

Jam-avoiding adaptive cruise control (ACC) and its impact on traffic dynamics

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Abstract. Adaptive-Cruise Control (ACC) automatically accelerates or decelerates a vehicle to maintain a selected time gap, to reach a desired velocity, or to prevent a rear-end collision. To this end, the ACC sensors detect and track the vehicle ahead for measuring the actual distance and speed difference. Together with the own velocity, these input variables are exactly the same as in car-following models. The focus of this contribution is: What will be the impact of a spreading of ACC systems on the traffic dynamics? Do automated driving strategies have the potential to improve the capacity and stability of traffic flow or will they necessarily increase the heterogeneity and instability? How does the result depend on the ACC equipment level?

We discuss microscopic modeling aspects for human and automated (ACC) driving. By means of microscopic traffic simulations, we study how a variable percentage of ACC-equipped vehicles influences the stability of traffic flow, the maximum flow under free traffic conditions until traffic breaks down, and the dynamic capacity of congested traffic. Furthermore, we compare different percentages of ACC with respect to travel times in a specific congestion scenario. Remarkably, we find that already a small amount of ACC equipped cars and, hence, a marginally increased free and dynamic capacity, leads to a drastic reduction of traffic congestion.

1 Introduction

Traffic congestion is a severe problem on European freeways. According to a study of the European Commission [1], its impact amounts to 0.5% of the gross national product and will increase even up to 1% in the year 2010. Since building new infrastructure is no longer an appropriate option in most (Western) countries, there are many approaches towards a more effective road usage and a more 'intelligent' way of increasing the capacity of the road network. Examples of advanced traffic control systems are, e.g., 'intelligent' speed limits, adaptive ramp metering, or dynamic routing. These examples are based on a centralized traffic management, which controls the operation and the response to a given traffic situation. In this contribution, we focus on a local strategy based on autonomous vehicles, which are equipped with adaptive cruise control (ACC) systems. The motivation is that a 'jam-avoiding' driving strategy of these automated vehicles

might also help to increase the road capacity and thus decrease traffic congestion. Moreover, ACC systems become commercially available to an increasing number of vehicle types.

An ACC system is able to detect and to track the vehicle ahead, measuring the actual distance and speed difference. Together with the own speed, these input data allow the system to calculate the required acceleration or deceleration to maintain a selected time headway, to reach a desired velocity, or to prevent a rear-end collision. It should be emphasized that ACC systems control the longitudinal driving task. Merging, lane changing or gap-creation for other vehicles still needs the intervention of the driver. ACC systems promise a gain in comfort and safety in applicable driving situations, but they are not yet applied in congested traffic conditions. The next generation of ACC will successfully extend the application range to all speed ranges and most traffic situations on freeways including stop-and-go traffic. This leads to the question: In which way does a growing market penetration of ACC-equipped vehicles influence the capacity and stability of traffic flow? Although there is considerable research on this topic [2], there is even no clarity up to now about the sign of the effect. Some investigations predict a positive effect [3,4], while others are more pessimistic [5,6].

The contribution is organized as follows: We start with a discussion of modeling issues concerning the description of human vs. automated driving and pinpoint the differences between ACC-driven vehicles and human drivers. In Sec. 3, we will model three ACC driving styles, which are explicitly designed to increase the dynamic capacity and traffic stability by varying the individual driving behavior. Since the impact on the traffic dynamics could solely be answered by means of traffic simulations, in Sec. 4 we perform a simulation study of mixed freeway traffic with a variable percentage of ACC vehicles. In Sec. 5, we conclude with a discussion of our results.

2 Modeling human and automated (ACC) driving behavior

Most microscopic traffic models describe the acceleration and deceleration of each individual 'driver-vehicle unit' as a function of the distance and velocity difference to the vehicle in front and on the own velocity [7,8]. Some of these car-following models have been successful to reproducing the characteristic features of macroscopic traffic phenomena such as traffic breakdowns, the scattering in the fundamental diagram, traffic instabilities, and the propagation of stop-and-go waves or other patterns of congested traffic. While these collective phenomena can be described by macroscopic, fluid-dynamic traffic models as well [9], microscopic models are more appropriate to cope with the heterogeneity of mixed traffic, e.g., by representing individual driver-vehicle units by different parameter sets or even by different models.

