Highly Automated Driving on Freeways in Real Traffic Using a Probabilistic Framework

Michael Ardelt, Constantin Coester, and Nico Kaempchen

***Abstract*—A system, particularly a decision-making concept, that facilitates highly automated driving on freeways in real traffic is presented. The system is capable of conducting fully automated lane change (LC) maneuvers with no need for driver approval. Due to the application in real traffic, a robust functionality and the general safety of all traffic participants are among the main requirements. Regarding these requirements, the consideration of measurement uncertainties demonstrates a major challenge. For this reason, a fully integrated probabilistic concept is developed. By means of this approach, uncertainties are regarded in the entire process of determining driving maneuvers. While this also includes perception tasks, this contribution puts a focus on the driving strategy and the decision-making process for the execution of driving maneuvers. With this approach, the BMW Group Research and Technology managed to drive 100% automated in real traffic on the freeway A9 from Munich to Ingolstadt, showing a robust, comfortable, and safe driving behavior, even during multiple automated LC maneuvers.**

***Index Terms*—Advanced driver-assistance systems (ADASs), highly automated driving, lateral vehicle guidance, probabilistic decision making.**

I. Introduction and Motivation

WITHIN the field of driver assistance and active safety systems, there has been a steady increase in the degree of automation during the recent decades. The reasons for this are diverse. In addition to ecological factors, such as reduction in energy consumption [1], economic and safety aspects are influential motives for this development [2].

From an economic point of view, driver assistance systems are nowadays among the main areas of innovation in automotive engineering. Hence, unique selling propositions can be generated for the manufacturers. In particular, safety systems, such as automatic braking systems (ABS) or electronic stability programs (ESP), reach a significant market penetration within a short time period. Furthermore, the development of systems that increase the overall traffic safety is promoted by the public sector, for instance, the European Commission, which formulated the objective to halve the number of traffic fatalities by 2020 [3]. The development of intelligent vehicles is one way of reaching this goal.

Manuscript received October 10, 2011; revised February 4, 2012 and April 12, 2012; accepted April 14, 2012. Date of publication May 16, 2012; date of current version November 27, 2012. This work was supported by the BMW Group Research and Technology in Munich, Germany. The Associate Editor for this paper was Z.-H. Mao.

The authors are with BMW Group Research and Technology, D-80788 Munich, Germany (e-mail: michael.ardelt@bmw.de; constantin.coester@bmw.de; nico.kaempchen@bmw.de).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TITS.2012.2196273

(a) (b)

Fig. 1. Automated vehicle guidance on (a) the freeway A9 and (b) route from Munich to Ingolstadt (Image source: [6]). (a) Freeway. (b) Route.

For these reasons, the BMW Group Research and Technology is developing highly automated assistance and active safety systems of the future and is investigating their potential. An example of this is the *Emergency Stop Assistant* (ESA). This system takes over vehicle control, safely steers the vehicle to the side of the road, and stops if the driver suffers a health irregularity, such as an acute problem with the cardiovascular system or, perhaps, even a heart attack [4], [5]. In a freeway scenario with right-hand traffic, this active safety system could conduct secured automated lane change (LC) maneuvers to the right to reach the breakdown lane to stop the vehicle. To realize such systems on freeways, the BMW Group Research and Technology is conducting a potential study of the topic *Highly Automated Driving on Freeways* (HAD). The objective is to temporarily execute the entire vehicle guidance by a control unit. During the automated driving mode, the driver merely has to monitor the system and not actively control the vehicle. The control system analyzes the situation, derives decisions regarding suitable driving maneuvers, and finally automatically conducts these maneuvers without requiring driver approval. The driver could, however, intervene at any time due to safety reasons. For the evaluation of this system, the objective has been formulated to drive automated on freeway A9 from Munich to Ingolstadt without driver intervention. Fig. 1 shows an image of automated vehicle guidance on freeway A9 and the complete route. During this test drive, the system operates in real traffic and conducts fully automated LC maneuvers with no need for driver approval.

There are numerous research projects within the field of autonomous and highly automated driving vehicles. These, however, differ in several aspects from the system presented in this contribution. Most of today's systems, such as the vehicles from the DARPA challenges [7]–[9] and the project

Stadtpilot [10], [11] or Google's autonomous vehicle [12], contain multiple eye-catching sensors that are mounted on the roof of the host vehicle to achieve a high-resolution full-surround environment perception. Due to special requirements regarding an attractive vehicle design of serial production vehicles to potential customers, however, the sensor locations of the applied test vehicle are restricted (see Fig. 7 later in the paper). Furthermore, the system within this contribution is designed for high velocities up to 140 km/h, which is significantly higher than the velocities of most of the previously mentioned vehicles. Projects that have been considerably similar are the *Intelligent Car* project of the Volkswagen AG [13] and the *HAVEit* project [14], [15]. Within these projects, vehicles also applied HAD; however, LC maneuvers were required to be approved by the driver before execution, which is not required within the system presented in this contribution.

From these objectives and challenges, several requirements for the highly automated driving system can be derived. Requirements, such as expandability and flexibility of the system structure, arise for future development and optimization of the system. As emphasized in [16] and [17], the most determining requirement concerning a potential future market launch, however, is the safety of all traffic participants. For this reason, the system has to be controllable, transparent, robust, and, thus, not error prone. This is a great challenge, particularly concerning the uncertainties that arise from measurement inaccuracy of the vehicle sensors.

This contribution is organized as follows: In Section II, the global system architecture and the significance of the consideration of uncertainties within this structure are presented. Section III discusses the driving strategy and the decision-making process regarding automated driving maneuvers. The total system is evaluated for an automated overtaking maneuver and for the automated test drive on freeway A9 from Munich to Ingolstadt in Section IV. The contribution concludes with a summary of the most significant results and a discussion concerning future directions in Section V.

II. Global System Structure

The global system addresses HAD. Due to the interdisciplinarity within the development of this system, a modular structure is applied to the global system architecture. This modularity facilitates the parallelization of the development process, which has a positive effect on development time and costs. Furthermore, this type of structure is highly flexible and can easily be extended or modified during the development process. The architecture of the global system is shown in Fig. 2.

The information concerning the host vehicle's environment (road, lanes, and objects) is provided online by the vehicle's sensors and by a high-precision digital map (centimeter-precise) that is generated beforehand. The raw sensor and map data are processed within the subsequent *Perception* unit. The *Object Tracking* module fuses the data of multiple sensors and generates a global object list with the objects' attributes [18]. The *Localization* module determines the location of the host vehicle within the digital map. All relevant information is forwarded to the *Functionality* unit. Within this unit, the *Driving Strategy* module makes decisions regarding driving maneuvers. These maneuvers are derived from the general objectives (e.g., ESA or HAD) and the traffic situation that is determined based on the digital image of the host vehicle's environment. The respective maneuvers are realized by the *Driving Trajectories & Control* module and finally by the steering, acceleration, and deceleration actuators. Furthermore, the system provides information, such as the current system states, to the driver and occupants via the human–machine interface (HMI) and further controls host vehicle functionalities, such as the indicators, via the vehicle bus.

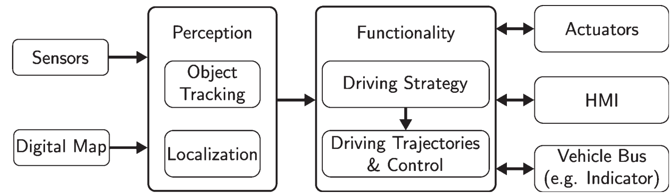

Fig. 2. Modular global system structure for highly automated driving.

