Extending adaptive cruise control (ACC) towards adaptive driving strategies

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Abstract

We present an adaptive cruise control (ACC) strategy where the acceleration characteristics, i.e., the 'driving style' automatically adapts to different traffic situations. The three components of the concept are the ACC itself implemented in form of a car-following model, an algorithm for the automatic real-time detection of the traffic situation based on local information, and a 'driving strategy matrix' to adapt the driving characteristics, i.e., the parameters of the ACC controller to the traffic conditions. Optionally, inter-vehicle and roadside-to-car communication can be used to improve the accuracy for determining the local traffic states. We simulated the complete concept microscopically on a road section with an on-ramp bottleneck using real loop-detector data for an afternoon rush-hour as input for the upstream boundary. Already a small percentage of 'traffic-adaptive' ACC vehicles, i.e., a relatively modest local change in the maximum free flow improves the traffic stability and performance significantly. While the traffic congestion in the reference case was completely eliminated when simulating a proportion of 25% of ACC vehicles, travel times for the drivers are reduced in a relevant way already for much lower penetration rates. The presented results are largely independent of details of the model, the boundary conditions, or the type of road inhomogeneity.

1 Introduction

Traffic congestion is a severe problem on freeways in many countries. In most countries, building new transport infrastructure is no longer an appropriate option. Therefore, considerable research in the area of intelligent transport systems (ITS) is attempted towards a more effective road usage and a more 'intelligent' way of increasing the capacity of the road network and thus to decrease congestion. Examples of advanced traffic control systems are, e.g., ramp metering, adaptive speed limits, or dynamic and individual route guidance. The latter examples are based on a *centralized traffic management*, which controls the operation and the system's response to a given traffic situation. On the other hand, automated highway systems (AHS) have been proposed as a *decentralized approach* based on automated vehicles (Varaiya, 1993). The concept of fully automated vehicle control allows for very small time gaps and platoon driving, which is a key to greater capacity. However, such systems need adapted infrastructure and dedicated lanes, which can only be justified if the percentage of automated vehicles is sufficiently high, which seems to make this scenario unlikely for the foreseeable future (Rao and Varaiya, 1993).

Nevertheless, partly automated driving is already commercially available for essential driving tasks such as accelerating and braking by means of adaptive cruise control (ACC). In fact, ACC systems are the first driver assistance systems with the potential to influence traffic flow characteristics. But as typical representatives of *driver assistance* systems, present implementations of ACC systems are exclusively designed to increase the driving comfort, while the influence on the surrounding traffic is not yet considered. This is justified as long as the number of ACC-equipped vehicles is negligible, but the expected growing penetration rate of these devices makes the question about their impact on traffic flow more pressing. Therefore, it is important to understand effects of ACC on capacity and stability of traffic flow at an early stage so that their design can be adjusted before adverse traffic effects are widely manifested.

In the literature, the effects of emerging driver assistance systems such as ACC on the traffic dynamics has been addressed by means of traffic simulation because large-scale field tests are barly feasible. Particularly, the microscopic modeling approach allows for a natural representation of the heterogeneous traffic stream consisting of ACC vehicles and manually driven vehicles (Kesting et al., 2006b; Davis, 2004; VanderWerf et al., 2002; Treiber and Helbing, 2001; Marsden et al., 2001; Minderhoud, 1999). For a further overview, we refer to VanderWerf et al. (2001). However, there is even no clarity up to now about the sign of these effects. Some investigations predict a positive effect (Treiber and Helbing, 2001; Davis, 2004), while others are more pessimistic (Marsden et al., 2001; Kerner, 2004). For realistic estimates of the impact of ACC on the capacity and traffic stability, the models have to capture the driving dynamics of ACC and manually driven vehicles and the relevant interactions between them. Therefore, the findings depend on the model fidelity, the modeling assumptions and, mainly, on the setting for the time gap, because the maximum capacity is approximately determined by the inverse of the average time gap T of the drivers.

In this paper, we propose an ACC-based *traffic-assistance system* aiming to improve traffic flow and road capacity and thus to decrease traffic congestion while retaining the driving comfort. To this end, we introduce a *driving strategy layer*, which controls the settings of the driving parameters of the ACC system. While the ACC *operational control layer* calculates the response to the input sensor data by means of accelerations and decelerations on a short time scale of seconds, the automated adaptation of the ACC parameters happens on a longer time scale of typically minutes. In order to resolve possible conflicts of objective between comfort and road capacity, we propose an *intelligent driving strategy that adapts the ACC driving characteristics according to the local traffic situation.* To this end, we consider a finite set of five 'traffic situations' that are associated with a specific set of ACC driving parameters. These traffic states have to be detected autonomously by each ACC-equipped vehicle.

For a concrete model formulation and implementation, we investigate the proposed system components within a microscopic multi-lane traffic simulator. The simulator generates surrounding traffic that is required as input for the autonomous detection model based on locally available information. Due to the inherent complexity, the interplay of the individual adaptation of each ACC-equipped vehicle and the impact on the resulting traffic dynamics can only be considered within a simulation framework. Moreover, the simulation tool also allows for an investigation of the effect of a given proportion of 'intelligent' ACC vehicles. A positive impact of the proposed traffic assistance system on the collective benefits already for low market penetration rates is an important precondition for the success of the proposed vehicle-based strategy.