Remarkably, the input quantities of car-following models are exactly those of an ACC system. As in microscopic models, the ACC controller unit calculates the acceleration with a negligible response time. Therefore, one might state that

car-following models describe ACC systems more accurately than human drivers despite of their intention to reproduce the traffic dynamics of human driving behavior.

Thus, the question arises, how to take into account the *human* aspects of driving for a realistic description of the traffic dynamics. The nature of human driving is apparently more complex. First of all, the *finite reaction time* of humans results in a delayed response towards the traffic situation. Furthermore, human drivers have to cope with imperfect estimation capabilities resulting in *perception errors* and *limited attention spans*. These destabilizing influences alone would lead to a more unsafe driving and a high number of accidents if the reaction time reached the order of the time headway. But in day-to-day situations the contrary is observed: In dense (not yet congested) traffic, the modal value of the time headway distribution on German or Dutch freeways (i.e., the value where it reaches its maximum) is around 0.9 s [10,11,12], which is of the same order of typical reaction times [13]. Moreover, single-vehicle data for German freeways [10] indicate that some drivers even drive at headways as low as 0.3 s, which is below the reaction time by a factor of at least 2-3 even for a very attentive driver. For principal reasons, therefore, safe driving is not possible in this case when considering only one vehicle in front.

This suggests that human drivers achieve additional stability and safety by scanning the traffic situation *several vehicles ahead* and by *anticipating* future traffic situations. The question is, how this behavior affects the overall driving behavior and performance with respect to ACC-like driving mimicked by car-following models. Do the stabilizing effects (such as anticipation) or the destabilizing effects (such as reaction times and estimation errors) dominate, or do they effectively cancel out each other? The *human driver model* (HDM) [14] extends the car-following modeling approach by explicitly taking into account reaction times, perception errors, spatial anticipation (more than one vehicle ahead) and temporal anticipation (extrapolating the future traffic situation). It turns out that the destabilizing effects of reaction times and estimation errors can be compensated for by spatial and temporal anticipation [14]. One obtains essentially the same longitudinal dynamics, which explains the good performance of the simpler, ACC-like car-following models.

Thus, for the sake of simplicity, we model both automated ACC-driving and human driving with the same microscopic traffic model, but differentiate the driving strategies by different parameter sets.

3 'Jam-avoiding' ACC driving strategies

As discussed in the previous section, both human drivers and ACC-controlled vehicles are effectively described by the car-following model approach. Here, we will use the *intelligent driver model* (IDM) [15], according to which the acceleration of each vehicle α is a continuous function of the velocity v_α , the net distance gap s_α , and the velocity difference (approaching rate) Δv_α to the leading vehicle:

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

The deceleration term depends on the ratio between the effective 'desired minimum gap'

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

and the actual gap s_α . The minimum distance s_0 in congested traffic is significant for low velocities only. The dominating term in stationary traffic is vT , which corresponds to following the leading vehicle with a constant safe time headway 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 . The IDM guarantees crash-free driving. The parameters for the simulations are given in Table 1.

In order to design a jam-avoiding behavior for the ACC vehicles, we modify the ACC model parameters. The (average) time headway has a direct relation to the maximum (static) road capacity: Neglecting the length of vehicles leads to the approximative relationship $Q \approx 1/T$ between the flow Q and the headway T (cf. Eq. (3) below). The crucial parameter controlling the capacity is, therefore, the safe time headway, which is an explicit parameter of the IDM. Moreover, the system performance is not only determined by the time headway distribution, but also depends on the *stability* of traffic flow. An ACC driving behavior aiming at increasing the traffic performance should, therefore, additionally consider a driving strategy which is able to stabilize the traffic flow, e.g. by a faster dynamic adaptation to the new traffic situation. The stability is mainly affected by the IDM parameters 'maximum acceleration' and 'desired deceleration', see [15].

In the following, we will investigate the potentials of three different parameter sets for jam-avoiding driving behavior, varying the IDM parameters T , a and b . In order to refer to the values given in Table 1, we express the parameter changes by simple multipliers. For example, $\lambda_a = 2$ represents an increased ACC parameter $a' = \lambda_a a$, where a is the value listed in Table 1.