Both the online data of the sensors and the *a priori* generated digital map contain uncertainties due to measurement inaccuracies. These uncertainties are modeled with a normal distribution due to the application of Kalman filters within the object tracking and localization modules. To secure a robust and safe functionality, the uncertainties have to be considered within the control system. However, probabilistic approaches can be error prone [19] due to an increased complexity and thus affect the robustness of the system. Hence, a major challenge is the consideration of uncertainties without affecting the system robustness. Within the presented fully integrated probabilistic concept for highly automated driving, measurement uncertainties are taken into account within the *Perception* unit, forwarded to the *Functionality* unit, and applied to the decision-making processes for driving maneuvers. This approach significantly contributed to the successful, comfortable, and safe automated test drive from Munich to Ingolstadt without driver intervention.

In the following, this contribution focuses on the *Driving Strategy* module of the *Functionality* unit and, particularly, on the decision-making process for the execution of driving maneuvers under the consideration of uncertainties.

III. Driving Strategy

Based on the traffic situation and the objectives of the functionality, decisions have to be made regarding suitable driving maneuvers for the host vehicle. To reduce the complexity of the vehicle guidance, a new hybrid concept has been developed that applies a discrete number of system states in which continuous driving maneuvers are conducted. This approach combines a network of deterministic hybrid automata with decision trees for the determination of the system states and is presented in [4] and [20]. While the automata network offers a highly flexible structure, the integrated decision trees facilitate robust and efficient decision-making processes. The system states that can be selected within this structure are listed in Table I. Generally, the driving task is divided into lateral and longitudinal guidance.

TABLE I
SYSTEM STATES FOR HAD ON FREEWAYS

	Lateral Guidance (q_{lat})	Longitudinal Guidance (q_{long})
0	Off	Off
1	Lane Keeping	DCC
2	LCGA (left)	ACC
3	LCGA (right)	LCGA
4	Lane Change (left)	Critical Control
5	Lane Change (right)	
6	LC-Abortion (left)	
7	LC-Abortion (right)	
8	Stopping-Trajectory	

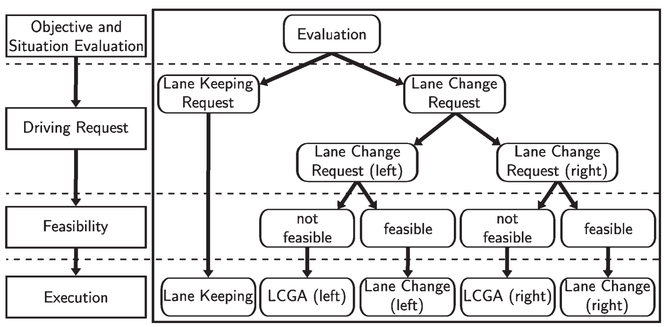

Fig. 3. Multilevel hierarchical decision-making process.

Within the lateral guidance, the vehicle is capable of keeping the current lane and changing lanes on both the left and right sides. To consider unpredictable situations, LCs can be aborted. Furthermore, the host vehicle can apply special trajectories for stopping maneuvers, such as stopping at the side of a lane and not at the middle. Within the *LC Gap Approach* (LCGA) states, the host vehicle is able to apply driving strategies to facilitate an LC if this maneuver is desired but not feasible. These strategies persist for lateral and longitudinal guidance. Within the lateral guidance, the host vehicle could slightly be moved toward the target lane, for instance, to signalize the motivation for an LC. Within the longitudinal guidance, the host vehicle could be positioned next to a traffic gap to facilitate an LC. During the *Dynamic Cruise Control* (DCC) state, no target object that could prevent the host vehicle from maintaining its desired velocity exists. Within the *Adaptive Cruise Control* (ACC) state, however, a target object exists, to which the host vehicle has to maintain a certain safety distance. This distance is also maintained in critical situations, in which the system applies enhanced braking maneuvers in a separate state.

As previously mentioned, a new concept is applied to select the current system states for lateral and longitudinal guidance. By means of the decision trees within this concept, a multilevel hierarchical decision-making process is conducted, which is shown in Fig. 3. The desired driving maneuver is derived from the objectives of the functionality and from the traffic situation. This request is subsequently examined concerning its feasibility, and a respective maneuver is executed. In Fig. 3, which shows a decision-making process for lateral guidance, an LC is executed if this maneuver is desired and feasible. If an LC is desired, however not feasible, the LCGA strategy is applied. This multilevel decision-making process contains several advantages, compared with directly deriving driving maneuvers from the current situation. Applying probability-based approaches with direct influence on driving maneuvers, such as those suggested in [2], can lead to nondeterministic behavior and to infringement of traffic rules [10], [11]. For this reason, the additional feasibility examination of driving requests increases the robustness of the decision-making process and the overall traffic safety. Furthermore, this concept facilitates a differing consideration of uncertainties for the respective decision steps. Consequently, a probability-based and creative approach can be applied for the generation of the desired driving behavior, whereas worst-case consideration with clear rule-based behavior is applied to the feasibility determination. Hence, uncertainties are considered within the decision-making process but without affecting the robustness of the system. In the following, this decision-making process is demonstrated in detail for LC decisions within the lateral guidance. In contrast to most previous publications, e.g., [21]–[24], this contribution focuses on the decision-making process and not on the trajectory planning and control for LC maneuvers.

A. Objective and Situation Evaluation

The objectives of the system differ, depending on the desired functionality. The ESA on freeways with right-hand traffic, for instance, merely applies LCs to the right to reach the breakdown lane. For HAD, however, LCs to the left adjacent lane are additionally required, such as for overtaking maneuvers. In this contribution, LC decisions are demonstrated for the HAD functionality.

The traffic situation is derived from the data provided by the *Perception* unit. Generally, road, lane, and object data are perceived. To generate a digital image of the host vehicle's surroundings, the objects from the *Object Tracking* module are matched on the road, and the lanes from the digital map and the objects' attributes, such as their locations and velocities, are transformed into a road coordinate system. This coordinate system contains its x-coordinate in the current direction of the road and its y-coordinate perpendicular to this direction. As a consequence, objects within the host vehicle's surroundings can be assigned to specific lanes and areas around the host vehicle, even on complex road courses [4].

B. LC Request

For HAD, it has to be determined if the current lane is the most suitable for the host vehicle or if an LC to one of the two adjacent lanes is desirable. As previously mentioned, the uncertainties from the sensor data, which are processed in the *Perception* unit, have to be taken into account. By considering these uncertainties in the decision-making process, the robustness of the generated LC requests can be increased, and incomprehensible driving behavior is avoided. Generally, the host vehicle should merely change lanes if there is a high probability that the respective adjacent lane is more suitable.