Our paper is structured as follows. We start with a discussion of the characteristics of ACC-based and manual driving and their representation in terms of microscopic traffic models. In Sec. 3, we present our concept of a 'traffic assistance system'. We introduce the proposed traffic states, the detection model and the traffic-state adaptive driving strategy. In Sec. 4, we investigate the impact of the proposed extension of ACC on the traffic dynamics by means of traffic simulations of a three-lane freeway with an on-ramp as bottleneck and a mixed traffic flow consisting of cars and trucks. We focus particularly on the collective dynamics and the travel times of various proportions of ACC-equipped vehicles. We conclude with a discussion and an outlook.

2 Modeling ACC-based and human driving behavior

The recent development and availability of *adaptive cruise control* systems (ACC) extends earlier cruise control systems, which were designed to reach and maintain a certain speed preset by the driver. The ACC system extends this functionality to situations with significant traffic where driving at constant speed is not possible. The driver can not only adjust the desired velocity but also set a certain 'safe' time gap determining the gap to the leader when following slower vehicles (typically in the range between 0.9 s and 2.5 s). The task of the ACC system is to determine the appropriate acceleration or deceleration as a function of the traffic situation and the driver settings. In order to do this, the system is able to detect and to track the vehicle ahead, measuring the actual distance and speed difference to the vehicle ahead by means of radar or IR sensors.

Present ACC systems offer a gain in comfort in most driving situations on freeways. Nevertheless, it should be emphasized that present-day ACC systems only operate above a certain velocity threshold and are limited in their acceleration range. The next generation of ACC will be designed to operate in all speed ranges and in most traffic situations on freeways including stop-and-go traffic. Additionally, future ACC systems will have the potential to prevent actively a rear-end collision and, thus, to achieve also a gain in safety. Moreover, ACC systems only control longitudinal driving. However, merging, lane changes or gap-creation for other vehicles still need the intervention of the driver. So, as the driver still takes the entire responsibility, he or she can always override the system.

Remarkably, the input quantities of ACC system, i.e., the own speed, the distance to the car ahead and the velocity difference, are exactly those of many time-continuous car-following models. Because the ACC response time, which is of the order of 0.1 s – 0.2 s, is generally negligible compared to the human reaction time of about 1 s (Green, 2000), suitable ACC models give the instantaneous acceleration $\dot{v}(t)$ of each vehicle in terms of a continuous function of the velocity $v(t)$, the net distance $s(t)$, and the approaching rate $\Delta v(t)$ to the leading vehicle. To be a suitable candidate for simulating ACC systems, car-following models have to meet the following criteria:

- The car-following dynamics has to be accident-free, at least, if this is physically possible.
- The dynamics should correspond to a natural and smooth driving style.
- Adaptations to new traffic situations (for example, when the predecessor brakes, or another vehicle cuts in) must be performed without any oscillations.
- The model should have only few parameters. Each parameter should have an intuitive meaning and plausible values after calibration. Ideally, the parameter list should include the desired velocity v_0 and the desired time gap T, which are preset by the driver.
- By varying the remaining parameters, it should be possible to model different driving styles such as experienced vs. inexperienced, or aggressive vs. relaxed as well as vehicle-based limitations such as finite acceleration capabilities.
- Calibration should be easy and leading to good results.

These criteria are met by the 'Intelligent Driver Model' (IDM) (Treiber et al., 2000). Moreover, the IDM algorithm recently served as base for an ACC implementation in a test car from Volkswagen within the German project (BMBF, 2005). In the following simulations, we therefore represent ACC vehicles by this model. The IDM acceleration $\dot{v}$ is given by

$$\dot{v}(s, v, \Delta v) = a \left[1 - \left(\frac{v}{v_0} \right)^4 - \left(\frac{s^*(v, \Delta v)}{s} \right)^2 \right]. \tag{1}$$

This expression combines the acceleration $\dot{v}_{\text{free}} = a[1 - (v/v_0)^4]$ on a free road with a braking term $\dot{v}_{\text{brake}}(s, v, \Delta v) = -a(s^*/s)^2$ which is dominant if the current gap $s(t)$ to the preceding vehicle becomes smaller than the 'effective desired minimum gap'

$$s^*(v, \Delta v) = s_0 + vT + \frac{v \Delta v}{2\sqrt{ab}}. \tag{2}$$

The minimum distance s_0 in congested traffic is significant for low velocities only. The dominating term of Eq. (2) in stationary traffic is vT, which corresponds to following the leading vehicle with a constant safe time gap T. The last term is only active in non-stationary traffic and implements an accident-free, 'intelligent' driving behavior including a braking strategy that, in nearly all situations, limits braking decelerations to the 'comfortable deceleration' b.

While the simple car-following approach is perfectly suited to model the dynamics of ACC-controlled vehicles, the *human* driving style differs from that in essential points such as the following:

1. The *finite reaction time* of humans results in a delayed response to the traffic situation.
2. Imperfect estimation capabilities result in *perception errors* and *limited attention spans.*
3. Human drivers scan the traffic situation *several vehicles ahead* while the ACC sensors are restricted to the immediate predecessor.
4. Furthermore, human drivers *anticipate* the future traffic situations by making use of further clues (such as brake lights) and by forming plausible hypotheses such as assuming constant accelerations of all neighboring vehicles in the next few seconds.