- (1) The reduction of the time headway T by a factor $\lambda_T = 2/3$ has a positive impact on the capacity. The other model parameters of Table 1 remain unchanged, i.e., in particular, $\lambda_a = 1$, $\lambda_b = 1$.
- (2) Besides setting $\lambda_T = 2/3$, we increase the desired acceleration by choosing $\lambda_a = 2$. The faster acceleration towards the desired velocity increases the traffic stability.
- (3) The additional reduction of the desired deceleration by $\lambda_b = 1/2$ corresponds to a more cautious and more anticipative driving style. This behavior also increases the stability.

Model Parameter	Value
Desired velocity v_0	120 km/h
Save time headway T	1.5 s
Maximum acceleration a	1.0 m/s ²
Desired deceleration b	2.0 m/s ²
Jam distance s_0	2 m

Table 1. Model parameters of the *intelligent driver model* (IDM) used in our simulations. The vehicle length is 5 m. In order to model 'jam-avoiding' ACC strategies, we modify the safe time headway parameter T , the 'maximum acceleration' a and the 'desired deceleration' b by multipliers λ_T , λ_a , and λ_b , respectively.

4 Microscopic simulations of mixed traffic

Let us now investigate the impact of ACC vehicles which are designed to enhance the capacity and stability of traffic flows. We will simulate mixed traffic consisting of human and automated (ACC) longitudinal control with a variable percentage of ACC vehicles.

Our simulation is carried out a single-lane road with an on-ramp serving as bottleneck and with open boundary conditions. To keep matters simple, we replace an explicit modeling of the merging of ramp vehicles to the main road by inserting ramp vehicles centrally into the largest gap within a 300 m long ramp section. In order to generate a sufficient velocity perturbation in the merge area, the speed of the accelerating on-ramp vehicles at the time of insertion is assumed to be 50% of the velocity of the respective front vehicle.

Moreover, we neglect trucks and multi-lane effects. While these aspects are relevant in real traffic, they do not change the picture qualitatively. Nevertheless, the induction of a second driver-vehicle type, e.g., ACC vehicles, always has the potential to reduce the traffic performance by an increased level of heterogeneity. We have compared the simulation results with Gaussian distributed model parameters, but found no qualitative difference for this single-lane scenario.

4.1 Spatiotemporal dynamics and travel time

Let us now demonstrate that already a moderate increase in the dynamic capacity obtained by a small percentage of 'jam-avoiding' ACC vehicles may have a significant effect on the system performance.

We have simulated idealized rush-hour conditions by linearly increasing the inflow at the upstream boundary over a period of 2 hours from 1200 vehicles/h to 1600 vehicles/h. Afterwards, we have linearly decreased the traffic volume to 1000 vehicles/h until $t = 5$ h. Moreover, we have assumed a constant ramp flow of 280 vehicles/h. Since the maximum overall flow of 1880 vehicles/h exceeds the road capacity, a traffic breakdown is provoked at the bottleneck. We have used the IDM parameters from Table 1 and parameter set (3) for ACC vehicles, i.e., $\lambda_T = 2/3$, $\lambda_a = 2$, $\lambda_b = 1/2$.

Figure 1 shows the spatiotemporal dynamics of the traffic density for 0% and 10% ACC vehicles. The increased capacity obtained by the induced ACC vehicles leads to a strong reduction of the traffic jam already for a small percentage of ACC vehicles. For 30% ACC vehicles, the traffic jam disappears completely.

An increased percentage of 'jam-avoiding' ACC vehicles has a strong effect on the travel time: Figure 2 shows the actual and cumulated travel times for various ACC percentages. At the peak of congestion ($t = 3.2$ h), the travel time for individual drivers is nearly triple that of the uncongested situation ($t < 1$ h). Already 10% ACC vehicles reduce the maximum travel time delay of individual drivers by about 30% (Fig. 2(a)), and the cumulated time delay (which can be associated with the economic cost of this jam) by 50% (Fig. 2(b)). Several factors contribute to this enhanced system performance. First, an increased ACC percentage leads to a delay of the traffic breakdown. Second, the ACC vehicles reduce the maximum queue length significantly. Third, the jam dissolves earlier. These effects, which are responsible for the drastic increase in the system performance already for a small proportion of 'jam-avoiding' ACC vehicles, will be investigated in the following.