Among existing LC models for automated driving and traffic simulation, versatile approaches for the selection of the target lane can be found. A common approach is the classification of LCs based on their motivation. LCs that are based on the desired route or the road properties (e.g., a lane ends) are called mandatory LCs (MLCs). Discretionary LCs (DLCs), on the other hand, are the result of dissatisfying driving conditions due to other vehicles [25]. This classification facilitates assigning a higher priority to the more relevant MLCs. When it comes to decision making within highly automated driving, the literature provides two main procedures. A considerable number of models contain rule-based decision-making processes [26]–[28], whereas the more advanced models tend to use utility functions [25], [29]–[31]. The advantage of the latter is that multiple criteria can be weighed against one another. Moreover, a utility function can be modified and extended with far less effort [32]. Rule-based systems, on the other hand, are suited for specified scenarios but poorly perform in complex situations. For an improved driving behavior, multiple models evaluate not only the current situation but also past and predicted traffic situations. A prediction of the object motion, as presented in [28] and [30], can improve the host vehicle's reaction time and hence avoid critical situations. In [30], past time steps are also introduced into the evaluation to represent a form of memory, which makes the resulting system behavior more similar to human driving behavior.

Although several of the presented approaches are suitable for specific tasks within highly automated driving, none of the existing models meets all system requirements presented in this paper. In particular, consideration of uncertainties is not covered. As a consequence, a new concept for the selection of the most suitable lane and for the generation of LC requests is developed. The general objective is to evaluate each lane concerning its utility/suitability for the host vehicle and to generate LC requests on the basis of a comparison of these lane utilities. The structure of the concept for the determination of a lane utility is shown in Fig. 4. Each lane is evaluated based on the driver settings (e.g., desired velocity), the host vehicle properties, and the previously mentioned environment information (road, lanes, and objects).

A special feature of the presented concept is that the utility of a lane is described by means of a probability distributed stochastic variable $U \sim N(\mu_U, \sigma_U^2)$, instead of a regular variable u. As a result, uncertainties of the provided data of the *Perception* unit can be regarded within the decision-making process of the driving strategy module. The calculation is separated into an object-based evaluation generating DLCs and a map-based evaluation for the generation of MLCs. In general, MLCs contain higher priority than DLCs due to the fact that the arrival at the final destination is more important than temporary driving conditions. As the road conditions on freeways are not very complex and the scenarios requiring MLCs are considerably obvious (e.g., a lane ends), a rule-based approach is applied to these decisions. The evaluation that is based on the surrounding traffic (DLCs), however, is carried out in a linear utility function, which facilitates a more sophisticated examination of the traffic situation. Moreover, the calculation is conducted for multiple time steps within a time horizon $[k - n_{\text{past}}, k + n_{\text{pred}}]$. The single elements of this approach are individually discussed in the following.

The utility function for the object-based assessment consists of multiple factors that evaluate a lane particularly based on

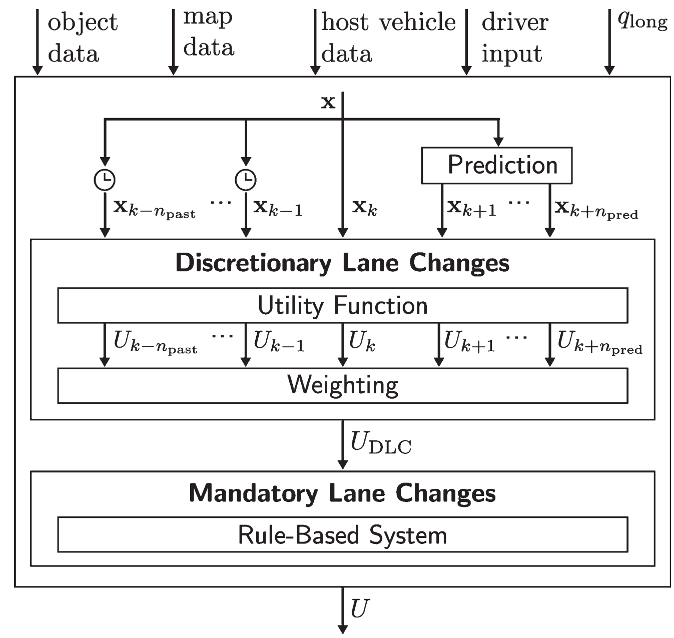

Fig. 4. Structure of the utility determination module.

comfort and safety criteria. The significance of the resulting single utilities $U_{k,i}$ for the overall utility U_k of time step k is specified by the corresponding weighting factors $w_{k,i}$, which are empirically determined. The basic pattern of this utility function is shown in

$$U_k = \sum_{i=1}^{m} w_{k,i} \cdot U_{k,i}. \tag{1}$$

For HAD, one of the main criteria is the currently and in future possible velocity on a lane with regard to the desired one. Further examples for influential factors are general traffic characteristics, such as the average longitudinal gap size between objects and the average velocity on a lane, or the specific velocities and distances of single objects. A low average gap size, for instance, decreases the utility of a lane due to disadvantages regarding safety. Special regulations, e.g., the German rule that overtaking on the right side is generally prohibited, are regarded within the utility function by modifying or limiting single-lane utilities in the respective traffic situations.

The utility function is calculated for several state vectors, which represent the development of the traffic situations from the past to the future. These vectors contain, for instance, the position and the velocity of objects. While state vectors can be stored and reused for past time steps, the future state has to be predicted. For this intention, two different approaches can be applied. The first is a linear prediction in which the objects are expected to move with constant velocities over a time increment Δt [33]. The acceleration is neglected, as this would lead to noisy prediction values. The second possibility is to forecast the objects' behavior due to certain circumstances, such as an LC if a lane is merging into another. This predicted motion is represented by the term $\mathbf{x}_{\text{fc},k}$. The position of a vehicle on a freeway entrance can thus be predicted on the adjacent lane on the freeway. The combined prediction for the determination of state vector $\mathbf{x}_{k+1}$ for time step $k + 1$ is computed within (2). By considering this prediction in the evaluation, the reaction time of the HAD system can be improved, i.e.,

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \dot{\mathbf{x}}_k \cdot \Delta t + \mathbf{x}_{\mathrm{fc},k}. \tag{2}$$

Past time steps are taken into account to create a situational memory. In [30], a weighted average over the past values is calculated, resulting in a smoother driving behavior but also negatively affecting the reaction time. As a consequence, a different approach is implemented within this concept. On the one hand, the past utilities can be weighed (see Fig. 4) by using $\Omega_{k-i} \in [0, 1])$ and applied to the calculation of the overall utility U_{DLC}, as shown in (3). However, on the other hand, these terms can be set to 0 by using δ_{k-i} to reset the memory of the system if the situation significantly changes. Thus, a memory can be realized without affecting the agility of the system behavior. If the utility of a lane is suboptimal and no significant situation change is detected for a certain period of time, the utility should slowly decrease. This represents the behavior that the dissatisfaction within a traffic situation increases. An example for this is a situation in which the host vehicle is driving behind a slightly slower object. The longer this situation persists, the more unsatisfied the driver of the host vehicle becomes. This behavior is facilitated by means of a negative influence of $\{1 - U_{k-1}, \ldots, 1 - U_{k-n_{\mathrm{past}}}\}$ on the total utility in (3). The negative influence is realized via δ_{k-i}, which can either be equal to 0 to reset the memory or equal to -1 for the negative influence. The entire weighted utility combination over the time horizon $(\Omega \in [0, 1])$, including the predicted utilities U_{k+i}, is shown in (3). The result is the utility regarding DLCs U_{DLC}

$$U_{\mathrm{DLC}} = \begin{pmatrix} \delta_{k-n_{\mathrm{past}}} \Omega_{k-n_{\mathrm{past}}} \\ \vdots \\ \delta_{k-1}\Omega_{k-1} \\ \Omega_k \\ \Omega_{k+1} \\ \vdots \\ \Omega_{k+n_{\mathrm{pred}}} \end{pmatrix}^T \begin{pmatrix} 1 - U_{k-n_{\mathrm{past}}} \\ \vdots \\ 1 - U_{k-1} \\ U_k \\ U_{k+1} \\ \vdots \\ U_{k+n_{\mathrm{pred}}} \end{pmatrix}. \tag{3}$$

The evaluation based on the road properties and the longitudinal state q_{long} is subsequently executed and results in the final lane utility U. Within this module, several rules are examined that determine in which situations an LC maneuver is mandatory (MLC) or has to be prevented. The utility of a lane U_{DLC} is passed if no need for an MLC is detected. However, in specific situations, such as critical situations, ending lanes, or freeway interchanges, the utility of respective lanes is set to zero to generate MLCs to an adjacent lane or to prevent the host vehicle from changing onto a wrong lane, such as an ending lane. In critical situations, the vehicle applies enhanced braking maneuvers, and no LC should be conducted. Finally, the utilities of both adjacent lanes are furthermore reduced by a constant value, modeling the effort for the respective LC maneuver.

