Abstract—The Institute of Measurement, Control and Microtechnology at Ulm University investigates advanced driver assistance systems for decades and concentrates in large parts on autonomous driving. It is well known that motion planning is a key technology for autonomous driving. It is first and foremost responsible for the safety of the vehicle passengers as well as of all surrounding traffic participants. However, a further task consists in providing a smooth and comfortable driving behavior. In Ulm, we have the grateful opportunity to test our algorithms under real conditions in public traffic and diversified scenarios. In this paper, we would like to give the readers an insight of our work, about the vehicle, the test track, as well as of the related problems, challenges and solutions. Therefore, we will describe the motion planning system and explain the implemented functionalities. Furthermore, we will show how our vehicle moves through public road traffic and how it deals with challenging scenarios like e.g. driving through roundabouts and intersections.

Index Terms—autonomous driving, automated vehicles, motion planning, trajectory planning.

I. INTRODUCTION

SINCE several years, intensive research has been conducted on automated driving. In 2007, 11 vehicles were sent into a race through an urban environment in Victorville, California. Thereby, the goal was to complete a 96 km course within 6 hours, whereas the vehicles had to navigate fully by themselves and obey Californian traffic rules. This event is well known as the Darpa Urban Challenge and accepted to be a milestone of autonomous driving [1]. In 2013, the S-Class Bertha made its way through a 103 km route from Mannheim to Pforzheim in Germany [2]. Since 2017, the companies Waymo and Uber are providing taxi services in a small city close to Phoenix in Arizona. But these are just the most recent and well known developments. Much effort is done in daily work behind closed doors of research institutes and companies. But still, automated driving functions are by far not yet included in every productive car. The problem arises from the complexity of road traffic due to the large variety of situations, the huge number of maneuver and behavior options and the difficulty in predicting traffic participants. Thus, its not astonishing that the ECUs of modern productive cars contain up to 100 Mio. lines of code. For comparison: The number of lines of code contained by the Boeing 787 is estimated to approximately 6.5 Mio. [3].

The Institute of Measurement Control and Microtechnology at Ulm University deals with autonomous driving especially in structured environments and on-roads scenarios. First successes were reached in the year 2014: A Mercedes Benz E-Class drove a challenging route including roundabouts, pedestrian crosswalks, traffic lights etc., around the University fully autonomously [4]. Meanwhile, the engineers of the institute equipped another vehicle, which is shown in figure 1. Recently, a new motion planning system was designed and integrated, which enables the vehicle to navigate through longitudinal traffic, perform lane change and overtaking maneuvers as well as handle complicated intersection and roundabout scenarios. Furthermore, an emergency mode was developed to plan full braking and evasive trajectories in safety critical situations. In this paper we’d like to give the readers an insight of the motion planning system and show how the related driving functions apply under real conditions in public road traffic.

The remainder of this paper is structured as follows: Section II can be seen as a summary of related work, in which we describe the requirements and challenges as well as a representative excerpt of todays state of the art motion planning techniques. In section [III] we present our motion planning system which is composed of several operational modes and describe how these modes are realized to retrieve an overall system. In the evaluation section, experiments are carried out and the performance of our system is shown by different maneuvers in public road traffic.
II. ON-ROAD MOTION PLANNING - REQUIREMENTS AND RELATED WORK

Motion planners are key components for automated vehicles. They are mainly responsible for the resulting driving behavior and their main task is to ensure safety for the vehicle passengers as well as of all surrounding traffic participants. In non-safety critical situations, they also have to provide non-jerky and comfortable driving behavior. Furthermore, the computation cycle time has to be small in order to react to dynamic changes of the environment in time.

A common environmental representation often used for on-road driving is shown in figure [2]. Thereby, the vehicle environment consists of multiple lanes which are represented by one center line and two associated freespace boundaries each. Static obstacles on the roadside are excluded from the drivable freespace by the boundary lines. Dynamic obstacles, such as cars are represented by rectangle boxes. Due to the importance of motion and trajectory planning, the corresponding research field is well advanced and many approaches exist already. Therefore, we’d like to briefly summarize some of the most widely spread techniques.

We acknowledge that some recent planning approaches leverage learning based methods and partially observable Markov decision processes (POMDPs) with promising results (e.g. [5], [6], [7], [8]). This summary, however, will be focused on classical, optimization based approaches, which are, at the current state of research, still more easily and safely applicable to real world vehicles.

In general, trajectory planning methods can be classified into discrete and continuous approaches. Using the former, the continuous space of trajectories gets discretized by generating a set of trajectory alternatives. This set might either consist of trajectory samples or corresponds to a search graph, whereas the graph edges represent motion alternatives from which the final trajectory has to be composed. By using continuous approaches however, no such discretization is done and the continuous space is investigated directly by applying numerical optimization techniques for instance. A strength of discrete methods consists of the fact, that the best solution within the discrete set will always be found. However, since no continuous optimization is applied, this discrete solution will always be suboptimal and located in the neighborhood of the continuous global optimum at best. In contrast, continuous approaches will find a local optimal solution and in case of a convex problem even the global optimum. In presence of multiple local optima however, such methods are dependent on an appropriate initial solution to converge into the desired optimum.

A discrete method based on polynomial sampling is presented in [9]. Therein, quintic polynomials which are optimal in terms of the squared jerk are used to describe the longitudinal and lateral movement within a Frenet frame. The resulting trajectories are smooth and lead to comfortable driving behavior. However, the flexibility of the resulting trajectories is limited by the polynomial degree and the method is not well suited for large temporal planning horizons. In [10] this problem is addressed, where a discrete action set is utilized in order to generate a state graph. Using graph-search methods, the best sequence of actions and associated states is extracted. As a result, a rough trajectory can be obtained which gets further optimized using the polynomial-based sampling approach presented in [9]. Another well-known discrete approach are the Rapidly Exploring Random Trees (RRT) which generate a search graph by using a probabilistic discretization scheme.