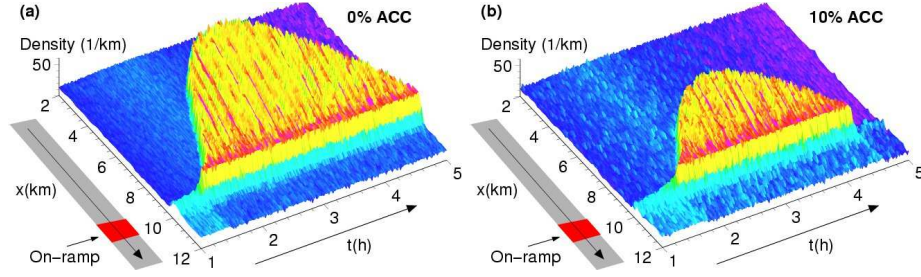


Fig. 1. Spatiotemporal dynamics of the traffic density (a) without ACC vehicles and (b) with 10% ACC vehicles (parameter set (3)). Already a small increase in the road capacity induced by a small percentage of 'jam-avoiding' ACC vehicles leads to a significant reduction of traffic congestion (light high-density area).

4.2 Maximum capacity in free traffic

The *static road capacity* Q_{\max}^{theo} , which corresponds to the maximum of the flow-density diagram, is mainly determined by the average time headway T . However, the theoretical capacity depends also on the 'effective' length $l_{\text{eff}} = l_{\text{veh}} + s_0$ of a driver-vehicle unit and is given by

$$Q_{\max}^{\text{theo}} = \frac{1}{T} \left(1 - \frac{l_{\text{eff}}}{v_0 T + l_{\text{eff}}} \right). \quad (3)$$

The maximum capacity Q_{\max}^{free} before traffic breaks down (which is a *dynamic* quantity), however, is typically lower than Q_{\max}^{theo} , since it depends on the traf-

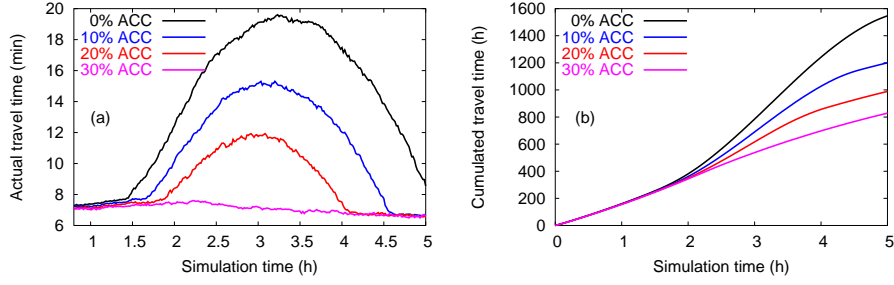


Fig. 2. Time series for (a) the actual and (b) the cumulated travel times for simulation runs with different percentages of ACC vehicles. The traffic breakdown leads to a significant prolongation of travel time. A proportion of 30% ACC vehicles can completely prevent the traffic breakdown.

fic stability as well. Therefore, we have analyzed the 'maximum free capacity' resulting from the traffic dynamics as a function of the average time headway T and the percentage of ACC vehicles. Our related simulation runs start with a low upstream inflow and linearly increase the inflow with a rate of $\dot{Q}_{\text{in}} = 800$ vehicles/h². We have checked other progression rates as well, but found a marginal difference only.

For determining the traffic breakdown, we have used 'virtual detectors' located 1 km upstream and downstream of the on-ramp location. In analogy to the real-world double-loop detectors, 'virtual detectors' count the passing vehicles, measure the velocities, and aggregate the data within a time interval of one minute. For each simulation run, we have recorded the maximum flow before traffic has broken down (single dots in Fig. 3(a)). Due to the complexity of the simulation and the 1-min data aggregation, $Q_{\text{max}}^{\text{free}}$ varies stochastically. We have, therefore, averaged the data with a linear regression using a Gaussian weight of width $\sigma = 0.2$, and plotted the expectation value and the standard deviation.