Within the entire calculation of the utilities, the uncertainties from the input signals are taken into account. As previously mentioned, these uncertainties are modeled with a normal distribution. *Via* linear transformation, the probability distributions are mapped from the input signals to the calculated utilities. The result is approximated again as a normally distributed variable $U \sim N(\mu_U, \sigma_U^2)$.

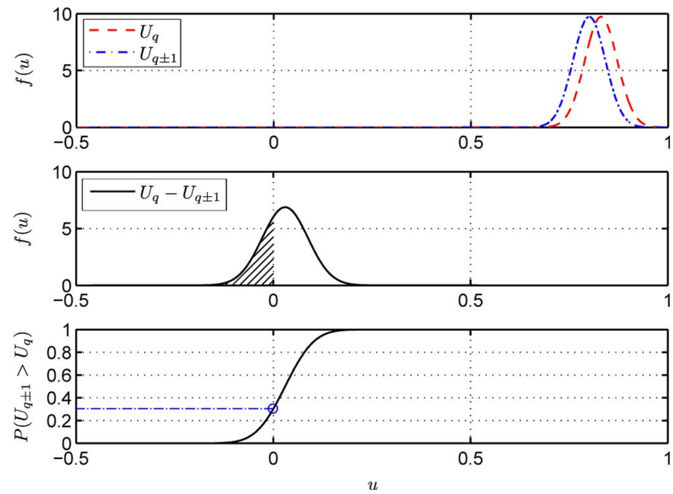

Fig. 5. Determination of the probability that an adjacent lane contains a higher utility via the difference distribution and the cumulative distribution function.

Altogether, the evaluation of the current and the two adjacent lanes results in three normally distributed utilities, i.e., U_{ego}, U_{left}, and U_{right}, which are compared to determine the most suitable lane. By means of the utilization of stochastic variables, this comparison provides a probability $P(\mathrm{LC}) = P(U_{q\pm1} > U_q)$ that an adjacent lane $q \pm 1$ contains greater utility than the current lane q and, thus, that an LC results in increased utility. For the determination of this probability, the difference distribution of two utilities (current and one adjacent lane) is calculated by subtracting their mean values $(\mu_{U_{\mathrm{diff}}} = \mu_{U_q} - \mu_{U_{q\pm1}})$ and adding their variances $(\sigma^2_{U_{\mathrm{diff}}} = \sigma^2_{U_q} + \sigma^2_{U_{q\pm1}})$. Probability $P(\mathrm{LC})$ is finally obtained by integrating the resulting distribution up to the value 0 due to the fact that this demonstrates the value where the utility of the respective adjacent lane is greater than the utility of the current lane. The integral represents the cumulative distribution function

$$P(\mathrm{LC}) = \frac{1}{\sigma_{U_{\mathrm{diff}}}\sqrt{2\pi}} \int_{-\infty}^{0} \exp\left(-\frac{1}{2}\left(\frac{u - \mu_{U_{\mathrm{diff}}}}{\sigma_{U_{\mathrm{diff}}}}\right)^2\right) du. \tag{4}$$

In Fig. 5, an example for the determination of this probability measure is shown. This figure illustrates the probability density functions $f(u)$ of two adjacent lane utility distributions U_q and $U_{q\pm1}$ and of the difference distribution $U_q - U_{q\pm1}$. Furthermore, the cumulative distribution function $P(U_{q\pm1} > U_q)$ is shown. The current lane q contains a utility mean value of $\mu_{U_q} = 0.83$, and the adjacent lane contains a value of $\mu_{U_{q\pm1}} = 0.80$. Both utilities contain identical standard deviation values $(\sigma_{U_q} = \sigma_{U_{q\pm1}} = 0.041)$. The integral over the difference distribution of the single distributions $(\mu_{U_{\mathrm{diff}}} = 0.03$, $\sigma_{U_{\mathrm{diff}}} = 0.058)$ or the cumulative distribution function provides the probability $P(U_{q\pm1} > U_q) = 0.3$ that the adjacent lane contains a greater utility than the current one.

This probability is calculated for both sides left and right. Finally, an LC request to one of the adjacent lanes is only generated if the corresponding probability $P(\mathrm{LC})$ exceeds a minimum value of 0.9 for a few seconds. This additionally increases the robustness of the decision-making process and reduces the risk of wrong decisions due to perception errors and inaccuracies.

C. Feasibility

The subsequent step in the decision-making process is feasibility examination, which contains a worst-case consideration of the traffic scenario. As a consequence, uncertainties are not applied to determine the most likely but the most critical situation possible for the host vehicle. Furthermore, a measure is provided with which probability the worst case is considered. Within this contribution, feasibility examination is exemplarily presented for the lateral guidance and, thus, for the determination if a desired LC maneuver is feasible.

In Fig. 6, a scenario is illustrated in which neither an LC to the left nor to the right adjacent lane is feasible. Generally, an LC is not conducted if an object is currently located in one of the side areas of the host vehicle (distance criterion) or if it is predicted into these areas due to a high relative velocity (deceleration criterion). For the prediction, a maximum acceptable induced deceleration of either the host vehicle or another object within the host vehicle's environment is applied in contrast with [34], where the maximum available deceleration is applied. That means that slight braking maneuvers that result from the LC maneuver to avoid a collision are acceptable, but strong induced braking maneuvers that require a higher deceleration value than the maximum threshold are not acceptable. Within Fig. 6, an LC to the right is not feasible due to the distance criterion. In this case, the worst-case consideration can be clarified. Object i in the lower right of Fig. 6 is probably not located within the side area. However, the error ellipse of the object position demonstrates that the object could be located within this area. To consider the worst possible situation, the side area is occupied, and an LC is prevented. Factor s determines with which probability the real object position should be considered. A 3σ-ellipse $(s = 3)$, for instance, represents a probability of 98.9% that it contains the real position of the object.