In view of these differences, the question arises, why the simple car-following approach is also able to capture many aspects of human driving, particularly with respect to the collective macroscopic dynamics (Treiber et al., 2000), but also on a microscopic level (Brockfeld et al., 2003). This question becomes more pressing as one can show that, for realistic human reaction times of the order of the time gaps, the destabilizing influences of point (1) and (2) alone would lead to traffic instabilities and accidents. Obviously, the stabilizing effects of spatial and temporal anticipation of points (3) and (4) are essential for human driving.

This has been investigated using the recently proposed 'human driver model' (HDM) (Treiber et al., 2006a) that extends the car-following modeling approach to include the points mentioned above. It turns out that the destabilizing effects of reaction times and estimation errors can be quantitatively compensated for by spatial and temporal anticipation. As important result, one obtains essentially the same longitudinal dynamics when including all four effects compared to the simulations with the car-following model where none of these effects is incorporated.

Therefore, we may conclude that, although the mode of operation is fundamentally different, ACC-equipped vehicles and manually controlled vehicles exhibit a similar *effective* driving behavior with respect to collective properties such as stability of traffic flow, traffic performance (measured in terms of capacity), or the emergence and propagation of congestion. Since this contribution investigates the influence of ACC on macroscopic properties of traffic flow, it is justified to simulate the human drivers with simple car-following models such as the IDM as well instead of using more complex models such as the HDM. The advantage of using simple models for both human-driven and automated vehicles lies in the reduced number of parameters that need to be calibrated.

3 ACC-based traffic assistance system with an adaptive driving strategy

In this central section, we generalize the ACC concept to a *traffic assistance* system, in which 'intelligent vehicles' automatically adapt their ACC parameters aiming to improve traffic flow and road capacity and thus to decrease traffic congestion while retaining the driving comfort. In order to resolve possible conflicts of objective between comfort and road capacity, we propose a *driving strategy that adapts the ACC driving characteristics according to the local traffic situation.* To this end, we consider a finite set of five 'traffic situations': Free traffic, approaching congestion (upstream front), congested traffic, leaving congestion (downstream front), and infrastructural bottleneck sections (such as road works or intersections). These traffic situations have to be detected autonomously by each ACC-equipped vehicle. Since autonomous detection alone is only possible with delays, we also consider to supplement the local information by roadside-to-car and inter-vehicle communication between the equipped vehicles (Schönhof et al., 2006; Yang and Recker, 2005; Schönhof et al., 2007).

The proposed traffic-assistance system consists of several system components: The main operational layer is still the ACC system calculating the acceleration $\dot{v}(t)$. The new feature of the proposed system is the strategic layer, which implements the changes in the driving style in response to the local traffic situation by changing some parameters of the ACC system. To this end, a detection algorithm determines, which of the five traffic situations mentioned above applies best to the actual traffic situation. The user adjusts the driving characteristics individually by setting the desired velocity and the time gap. In contrast to conventional ACC systems, the driving behavior of our traffic-assistance system, i.e., the acceleration, is determined in a two-step process:

1. On the *strategic level*, the traffic situation is determined locally and the driving style is adapted accordingly by changing some ACC *parameters.* The parameter settings related to the detected traffic state changes typically on time scales of minutes and in a range of typically a few hundred meters. This is analog to manual changes of the desired velocity or the time gap in conventional ACC systems by the driver, which, of course, is possible in the proposed system as well.

2. The *operational level* consists in responding to changes of the ACC *input quantities* s, v, and Δv. The time scale is of the order of seconds and the spatial range is limited to the immediate predecessor. Notice that this is the only level of conventional ACC systems.

In the following subsections, we discuss the system components for a traffic-adaptive ACC system in more detail. First, we introduce a general concept for a driving strategy that is designed to improve the traffic flow efficiency while retaining comfort and safety for the driver. In Sec. 3.2, we implement such a strategy in terms of a *driving strategy matrix.* In Sec. 3.3, we describe the detection model for determining the traffic situation based on the evaluation of the locally available floating-car data. Finally, in Sec. 3.4, we discuss the extended use of non-local information sources such as inter-vehicle and roadside-to-car communication for an improved detection of the local traffic state.

3.1 General considerations for a comfortable and efficient driving strategy

The design of an ACC-based traffic assistance system is subject to several, partly contradicting, objectives. On the one hand, the resulting driving behavior has to be safe and comfortable to the driver. This implies comparatively large gaps and low accelerations. On the other hand, the performance of traffic flow is enhanced by lower time gaps T and higher accelerations, which can be seen when considering the main aspects of traffic performance: The *static road capacity* C defined as maximum number of vehicles per time unit and lane is strictly limited from above by the inverse of the time gap, $C < 1/T$. Moreover, simulations show that higher accelerations increase both the *traffic stability* and the *dynamic bottleneck capacity*, i.e., the outflow from congested traffic at the bottleneck, which, typically, is lower than the free-flow capacity (Kesting et al., 2006b). Our approach in solving this conflict of goals is based on following observations:

- Most traffic breakdowns are initiated at some sort of road inhomogeneities or infrastructure-based 'bottlenecks' such as on-ramps, off-ramps, or sections of road works (Schönhof and Helbing, 2004; Bertini et al., 2004).
- An effective measure to avoid or delay traffic breakdowns is to homogenize the traffic flow.
- Once a traffic breakdown has occurred, the further dynamics of the resulting congestion is uniquely determined by the traffic demand (which is outside the scope of this investigation), and by the traffic flow in the immediate neighborhood of the downstream boundary of the congestion (Daganzo et al., 1999). In many cases, the downstream boundary is fixed and located near a bottleneck as found in empirical investigations (Schönhof and Helbing, 2004).
- Traffic safety is increased by reducing the spatial velocity gradient at the upstream front of traffic congestion, i.e., by reducing the risk of rear-end collisions.