Figure 3(a) shows the maximum free capacity as a function of the ACC percentage for the three different parameter sets representing different ACC driving styles. $Q_{\text{max}}^{\text{free}}$ increases approximately linearly with increasing percentage of ACC vehicles. The parameter a mainly increases the traffic stability, which leads to a delayed traffic breakdown and, thus, to higher values of $Q_{\text{max}}^{\text{free}}$. Remarkably, the values are nearly identical with those for heterogenous traffic consisting of driver-vehicle units with Gaussian distributed parameters.

In Fig. 3(b) the most important parameter, the time headway T , is varied for a homogeneous ensemble of 100% ACC vehicles. Obviously, $Q_{\text{max}}^{\text{free}}$ decreases with increasing T . Furthermore, the dynamic quantity $Q_{\text{max}}^{\text{free}}$ remains always lower than the theoretical capacity $Q_{\text{max}}^{\text{theo}}$ given by Eq. (3), which is only reached for perfectly stable traffic. The three parameter sets show the influence of the IDM parameters a and b : The acceleration a has a strong impact on traffic stability, while the stabilizing influence of b is smaller. Finally, as the difference between

Q_{\max}^{theo} and the dynamic maximum free capacity Q_{\max}^{free} increases for lower values of T , one finds that a smaller T reduces stability as well.

In order to assess the potentials of various driving styles, we have evaluated an approximate relationship as a function of the ACC equipment level α_{ACC} . The relative gain γ in system performance is given by

$$\gamma \approx [0.95(1 - \lambda_T) + 0.07\lambda_a + 0.08(1 - \lambda_b)] \alpha_{\text{ACC}}. \quad (4)$$

Thus, λ_T is the most crucial parameter, while λ_b has hardly any influence. For example, lowering the time headway by $\lambda_T = 0.7$ with $\alpha_{\text{ACC}} = 1$ results in a maximum gain of $\gamma \approx 30\%$.

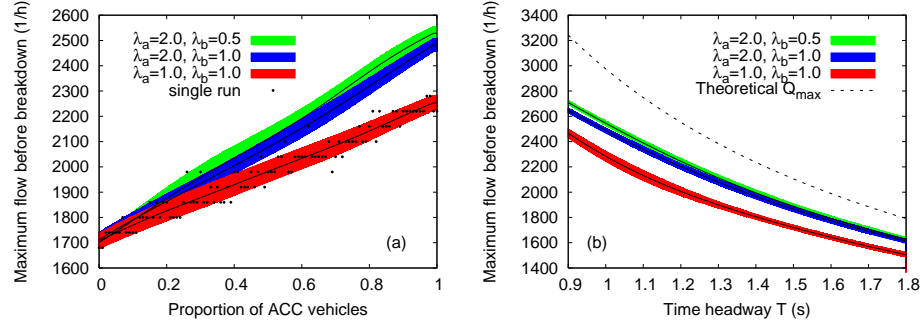


Fig. 3. Maximum free capacity as a function of (a) the percentage of ACC vehicles, and (b) the time headway T for 100% ACC vehicles. We have simulated three different parameter sets for ACC vehicles with $\lambda_T = 2/3$ and varying values of λ_a and λ_b (see main text). Dots indicate results of single simulation runs, while the solid lines correspond to averages over several simulations and the associated bands to plus/minus one standard deviation.

4.3 Dynamic capacity after a traffic breakdown

Let us now investigate the system dynamics after a traffic breakdown. The crucial quantity is the *dynamic capacity*, i.e., the downstream outflow from a traffic congestion Q_{out} [16]. The difference between the free capacity Q_{\max}^{free} and Q_{out} is denoted as *capacity drop* with typical values between 5% and 30%.

We have used the same simulation setup as in the previous section. After a traffic breakdown was provoked by an increasing inflow, we have averaged over the 1-min flow data of the 'virtual detector' 1 km downstream of the bottleneck. We have identified the congested traffic state by filtering out for velocities smaller than 50 km/h at a cross-section 1 km upstream of the bottleneck. Again, we have averaged over multiple simulation runs by applying a Gaussian-weighted linear regression.

Figure 4(a) shows the dynamic capacity for a variable percentage of ACC vehicles for the three different parameter sets specified before. Interestingly, the capacity increase is not linear as in Fig. 3(a). Above approximately 50% ACC vehicles, the dynamic capacity increases faster than for lower percentages. We explain this behavior with an 'obstruction effect': the faster accelerating ACC vehicles are hindered by the slower accelerating drivers. In fact, the slowest vehicle type determines the dynamic capacity, which could be called a 'weakest link effect'. In conclusion, distributed model parameters have a quantitative effect on the outflow from congested traffic (it is lower than for homogeneous traffic with averaged parameters), while such an effect is not observed for the free-flow capacity!