The LC to the left is prevented due to the deceleration criterion. Again, the worst-case scenario is considered. For the presented example, the minimum possible distance to the object and the maximum possible velocity of the object are applied, i.e.,

$$d_{x,j,\min} = \mu_{d_x,j} + s\sigma_{d_x,j} + \frac{l_j}{2} \tag{5}$$
$$v_{x,j,\max} = \mu_{v_x,j} + s\sigma_{v_x,j}. \tag{6}$$

To determine the feasibility with this criterion, the relative longitudinal motion of the host vehicle and the object on the target lane are compared during an LC maneuver of the host vehicle (7). The object is expected to brake after recognizing the LC. If the object would enter the side area during this braking maneuver, the LC is declared to be not feasible. For this braking maneuver, the object requires a certain braking time $t_{j,\mathrm{br}}$ and applies a maximum deceleration $a^{\mathrm{dec}}_{x,j,\max}$. The total time t_{total} consists of the reaction and the required braking time, i.e.,

$$\begin{gathered} d_{x,j,\min} + v_{x,j,\max} \cdot t_{\mathrm{total}} + \left(\frac{1}{2} \cdot a^{\mathrm{dec}}_{x,j,\max} \cdot t^2_{j,\mathrm{br}}\right) \\ > \\ d_{x,\mathrm{saf,lc}} + v_{x,\mathrm{ego}} \cdot t_{\mathrm{total}}. \end{gathered} \tag{7}$$

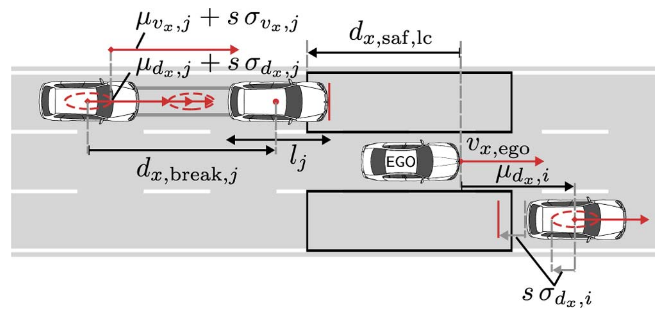

Fig. 6. Determination of the LC feasibility.

As presented in the example, this concept considers the current and the predicted situation. Furthermore, the worst-case consideration and the application of clear thresholds emphasize the focus on robustness and on the overall traffic safety.

D. Execution of LC Maneuvers

The conduction of the lateral driving maneuvers is facilitated by means of the *Driving Trajectories & Control* module. The required trajectories are generated, depending on the current system state q_{lat}, and concatenated for successive states. If the current state is the *Lane Keeping* state, for instance, the middle of the current lane represents the desired host vehicle location. For the LC states, however, a respective LC trajectory is generated. The host vehicle follows these trajectories by means of an optimal state controller that applies the dynamic programming equation of Bellman to solve the controller's cost functional. The entire concept for trajectory planning and control is covered in detail in [20].

The nominal and actual driving trajectories and the controller performance are presented in the next section.

IV. Evaluation

The evaluation of the presented system is conducted on a specially equipped test vehicle (see Fig. 7). This vehicle contains several sensors (differential Global Positioning System (DGPS), radar, camera, laser scanner, and ultrasonic) for localization and positioning and for the detection of other traffic participants. Additionally, high-precision digital maps are provided, which deliver relevant data regarding the road and the lanes. Furthermore, the test vehicle contains serial produced actuators that facilitate electronic control of the steering, the brake, and the throttle.

Within the first part of the evaluation, the system behavior is evaluated in detail for an automated overtaking maneuver. This maneuver is conducted on a closed test track. In the second part, a quantitative evaluation is conducted for a highly automated test drive on the freeway A9 from Munich to Ingolstadt in real traffic. After activation of the system (on the freeway), the entire test drive was completed 100% automated without driver intervention.

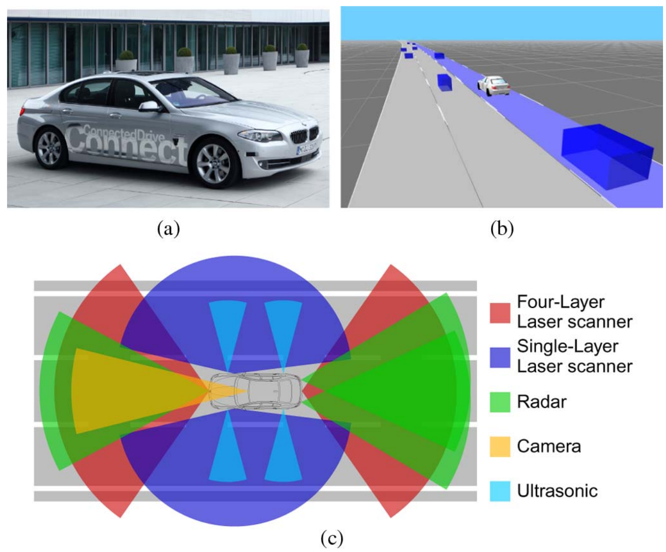

Fig. 7. (a) BMW 5 Series test vehicle for HAD. (b) Visualization tool for the digital image of the environment. (c) Surround sensor configuration.

Fig. 8. Automated overtaking maneuver on a closed test track.

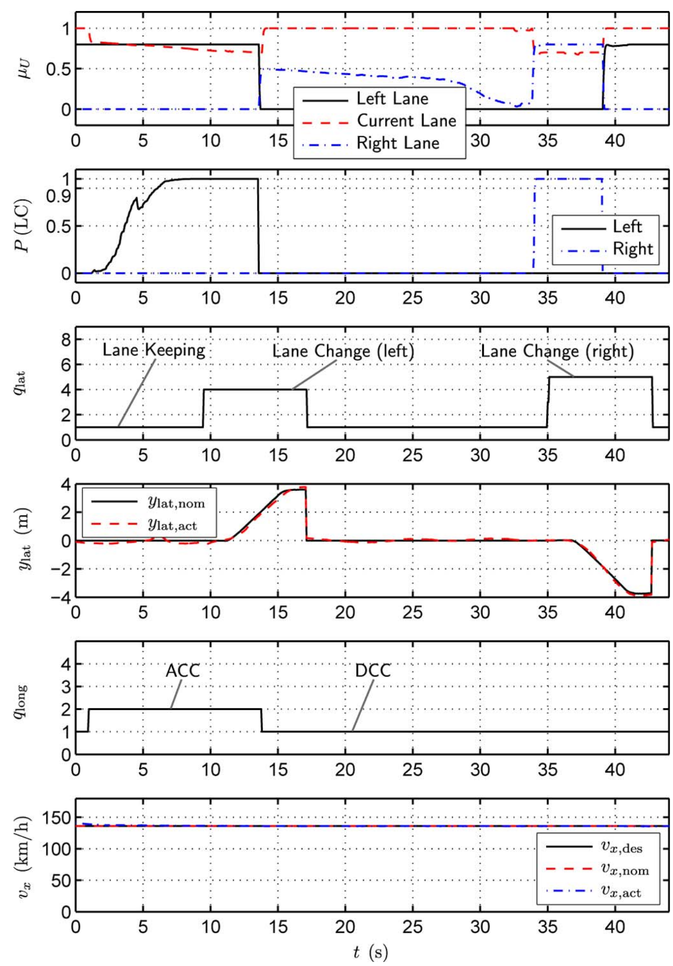

Fig. 9. Measurement data of an automated overtaking maneuver with a LC to the left and a subsequent LC to the right.