In the context of the ACC-based traffic assistance system, we make use of these observations by *only temporarily changing the comfortable settings of the ACC in specific traffic situations.* The selected situations have to be determined autonomously by the equipped vehicles and they have to allow for specific actions to improve the traffic performance. To this end, we propose the following discrete set of five traffic situations and the corresponding actions:

1. **Free traffic**. This is the default situation. The ACC settings are determined solely with respect to a maximum driving comfort. Since each driver can set the parameters for the time gap and the desired velocity individually, this may lead to different settings of the ACC systems.
2. **Upstream jam front**. Here, the objective is to increase safety by decreasing velocity gradients. Compared to the default situation, this implies earlier braking when approaching slower vehicles. Notice that the operational layer always assures a safe approaching process independantly from the detected traffic state.
3. **Congested traffic**. Since drivers cannot influence the development of traffic congestion in the bulk of a traffic jam, the ACC settings are reverted to their default values.
4. **Downstream jam front**. To increase the dynamic bottleneck capacity, accelerations are increased and time gaps are temporarily decreased.

5. **Bottleneck sections**. Here, the objective is to locally increase the capacity, i.e., to *dynamically fill the capacity gap*, which is the defining property of bottlenecks. This implies a temporal reduction of the time gap.

Notice that drivers typically experience the sequence of these 5 traffic states when traveling through congested traffic. We emphasize that the total fraction of times where the ACC settings deviate from the default state is only a few percent in most situations. Moreover, we show in Sec. 4 that even a small percentage of equipped vehicles driving according to the above strategy substantially decrease the size and duration of congestion and thus the travel time. This means, despite a temporary deviation from the most comfortable ACC settings, the drivers of such systems will profit on the whole.

3.2 Implementation of the ACC driving strategy

In this section, we implement the above concept for an ACC based on the Intelligent Driver Model (IDM) (Treiber et al., 2000) as discussed in Sec. 2. Three from the five IDM parameters listed in Table 2 below correspond directly to the different aspects of the adaptation strategy: The *acceleration parameter* a gives an upper limit for the acceleration $\dot{v}(t)$ of the ACC-controlled vehicle. Consequently, this parameter is increased when leaving congestion, i.e., when the state 'downstream front' has been detected. The *comfortable deceleration* b characterizes the deceleration when approaching slower or standing vehicles. Obviously, in order to be able to brake with lower decelerations, one has to initiate the braking maneuver earlier corresponding to higher levels of anticipation. Since this smoothes upstream fronts of congestion, the parameter b is decreased when the state 'upstream front' has been detected. Notice that, irrespective of the value of b, the ACC vehicle brakes stronger than b if this is necessary to avoid collisions. Finally, the *time gap parameter* T is decreased if one of the states 'bottleneck' or 'downstream front' is detected.

In order to be acceptable for the drivers, the system parameters need to be changed in a way that preserves the individual settings and preferences of the different drivers and also the driving characteristics of different vehicle categories such as cars and trucks. Particularly, the preferred time gap T can be changed both by the driver, and by the event-oriented automatic adaptation. This can be fulfilled by formulating the changes in terms of *multiplication factors* λ_a, λ_b, and λ_T defined by the relation

$$a^{(\mathrm{s})} = \lambda_a^{(\mathrm{s})}\, a, \quad b^{(\mathrm{s})} = \lambda_b^{(\mathrm{s})}\, b, \quad T^{(\mathrm{s})} = \lambda_T^{(\mathrm{s})}\, T, \tag{3}$$

where the superscript (s) denotes one of the five traffic states, to which the respective value is applicable. Furthermore, a, b, and T denote the default values of the IDM parameters as given in Table 2 below. In summary, this implementation can be formulated succinctly in terms of a *strategy matrix* as depicted in Table 1. Of course, all changes are subject to restrictions by legislation (lower limit for T), or by the vehicle type such as an upper limit for a, particularly for trucks.

Table 1: The *driving strategy matrix* shows the implementation of the ACC driving strategy in a nutshell. Each of the traffic situations corresponds to a different set of ACC parameters. We represent the ACC driving characteristics by the *time gap* T, the *maximum acceleration* a, and the *comfortable deceleration* b, which are direct model parameters of the 'Intelligent Driver Model'. λ_T, λ_a, and λ_b are relative multiplication factors for the relation (3). For example, $\lambda_T = 0.5$ denotes a reduction of the default time gap T of 50% in the bottleneck situation.