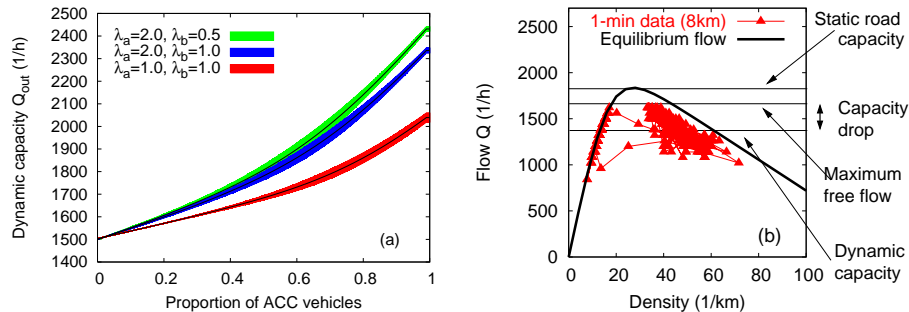


Fig. 4. (a) Dynamic capacity as a function of the percentage of ACC vehicles. The curves represent three different parameter sets corresponding to different ACC driving strategies. The results from multiple simulation runs are averaged using a linear regression with a Gaussian weight of width $\sigma = 0.2$. (b) Flow-density data for the traffic breakdown determined from a 'virtual' detector 2 km upstream of the bottleneck without ACC vehicles. The equilibrium flow-density curve of identical vehicles corresponds to the parameter set given in Table 1.

5 Discussion

Adaptive cruise control (ACC) systems are already available on the market. The next generations of ACC systems will extend their range of applicability to all speeds, and it is assumed that their spreading will grow in the future. In this contribution, by means of microscopic traffic simulations we have investigated the impact that an automated longitudinal driving control of ACC systems based on the intelligent driver model (IDM) is expected to have on the traffic dynamics.

ACC systems are closely related to car-following models as their reaction is restricted to a leading vehicle. Moreover, we have explained why such a car-following approach also captures the main aspects of longitudinal driver behavior so well. We, therefore, expect that both ACC systems and human driver behavior

will mix consistently in future traffic flows although the driving operation is fundamentally different.

The equipment level of ACC systems provides an interesting option to enhance the traffic performance by automated driving strategies. In order to analyze the potentials, we have studied ACC driving styles, which are explicitly designed to increase the capacity and stability of traffic flows. We have varied the percentage of ACC vehicles and found that already a small proportion of ACC vehicles, which implies a marginally increased free and dynamic capacity, leads to a drastic reduction of traffic congestion. Furthermore, we have shown that, capacity and stability do have similar importance for the traffic dynamics.

We have assumed that the ACC systems have a more 'jam-avoiding' driving style than the human drivers. One might additionally take into account inefficient human behavior when traffic gets denser and the time headway increases with increasing local velocity variance [12,17]. In this case, a constant time headway policy for automated driving is expected to improve the system performance even more.

Up to now, ACC systems are only optimized for the user's driving comfort and safety. In fact, present ACC systems may have a negative influence on the system performance when their percentage becomes large. The design of ACC strategies, which also consider their impact on traffic dynamics, will be crucial for the next ACC generations.

Furthermore, we propose to implement an 'intelligent' ACC strategy that adapts the ACC driving style *dynamically* to the overall traffic situation. For example, in dense, but not yet congested traffic, a jam-avoiding parameter set could help to delay or suppress traffic breakdowns as shown in our simulations, while in free traffic a parameter set mimicking natural driver behavior may be applied instead. The respective 'traffic state' could be autonomously detected by the vehicles using the history of their sensor data in combination with digital maps. Moreover, inter-vehicle communication could contribute information about the traffic situation in the neighborhood, e.g., by detecting the downstream front of a traffic jam [18].

Acknowledgments: The authors would like to thank Hans-Jürgen Stauss, and Klaus Rieck for the excellent collaboration and the Volkswagen AG for partial financial support within the BMBF project INVENT.

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