A. Automated Overtaking Maneuver

A common and frequent maneuver for HAD on freeways is an automated overtaking maneuver. In Fig. 8, this maneuver is shown on a closed test track. The inner system behavior is plotted in Fig. 9. The maneuver is conducted at a velocity of 140 km/h. Initially, the host vehicle travels on the right-most lane ($q_{\text{lat}} = 1$), and no target object exists ($q_{\text{long}} = 1$). (The states are listed in Table I.) The utility mean value μ_U of the current lane is equal to one and, thus, is highest compared with the utility mean values of the adjacent lanes. As there is no valid right lane, the utility mean value of this lane is automatically zero. The utility mean value of the left lane only amounts to 0.8 due to the fact that the cost for an LC maneuver (0.2) is subtracted from the utilities of the adjacent lanes. At this point in time, a constant cost is applied to an LC. In the future, however, this value can be adapted to several factors, such as the current traffic situation or the criticality. Once the object in the front area enters the sensor range, the utility of the current lane decreases. As previously mentioned, the utility is determined out of several factors, such as the distance to this object or its relative velocity. Consequently, the utility of the current lane continuously decreases as the object approaches. Comparison of the utility (including uncertainty) of the current lane with those of the adjacent lanes results in the probability $P(\text{LC})$ that the respective adjacent lane is more suitable for the host vehicle. The path of $P(\text{LC})$ clearly shows the shape of the previously mentioned cumulative distribution function. However, at time $t \approx 5$ s, the probability that the left adjacent lane is more suitable fluctuates for a short time period. As the illustrated mean values of the utilities in this figure do not fluctuate, the uncertainties of the utilities and, thus, of the object distance or/and velocity are responsible for this phenomenon. A reason for an increased uncertainty could be that one of the front sensors temporarily does not detect the object (e.g., for one to two cycles). As soon as this probability is over 90% for a time period of a few seconds, an LC request to the left is generated through a discrete event. As this maneuver is feasible, the lateral state $q_{\text{lat}} = 4$ is selected, and a smooth LC maneuver to the left is conducted (see y_{lat} in Fig. 9). After the overtaking maneuver, the utility of the right adjacent lane increases as no slower object is located within the front area on that lane. Additionally, the German *Rechtsfahrgebot*, which states that one must generally drive on the right-most lane, results in a decrease in the utility for the current lane. Hence, the probability that the right adjacent lane is more suitable increases, and an LC request to the right is generated. Via the lateral state $q_{\text{lat}} = 5$ and the LC, the host vehicle returns to the right-most lane.

Within the longitudinal guidance, the system is in the *ACC* state ($q_{\text{long}} = 2$) as long as the object is selected as the target object. As soon as the host vehicle reaches the left lane, the object is no longer relevant for distance control, and the state *DCC* ($q_{\rm long} = 1$) is selected. $v_{x,\rm des}$ is set by the driver. As the nominal and actual velocities ($v_{x,\rm nom}$ and $v_{x,\rm act}$) are not affected during the overtaking maneuver, the LC to the left is sufficiently generated early so that the object does not enter the distance control range.

The entire overtaking maneuver demonstrates consideration of the defined requirements. This concept makes LC decisions only if there is a high probability that the adjacent lane is more suitable. The decisions that are made by this module in the presented example are robust, comprehensible, and transparent. Within HAD, these characteristics not only simplify the development process but increase the overall traffic safety and the acceptance of this system for the driver and other occupants as well.

B. Highly Automated Driving from Munich to Ingolstadt

After the HAD functionality has been demonstrated for specific maneuvers on a closed test track, the system is tested and evaluated on a freeway in public traffic. As previously mentioned, the main objective is to drive 100% automated on the freeway A9 from Munich to Ingolstadt without driver intervention. In Fig. 1, the freeway route from Munich to Ingolstadt and an image of the freeway are illustrated. Furthermore, this figure shows that the driver only monitors the system but does not actively control the host vehicle (lateral and longitudinal). For the automated test drive and the evaluation within this section, only the freeway A9 that connects the cities is applied. Generally, the freeway contains between three and four relevant lanes and stretches a distance of about 65 km.

Applying the probabilistic framework presented in this contribution, the objective of driving automated on the freeway A9 from Munich to Ingolstadt was, for the first time, achieved on June 16, 2011. In Fig. 10, the HMI is illustrated for an exemplary traffic scenario during highly automated driving on a four-lane section of this freeway. This figure shows the digital image of the host vehicle's surroundings including digital map and objects that are located around the host vehicle. In this scenario, the host vehicle conducts an LC into a traffic gap on the left adjacent lane (*LC (left)* state) as this lane is determined to be most suitable for the host vehicle using the probabilistic approach presented in Section III-B and due to the fact that this maneuver is determined to be feasible. The utilities of the single lanes are illustrated by means of the three bars in the right lower corner. The fact that the left bar is darker means that there is a high probability that this lane is more suitable than the current lane of the host vehicle. Due to the fact that a safety distance is kept to the front vehicle on the current lane within the *ACC* state, the desired velocity (horizontal line next to the velocity scale) is currently not maintained (bar = actual velocity). This figure additionally depicts a false detection in the rear area on the left-most lane, which could result from reflections from either the road or the closest object. These reflections are detected by one of the radar sensor.

During the 65-km-long test drive, there was frequently dense traffic but no congestions or stop-and-go traffic. In Fig. 11, the percentages of the lateral guidance state $q_{\rm lat}$ during this test drive are shown. The *Lane Keeping* state demonstrated the state with the highest percentage. Approximately 80% of the driving time, the system decided to keep the lane. The percentages of the LC states were 6.1% for LCs to the left and 5.4% for LCs to the right. In 6% of the time, the system was in the *LCGA (left)* state, which means that an LC to the left was desired but not feasible. In detail, the number of lateral driving maneuvers is shown in Fig. 12. This figure shows that no LC had to be aborted and that the host vehicle did not have to stop. In total, the host vehicle conducted 17 automated LCs to the left and 15 to the right. There were two more LCs to the left due to the fact that the test started on the right-most lane but ended on the middle lane and as the right-most lane ended once when the road narrowed from a four-lane to a three-lane freeway. Another interesting observation is the fact that desired LCs to the left were far more frequently not feasible than those to the

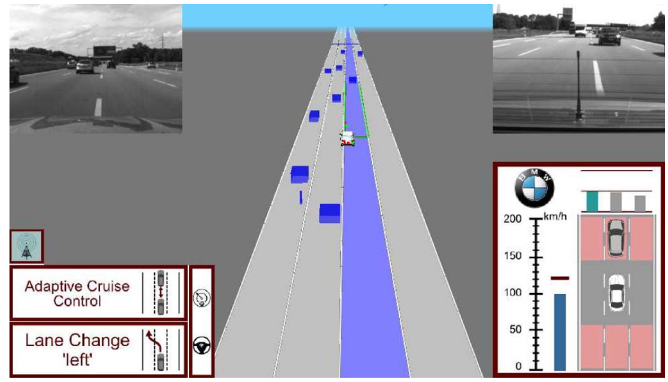

Fig. 10. Visualization during an automated LC maneuver on the freeway A9 in real traffic.

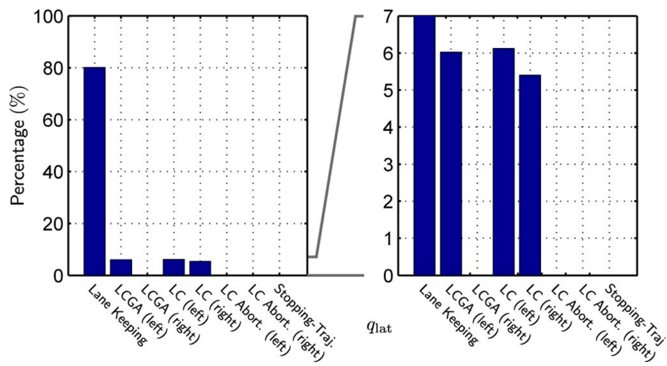

Fig. 11. Percentage of $q_{\rm lat}$ states during the test drive.