Traffic situation	$\boldsymbol{\lambda_T}$	$\boldsymbol{\lambda_a}$	$\boldsymbol{\lambda_b}$	**Driving behavior**
Free traffic	1	1	1	Default/Comfort
Upstream front	1	1	0.7	Increased safety
Congested traffic	1	1	1	Default/Comfort
Bottleneck	0.5	1.5	1	Breakdown prevention
Downstream front	0.5	2	1	High dynamic capacity

3.3 Traffic-state detection model

Let us now present a detection model for an automated, vehicle-based identification of the local traffic situation as required for the proposed driving strategy. Our detection model is based on the locally available floating-car time series data. The Controller Area Network (CAN) of the vehicle provides the own speed, whereas the velocity of the leader is measured by the radar sensor of the ACC system. Both velocities can be used in a weighted average, but for the sake of simplicity we only focus on the own velocity. Due to short term fluctuations, the time series data require a smoothing in time in order to reduce variation. In our traffic simulator (cf. Sec. 4 below), we have used an exponential moving average (EMA) for a measured quantity $x(t)$,

$$x_{\mathrm{EMA}}(t) = \frac{1}{\tau} \int\limits_{-\infty}^{t} dt' e^{-(t-t')/\tau}\, x(t'), \tag{4}$$

with a relaxation time of $\tau = 5\,\mathrm{s}$. The EMA allows for an efficient real-time update by using an explicit integration scheme for the corresponding ordinary differential equation

$$\frac{\mathrm{d}}{\mathrm{d}t} x_{\mathrm{EMA}} = \frac{x - x_{\mathrm{EMA}}}{\tau}. \tag{5}$$

For an identification of the proposed five traffic states we define the following criteria. The *free traffic state* is characterized by a high average velocity,

$$v_{\mathrm{EMA}}(t) > v_{\mathrm{free}}, \tag{6}$$

with a typical value for the threshold of $v_{\mathrm{free}} = 60\,\mathrm{km/h}$. In contrast, the *congested traffic state* is characterized by a low average velocity,

$$v_{\mathrm{EMA}}(t) < v_{\mathrm{cong}}, \tag{7}$$

with a threshold of $v_{\mathrm{cong}} = 40\,\mathrm{km/h}$. The detection of an upstream or downstream jam front relies on a *change* in speed compared to the exponentially averaged past of the speed. Approaching an *upstream jam front* is therefore characterized by

$$v(t) - v_{\mathrm{EMA}}(t) < -\Delta v_{\mathrm{up}}, \tag{8}$$

whereas a *downstream front* is identified by an acceleration period,

$$v(t) - v_{\mathrm{EMA}}(t) > \Delta v_{\mathrm{down}}. \tag{9}$$

Both thresholds are of the order of $\Delta v_{\mathrm{up}} = \Delta v_{\mathrm{down}} = 10\,\mathrm{km/h}$.

The most important adaptation for an efficient driving style is related with the *bottleneck state*. The identification of this state requires information about the infrastructure, because bottlenecks are typically associated with spatial modifications in the freeway road design such as on-ramps, off-ramps, lane closures, or construction sites. We assume that this information is provided by a digital map database containing the position of a bottleneck $(x_{\mathrm{begin}}, x_{\mathrm{end}})$ in combination with a positioning device (GPS receiver), which provides the actual vehicle position $x(t)$. This information allows for an identification of the bottleneck state by the spatial criteria

$$x(t) > x_{\mathrm{begin}} \quad \mathrm{AND} \quad x(t) < x_{\mathrm{end}}. \tag{10}$$

The proposed criteria offer the possibility that no criterion is fulfilled or, vice versa, multiple criteria are met simultaneously. To this end, we need a *heuristics* for the discrete choice problem. From our visualized traffic simulations (cf. Fig. 1), we found that the following decision order is the most adequate one: *downstream front* → *bottleneck* → *traffic jam* → *upstream front* → *free traffic* → *no change*. This order also reflects the relevance of the driving strategy associated with these traffic states for an efficient traffic flow. A more sophisticated heuristics would consist in a dynamic adaptation of the thresholds used in the criteria of Eqs. (6) – (9).

3.4 Inclusion of inter-vehicle and roadside-to-car communication

So far, the detection model is exclusively based on *local information* that is provided autonomously by the own floating car data, the ACC sensor data, and the positioning device. Let us finally discuss the principal limitations of this approach. An autonomous detection in real-time has to struggle with the time-delay due to the exponential moving average, that is of the order of τ. This fact limits the timing of the traffic state identification. Particularly, the adaptation towards a smooth deceleration behavior when approaching a dynamically propagating upstream front requires the knowledge of the jam front position at an early stage in order to be able to switch to the new driving strategy in time. For a more advanced vehicle-based traffic state estimation, non-local information can be additionally incorporated in order to improve the detection quality (de Bruin et al., 2004). For example, a short-range inter-vehicle communication (IVC) (Schönhof et al., 2006; Yang and Recker, 2005; Schönhof et al., 2007) is a reasonable extension providing up-to-date information about *dynamic* up- and downstream fronts of congested traffic, which cannot be estimated without delay by only local measurements. Furthermore, in case of a *temporary bottleneck* such as a construction site that is not

Table 2: Model parameters of the Intelligent Driver Model (IDM) for cars and trucks as used in the simulations. The website `http://www.traffic-simulation.de` provides an interactive simulation of the IDM.

Model Parameter	**Car**	**Truck**
Desired velocity v_0	120 km/h	85 km/h
Safe time gap T	1.5 s	2.0 s
Maximum acceleration a	1.4 m/s^2	0.7 m/s^2
Desired deceleration b	2.0 m/s^2	2.0 m/s^2
Jam distance s_0	2 m	2 m

attributed in the digital map database, the information about the location could be provided by the communication with a stationary sender upstream the bottleneck (roadside-to-car communication). Notice that we do not use IVC for a direct *control* of ACC. We merely incorporate additional, non-local information sources for an improved traffic-state estimation.

