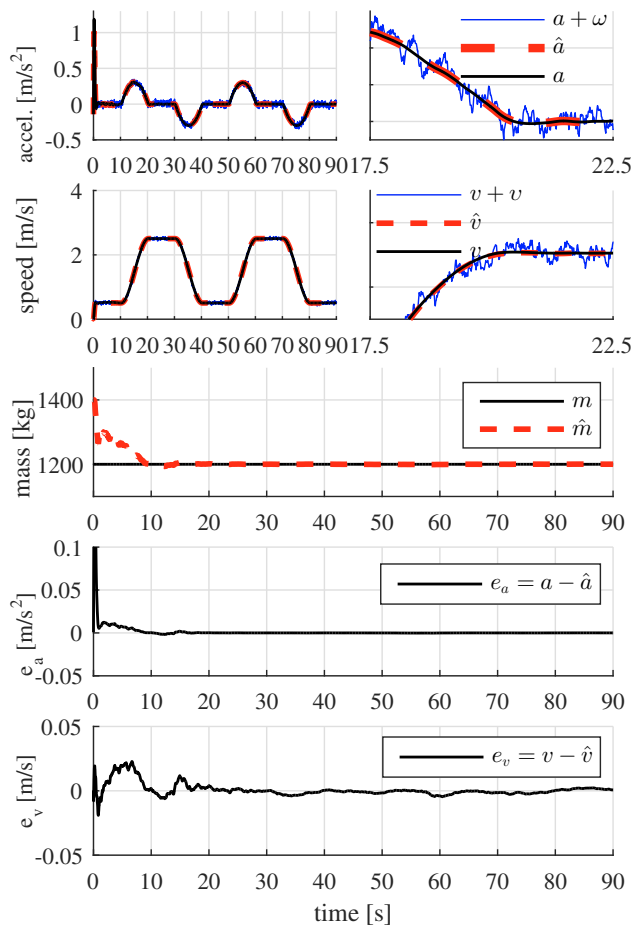


Fig. 2. Simulation of a drive cycle with vehicle mass estimation. Although the initial estimate of the vehicle mass is wrong, it converges together with the states estimates to the true values within seconds, and estimation errors e become close to zero.

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