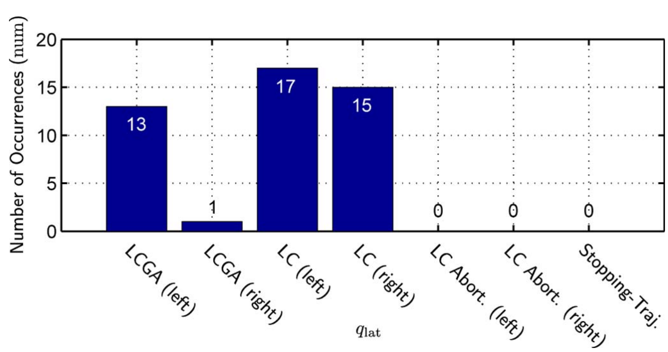

Fig. 12. Number of occurrence of $q_{\rm lat}$ states during the test drive.

right (LCGA states). This is due to a common traffic situation in which the host vehicle follows a considerably slower object, such as a truck, and cannot overtake as there are objects on the left adjacent lane that contain a significantly higher velocity. As safety is among the main requirements, the system waits for a considerably large traffic gap to not obstruct other traffic participants during an overtaking maneuver.

In general, all maneuvers showed a high safety particularly due to the fully integrated consideration of uncertainties and due to the robust decision-making processes, particularly in the request and the feasibility layer. During the entire test drive, the HAD system successfully mastered all occurring traffic situations. In addition to DLCs, due to temporarily dissatisfying driving conditions, MLCs were also conducted, for instance, to leave an ending lane. The system managed the entire 65-km-long automated test drive in approximately 40 min and showed automated LC maneuvers with no need for driver approval. In this contribution, the system has been evaluated for one exemplary test drive. In total, however, the system has already been tested on several thousand kilometers, mastering this route multiple times. During these test drives, the system also conducted LC abortion maneuvers and proved its functionality in congestions and stop-and-go traffic.

V. Conclusion and Future Directions

In this contribution, a new probabilistic approach for LC decisions within a probabilistic framework for HAD has been presented. This concept considers uncertainties in the decision-making process for suitable driving maneuvers to increase the robustness of the system and the overall traffic safety during HAD. In particular, the driving strategy and the included decision-making process for HAD have been highlighted. Due to the multilevel process, different approaches, particularly regarding the consideration of uncertainties, can be applied for the single steps. While probability-based and creative approaches that facilitate a weighted comparison of multiple but also concurrent goals can be applied within the driving request generation, a worst-case consideration is applied to the feasibility determination. By means of the presented concept, the challenge to drive 100% automated in real traffic on the freeway A9 from Munich to Ingolstadt was successfully mastered. Presenting the system to the public in August 2011, journalists were even allowed to drive themselves due to the highly robust and safe functionality.

However, until serial production of highly automated driving systems, there is still a long way to go. In a first step, the legal framework conditions for a market launch of highly automated driving vehicles have to be defined. In this context, the Vienna conventions on road traffic represent the major barrier [35]. To satisfy the high requirements of series systems regarding robustness, availability, and comfort, further special traffic situations, such as construction sites, have to be considered. For this purpose and for a more dynamic driving behavior in general, a dynamic trajectory planning concept will be required. Finally, route-planning algorithms could facilitate longer journeys by selecting the required freeway sections to reach a desired goal from a certain starting point.

Acknowledgment

The authors would like to thank their team members M. Aeberhard, S. Rauch, and P. Waldmann for helpful discussions and for their great contribution to the project.

References

[1] S. Glaser, B. Vanholme, S. Mammar, D. Gruyer, and L. Nouvelière, "Maneuver-based trajectory planning for highly autonomous vehicles on real road with traffic and driver interaction," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 3, pp. 589–606, Sep. 2010.
[2] R. Schubert, K. Schulze, and G. Wanielik, "Situation assessment for automatic lane-change maneuvers," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 3, pp. 607–616, Sep. 2010.
[3] Eur. Commiss., Towards a European Road Safety Area: Policy Orientations on Road Safety 2011–2020, 2010.
[4] M. Ardelt, P. Waldmann, N. Kämpchen, and F. Homm, "Strategic decision-making process in advanced driver assistance systems," in *Proc. IFAC Symp. AAC*, Munich, Germany, 2010.
[5] BMW Group PressClub Global, Stopping Safely in an Emergency, 2009. [Online]. Available: https://www.press.bmwgroup.com/
[6] Autobahnatlas, Autobahnen und Bundesstraßen, 2011. [Online]. Available: http://www.autobahnatlas-online.de/AutobahnkarteOhneAS.pdf
[7] S. Thrun, M. Montemerlo, H. Dahlkamp, D. Stavens, A. Aron, J. Diebel, P. Fong, J. Gale, M. Halpenny, G. Hoffmann, K. Lau, C. Oakley, M. Palatucci, V. Pratt, P. Stang, S. Strohband, C. Dupont, L.-E. Jendrossek, C. Koelen, C. Markey, C. Rummel, J. V. Niekerk, E. Jensen, P. Alessandrini, G. Bradski, B. Davies, S. Ettinger, A. Kaehler, A. Nefian, and P. Mahoney, "Stanley: The robot that won the DARPA grand challenge," *J. Field Robot.*, vol. 23, no. 9, pp. 661–692, Jun. 2006, Special Issue on the DARPA Grand Challenge, Part 2.
[8] M. Montemerlo, J. Becker, S. Bhat, H. Dahlkamp, D. Dolgov, S. Ettinger, D. Haehnel, T. Hilden, G. Hoffmann, B. Huhnke, D. Johnston, S. Klumpp, D. Langer, A. Levandowski, J. Levinson, J. Marcil, D. Orenstein, J. Paefgen, I. Penny, A. Petrovskaya, M. Pflueger, G. Stanek, D. Stavens, A. Vogt, and S. Thrun, "Junior: The Stanford entry in the urban challenge," *J. Field Robot.*, vol. 25, no. 9, pp. 569–597, Sep. 2008.
[9] C. Urmson, J. Anhalt, H. Bae, J. Bagnell, C. Baker, R. Bittner, T. Brown, M. Clark, M. Darms, D. Demitrish, J. Dolan, D. Duggins, D. Ferguson, T. Galatali, C. Geyer, M. Gittleman, S. Harbaugh, M. Hebert, T. Howard, S. Kolski, M. Likhachev, B. Litkouhi, A. Kelly, M. McNaughton, N. Miller, J. Nickolaou, K. Peterson, B. Pilnick, R. Rajkumar, P. Rybski, V. Sadekar, B. Salesky, Y. Seo, S. Singh, J. Snider, J. Struble, A. Stentz, M. Taylor, W. R. Whittaker, Z. Wolkowicki, W. Zhang, and J. Ziglar, "Autonomous driving in urban environments: Boss and the urban challenge," *J. Field Robot.*, vol. 25, no. 8, pp. 425–466, Jun. 2008.
[10] J. M. Wille, F. Saust, and M. Maurer, "Stadtpilot: Driving autonomously on Braunschweig's inner ring road," in *Proc. IEEE IV*, 2010, pp. 506–511.
[11] J. M. Wille, F. Saust, and M. Maurer, "Comprehensive treated sections in a trajectory planner for realizing autonomous driving in braunschweig's urban traffic," in *Proc. 13th ITSC*, 2010, pp. 647–652.
[12] P. Hansen, "Google's self-driving cars zoom in on the future," *Hansen Rep. Autom. Electron.*, vol. 24, no. 6, pp. 1–3, 2011.
[13] A. Bartels, C. Berger, H. Krahn, and B. Rumpe, "Qualitätsgesicherte Fahrentscheidungsunterstützung für automatisches Fahren auf Schnellstraßen und Autobahnen," in *Proc. 10th Braunschweig Symp.—AAET*, Braunschweig, Germany , Feb. 2009.
[14] R. Hoeger, A. Amditis, M. Kunert, A. Hoess, F. Flemish, H.-P. Krueger, A. Bartels, A. Beutner, and K. Pagle, "Highly automated vehicles for intelligent transport: Have-it approach," in *Proc. 15th World Congr. Intell. Transp. Syst. ITS Amer. Annu. Meeting*, New York, 2008.
[15] G. Grubb, E. Jakobsson, A. Beutner, and M. Ahrholdt, "Automatic queue assistance to aid under-loaded drivers," in *Proc. 16th ITS World Congr. Exhib. Intell. Transp. Syst. Serv.*, Stockholm, Sweden, 2009.
[16] M. Althoff, O. Stursberg, and M. Buss, "Model-based probabilistic collision avoidance in autonomous driving," *IEEE Trans. Intell. Transp. Syst.*, vol. 10, no. 2, pp. 299–310, Jun. 2009.
[17] R. Schubert, "Evaluating the utility of driving: Toward automated decision making under uncertainty," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 1, pp. 354–364, Mar. 2011.
[18] M. Aeberhard, S. Paul, N. Kaempchen, and T. Bertram, "Object existence probability fusion using Dempster-Shafer theory in a high-level sensor data fusion architecture," in *Proc. IEEE Intell. Veh. Symp.*, Baden-Baden, Germany, Jun. 2011, pp. 770–775.