4 Microscopic freeway simulations

Let us now evaluate the impact of the proposed ACC-based traffic assistance system by means of traffic simulations. The microscopic modeling approach allows for a detailed specification of the parameters and proportions of cars and trucks, as well as ACC and manually controlled vehicles. As introduced in Sec. 2, we use the Intelligent Driver Model (IDM) (Treiber et al., 2000) with the parameter sets for cars and trucks given in Table 2. The vehicle length has been set to 4 m for cars and 12 m for trucks. Furthermore, lane-changing is a required ingredient for realistic simulations of freeway traffic and merging zones. We modeled the lane-changing decision by the MOBIL algorithm ('Minimizing Overall Braking Induced by Lane Changes') that is based on the expected (dis-)advantage in the new lane in terms of the difference in the acceleration (Kesting et al., 2007). Notice that the ACC system only controls the longitudinal driving task. For this reason, we do not differentiate the lane-changing parameters for ACC and manually controlled vehicles.

In a simulation run, a given proportion of vehicles is equipped with ACC. Each ACC vehicle determines the local traffic situation dynamically by evaluating the autonomously available floating-car data according to the detection model presented in Sec. 3.3. According to the detected traffic state, the individual ACC parameters T, a, and b are changed by the multipliers of the driving strategy matrix listed in Table 1. As indicated in Fig. 1, the current traffic state of each ACC vehicle is displayed by a changing color allowing for a direct, visual assessment of the implemented detection criteria. In contrast, non-ACC vehicles are displayed in grey color. The parameters of the strategy matrix can be changed interactively by the user in order to test new strategies directly. The driving adaptations influences the traffic dynamics of the overall system as intended for an improved traffic flow. The impact of the proportion of ACC

Figure 1: Screenshot of our traffic simulator, showing the on-ramp scenario studied in Sec. 4.1. For matters of illustration, two simulation runs are displayed. In the upper simulation, 100% of the vehicles are equipped with the ACC-based traffic assistance system. The different vehicle colors indicate the locally detected traffic state. The reference case without ACC equipment (grey vehicle color) displayed in the lower simulation run shows congested traffic at the bottleneck. In both simulations, the same time-dependent upstream boundary conditions have been used, cf. Fig. 2.

vehicles, the driving strategies, and the boundary conditions on the capacity and stability of traffic flow are evaluated by means of numerical simulations in the following subsections. For a direct evaluation of the effects of the proposed adaptive driving strategy of ACC vehicles, we set the same default parameter for human drivers and ACC-equipped vehicles, which is in line with the principal considerations of Sec. 2.

4.1 Spatiotemporal dynamics for various ACC proportions

We investigate a traffic scenario with open boundary conditions an on-ramp as typical representative for a stationary bottleneck. The simulated three-lane freeway section is 13 km long. The on-ramp merging zone of length $L_{\mathrm{rmp}} = 250\,\mathrm{m}$ is located symmetrically around $x = 10\,\mathrm{km}$. As upstream boundary condition, we have used empirical detector data from the German freeway A8 East from Munich to Salzburg. Figure 2 shows the 1-min data of the lane-averaged traffic flow and the proportion of trucks during the evening rush-hour between 15:30h and 20:00h. Moreover, we have assumed a constant ramp flow of 750 vehicles/h with 10% trucks. The parameters in Table 2 are calibrated in order to reproduce qualitatively the empiric traffic breakdown further downstream at a bottleneck. For details, we refer to Ref. (Treiber et al., 2000).

For an investigation of the impact of the proposed traffic assistance system on the traffic dynamics, we have carried out several simulations with varying proportion of vehicles equipped with ACC. The resulting spatiotemporal dynamics for ACC penetrations of 0%, 5%, 15% and 25% are shown in Fig. 2. For matters of better illustration, we have plotted inversely the lane-averaged mean velocity. Thus, a decrease in the speed due to the increase of the inflow as well as congested traffic are clearly displayed. The simulation scenario without ACC vehicles shows a traffic breakdown at $t \approx 17{:}00\,\mathrm{h}$ at the on-ramp due to the increasing incoming traffic at the upstream boundary during the rush-hour. The other three diagrams of Fig. 2 show simulation results for an increasing proportion of ACC-equipped vehicles. An increasing proportion of ACC vehicles reduces traffic congestion significantly. Already a proportion of 5% ACC vehicles improves the traffic flow demonstrating the efficiency of the proposed automated driving strategy and their positive effect on capacity already for small penetration levels. An equipment level of 25% ACC vehicles avoids the traffic breakdown in this scenario completely. We have also considered simulations with uniformly distributed time gaps T and desired velocities v_0 in order to represent individual differences between the drivers, but we found no qualitative difference.

4.2 Instantaneous and cumulated travel times

Let us now consider the travel time as the most important quantity for a user-oriented quality of service (Hall et al., 2000). While the *instantaneous travel time* as a function of simulation time reflects mainly the perspective of the drivers, the *cumulated travel time* is a performance measure of the overall system that can be associated with the economic costs of traffic jams. We define the instantaneous travel time by

$$\tau_{\mathrm{inst}}(t) = \int\limits_{x_{\mathrm{start}}}^{x_{\mathrm{end}}} \frac{\mathrm{d}x}{V(x,t)}. \qquad (11)$$

In a microscopic simulation, the average velocity $V(x,t)$ can be approximated from the velocities v_i and gaps $\Delta x_i = x_{i-1} - x_i$ of all vehicles i according to

$$\tau_{\mathrm{inst}}(t) = \sum_i \frac{\Delta x_i(t)}{v_i(t)}. \qquad (12)$$

Moreover, the cumulated travel time is simply the discretized integral over time of the vehicles in the simulation.

Figure 3 shows the instantaneous and cumulated travel times for the simulation runs in Fig. 2. Obviously, the breakdown of the traffic flow has a strong effect on the travel time. For example,

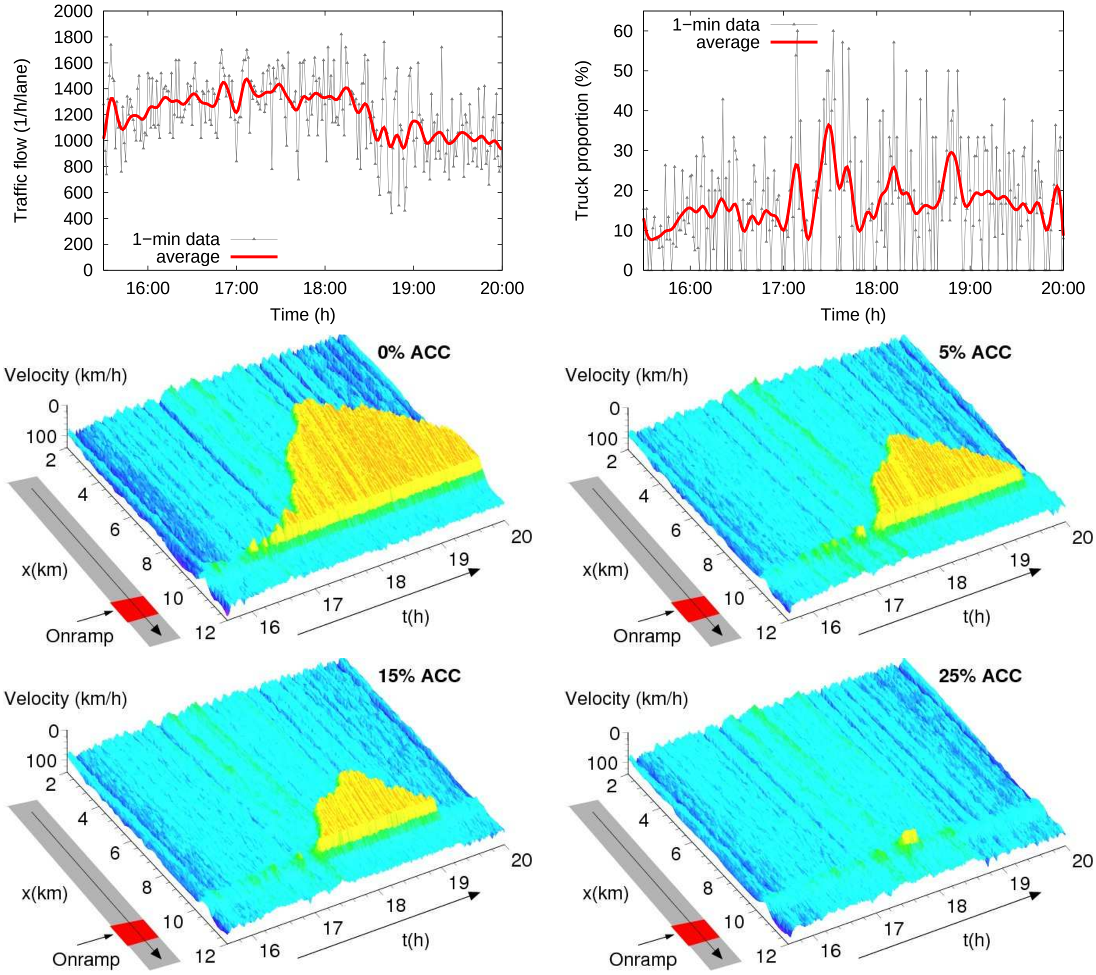

Figure 2: (Upper row) Time series of 1-min loop detector data of the lane-averaged traffic flow and truck proportion used as upstream boundary conditions in our traffic simulations. The data show the afternoon rush-hour peak of the German autobahn A8 from Munich to Salzburg. The moving average values (red thick lines) are only plotted for a better overview over the strongly fluctuating quantities. (Lower rows) Spatiotemporal dynamics displayed as lane-averaged velocity of a three-lane freeway with an on-ramp located at $x = 10\,\text{km}$ for different proportions of ACC vehicles. The simulations show the positive impact of the *traffic assistance system* for ACC-equipped vehicles introduced in Sec. 3.