[19] C. Stiller, G. Färber, and S. Kammel, "Cooperative cognitive automobiles," in *Proc. IEEE IV*, 2007, pp. 215–220.
[20] M. Ardelt and P. Waldmann, "Hybrides Steuerungs- und Regelungskonzept für das hochautomatisierte Fahren auf Autobahnen," *Automatisierungstechnik*, vol. 59, no. 12, pp. 738–750, 2011.
[21] S. K. Gehrig and F. J. Stein, "Collision avoidance for vehicle- following systems," *IEEE Trans. Intell. Transp. Syst.*, vol. 8, no. 2, pp. 233–244, Jun. 2007.
[22] C. Hatipoglu, U. Özgüner, and K. A. Redmill, "Automated lane change controller design," *IEEE Trans. Intell. Transp. Syst.*, vol. 4, no. 1, pp. 13–22, Mar. 2003.
[23] H. C.-H. Hsu and A. Liu, "Kinematic design for platoon-lane-change maneuvers," *IEEE Trans. Intell. Transp. Syst.*, vol. 9, no. 1, pp. 185–190, Jan. 2008.
[24] J. E. Naranjo, C. González, R. García, and T. de Pedro, "Lane-change fuzzy control in autonomous vehicles for the overtaking maneuver," *IEEE Trans. Intell. Transp. Syst.*, vol. 9, no. 3, pp. 438–450, Sep. 2008.
[25] K. I. Ahmed, "Modeling drivers' acceleration and lane changing behavior," Ph.D. dissertation, Mass. Inst. Technol., Cambridge, MA, 1999.
[26] U. Sparmann, "Spurwechselvorgänge auf zweispurigen BAB- Richtungsfahrbahnen," in *Forschung Straßenbau und Straßenverkehrstechnik*. Straßenbau, Germany : Bundesministerium für Verkehr, 1978.
[27] P. G. Gipps, "A model for the structure of lane-changing decisions," *Transp. Res. B, Methodol.*, vol. 20, no. 5, pp. 403–414, Oct. 1986.
[28] A. Niehaus and R. Stengel, "Probability-based decision making for automated highway driving," *IEEE Trans. Veh. Technol.*, vol. 43, no. 3, pp. 626–634, Aug. 1994.
[29] T. Toledo, "Integrated driving behavior modeling," Ph.D. dissertation, Mass. Inst. Technol., Cambridge, MA, 2003.
[30] D. Ehmanns, "Modellierung des taktischen Fahrerverhaltens bei Spurwechselvorgängen," Ph.D. dissertation, RWTH Aachen, Forschungsgesellschaft Kraftfahrwesen, Aachen, Germany, 2003.
[31] A. Kesting, M. Treiber, and D. Helbing, "General lane-changing model mobil for car- following models," *J. Transp. Res. Board*, vol. 1999, no. 1999, pp. 86–94, 2007.
[32] R. Sukthankar, J. Hancock, S. Baluja, D. Pomerleau, and C. Thorpe, "Adaptive intelligent vehicle modules for tactical driving," in *Proc. AAAI Workshop Intell. Adaptive Agents*, 1996, pp. 13–22.
[33] S. Thrun, W. Burgard, and D. Fox, *Probabilistic Robotics*. Cambridge, MA: MIT Press, 2006.
[34] A. Eidehall, J. Pohl, F. Gustafsson, and J. Ekmark, "Towards autonomous collision avoidance by steering," *IEEE Trans. Intell. Transp. Syst.*, vol. 8, no. 1, pp. 84–94, Feb. 2007.
[35] United Nations Economic Commission for Europe, 19. Convention on Road Traffic, Nov. 1968. [Online]. Available: http://live.unece.org/trans/conventn/legalinst_08_RTRSS_RT1968.html

Michael Ardelt received the Diploma degree in mechanical engineering, in 2008, from the Technical University of Munich, Munich, Germany, where he is currently working toward the Dr.-Ing. degree with the Institute of Automatic Control Engineering, in conjunction with the BMW Group Research and Technology, Munich.

His research interests include highly automated systems, such as advanced driver-assistance systems, as well as hybrid systems and probabilistic decision making.

Constantin Coester received the Diploma degree in automotive engineering from the Technical University of Munich, Munich, Germany, in 2011. He wrote his diploma thesis about lane selection for highly automated driving in collaboration with the BMW Group Research and Technology, Munich.

He is currently with the BMW Group Research and Technology.

Nico Kaempchen received the M.Sc. degree in artificial intelligence from the University of Edinburgh, Edinburgh, U.K., in 2000, the Dipl.-Ing. degree in electrical engineering from the University of Stuttgart, Stuttgart, Germany, in 2001, and the Dr.-Ing. degree from the University of Ulm, Ulm, Germany, in 2007.

Since 2006, he has been with the BMW Group Research and Technology, Munich, Germany, working on driver-assistance systems. His research interests include highly automated driving, environment perception, and sensor data fusion.

Dr. Kaempchen received an Award from the Heidelberg Academy of Sciences, Germany, in 2007 for his doctoral thesis on feature-level fusion of laser scanner and video data for advanced driver-assistance systems.