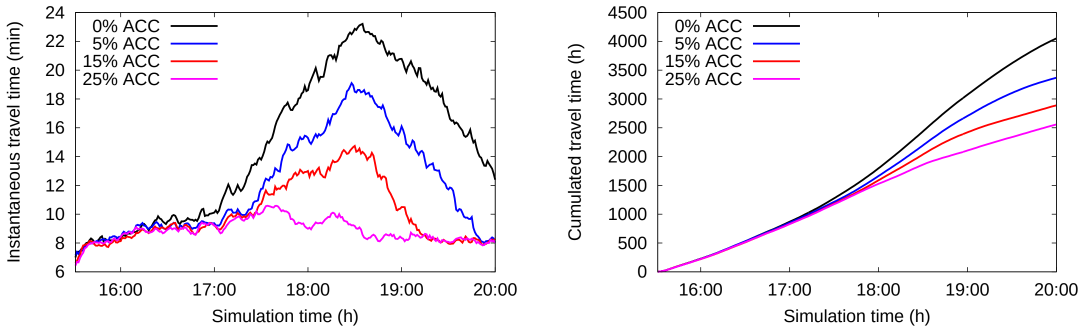

Figure 3: The instantaneous and cumulated travel times for different ACC equipment levels. The left diagram demonstrates the strong effect of a traffic breakdown on the resulting travel times, while the cumulated travel time indicates the impact of congestion on the overall system.

the cumulated travel time without ACC vehicles amounts to about 4000 h, whereas the scenario with a fraction of 25% ACC vehicles results only in approximately 2500 h. Therefore, the traffic breakdown leads to an increase of the overall travel time by 60% compared to free flow conditions. In comparison, the travel time of individual drivers at the peak of congestion ($t \approx$ 18:45 h) is even tripled compared to the situation without congestion. The time series of the instantaneous travel times indicate that an increased ACC proportion delays the traffic breakdown. Already for 5% ACC vehicles, the traffic breakdown is shifted by 20 min compared to the traffic breakdown at $t \approx$17:00 h in the scenario without ACC vehicles.

The results in Fig. 3 demonstrate that both the instantaneous and the cumulated travel time are sensitive measures for the impact of traffic congestion and, thus, the quality of service. In contrast to other macroscopic quantities such as traffic flow or average velocity, the travel time sums up over *all vehicles* in the simulation and weights their influence directly in terms of the travel time. As shown in our simulations, already a slightly increased capacity due to the adaptive driving strategy of a small fraction of traffic-assisted vehicles can have a significant positive impact on system performance.

5 Discussion and outlook

Adaptive cruise control (ACC) systems are already available on the market, these systems will spread in the future, and the next generation of ACC systems is expected to extend their range of applicability to all speeds. This offers a realistic perspective for a decentralized traffic optimization strategy based on ACC-equipped vehicles.

Up to now, ACC systems are only optimized for the user's driving comfort and safety. In fact, current ACC systems may have a negative influence on the system performance when their market penetration becomes larger. In order to ensure that ACC systems are implemented in ways that improve, rather than degrade, traffic conditions, we have proposed an ACC-based *traffic assistance system* implementing a jam-avoidance strategy. The main innovation of our concept is that ACC vehicles implement variable driving strategies and choose a specific driving strategy according to the actual traffic state. Based on local information, each vehicle detects autonomously the traffic situation and adapts automatically the parameters of the ACC system accordingly. The local traffic state detection can be improved by infrastructure-to-car and inter-vehicle communication, which offers an interesting field for applications of communication technologies.

We have presented a concrete model specification of the traffic assistance system and implemented the components within a microscopic simulation framework. The simulations served as test of our *driving strategy matrix* based on a finite set of 5 traffic states in order to resolve conflicting objectives between driving comfort and road capacity. Traffic simulations of a freeway with an on-ramp serving as bottleneck showed that the temporary reduction of the time gap in the 'bottleneck state' and the 'downstream front' of congested traffic is sufficient for an improvement of the traffic flow efficiency. As a bottleneck is *defined* by a capacity reduction, the *reduction of the time gap at a bottleneck in order to fill the capacity gap* is a general approach applicable to other kinds of bottlenecks as well (Kesting et al., 2006a).

Furthermore, our simulations of the afternoon rush-hour peak of a German autobahn rush-hour showed that already a small percentage of 'intelligent' ACC vehicles, i.e., a relatively modest change in the maximum free flow can significantly improve the traffic performance. The breakdown of the traffic flow is delayed (or avoided), which (together with an increased dynamic capacity) results in reduced queue lengths in congested traffic. The simulations demonstrate that already an ACC equipment level of 5% improves the traffic flow quality and reduces the travel times for the drivers in a relevant way. The presented results are largely independent of details of the model, the upstream boundary conditions, or the type of road inhomogeneity. Note that a positive impact of the proposed jam-avoidance assistance system already for a gradual market penetration is important for the success of such a system.

The simulations were based on the assumption that only a small fraction of ACC vehicles adapts their parameters according to the proposed *jam-avoiding* driving strategy, while the manually controlled vehicles applied a time-independant driving style. On the other hand, human drivers may adapt their driving style as well (Treiber et al., 2006b; Treiber and Helbing, 2003). It is an interesting research problem to identify empirically the character of human adaptations, their sign and magnitude on the scale of the microscopic driving behavior.

The presented work was developed in cooperation with a car manufacturer. A real-world implementation of an ACC based on the Intelligent Driver Model has recently been presented within the German research project INVENT (BMBF, 2005). Our current research focusses on the implementation of the presented driving strategies and the transition between them in test vehicles (Kranke et al., 2006).

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