RRTs were e.g. used by the MIT during the Darpa Urban Challenge [11]. These discrete approaches have proven great practicability in real world scenarios, but as discussed, always yield suboptimal trajectories.

A local continuous approach which was used during the Bertha Benz Drive in 2013 is presented in [12]. Therein, a static optimization problem is formulated, whereas the optimization variables are the spatio-temporal positions of the vehicle’s reference position. In principle, arbitrary maneuvers or trajectories respectively can be planned, provided they satisfy acceleration and curvature constraints. Thus, the resulting trajectory model is flexible and the method is well suited for long term planning.

In [13], convex quadratic programming for planning lane change maneuvers is utilized. Therein, the onedimensional longitudinal motion is stated as a convex quadratic optimization problem in the first step. Based on the longitudinal motion, a further convex quadratic problem, to compute the lateral movement, is solved. Convexity guarantees that there is only one optimum and thus, the optimal solution always corresponds to the global optimum. Furthermore, the quadratic nature of the problem formulations allows for fast convergence and small computation times.

Another approach based on convex quadratic optimization is the one in [14]. Thereby, a linearized model is used to describe the lateral vehicle dynamics. Subsequently, a time variant model predictive control problem is formulated to compute the optimal lateral movement. Convex quadratic optimization for planning fail safe trajectories in safety-critical situations is also used in [15].

For more information regarding on-road motion planning, the reader is referred to [16]. Nevertheless, it becomes obvious that much effort was spent already, many discretization schemes were applied and many continuous problem formulations stated. Thus, the question arises: How can the existing methods be combined to improve the driving performance while...
reducing the computation time? Subsequently, this question is also subject of current research work. Accordingly, we’d like to describe two representative works:

A motion planning framework based on graph search and convex quadratic optimization is presented in [17]. In the first step, the algorithm of [10] is applied to obtain a rough longitudinal motion prediction. This rough motion is then smoothed by solving a convex quadratic optimization problem. The lateral motion is computed via a graph search method as well and the final trajectory is smoothed by solving a convex quadratic problem to obtain the trajectory in two dimensions. Another motion planning framework is the one described in [18]. Thereby, splines are used to create a path lattice in the first step. This path gets further optimized by solving a convex optimization problem. Subsequently, a speed profile on the computed path is planned by applying a lattice search using velocity primitives. The final trajectory gets smoothed by the solution of a convex quadratic optimization problem.

A crucial feature of our motion planning system is the deep integration of driver models. Therefore, we’d like to briefly summarize some state of the art motion planning techniques also utilizing driver models. Driver models, which are subject to the traffic flow science, are promising with regard to describing social interaction between vehicles. In [19], the Intelligent Driver Model (IDM) is incorporated into the cost functional of the sampling based planner of [9] to plan interaction aware trajectories in merging scenarios. In [20], the IDM was used together with the quadratic cost function of [17] to compute human like trajectories and stopping maneuvers. In [21], a graph-based trajectory planning approach is presented using the IDM in order to estimate arising costs for other vehicles and to enable courteous behavior.

Based on the previous discussion, our motion planning framework is designed to combine the flexibility and efficiency of continuous optimization with driver models in order to enable social compliant behavior.

III. METHODOLOGY

Our motion planning system is designed to enable level 4 automated driving according to the SAE [22]. This means, the vehicle drives fully autonomously and does not expect the driver to intervene at any time. Therefore, the vehicle has to navigate through longitudinal traffic, keep safe distances to preceding vehicles and stop if necessary. To react to congestions and to reduce travel time, the vehicle must be capable of performing lane changes and overtaking maneuvers.

To avoid handover requests, according functionalities to handle intersections and roundabouts must be implemented as well. In safety critical situations, full braking or evasive maneuvers have to be planned.

In the following, all components of our system are described and discussed separately. Subsequently, we present our final system architecture and show how the components are put together to derive an effective overall framework for level 4 automated driving.

1) Central Optimization Problem: To exploit the advantages of continuous trajectory planning methods according to section II, we based our system on a corresponding continuous problem formulation. Precisely, we use the quadratic cost functional presented in [17], which is essentially as follows

$$\min_{\xi} J = \sum_{i} w_b ||x_i - x_{b,i}||^2 + w_a ||x_i||^2$$

The 2-dimensional positions $x_i$ correspond to the trajectory support points of the vehicles’ gravity center at each time instant $t_i$ on the discretized planning horizon. These variables are to be optimized and are summarized in the vector of optimization variables $\xi$. The points $x_{b,i}$ on the other hand have to be computed beforehand and remain constant during the optimization. Obviously, these points strongly affect the pose of the global minimum of the functional [1] and, therefore, the computation result as well as the resulting driving behavior. This is why we will refer to the points $x_{b,i}$ as the "behavior trajectory" throughout the remaining paper. In addition to [17], we penalize the term $||\dot{x}_i||^2$ which can help to avoid steps within the derivative of the acceleration and thus contributes to smooth acceleration. Derivatives are approximated by using finite differences as described in [12] and [17]. For collision avoidance, we use the strategy in [12]. Therein, obstacles are represented by polygons and a so called "pseudo distance" was designed to compute the distance to these polygons. Furthermore, circles are used to approximate the area covered by the vehicle along the trajectory. Finally, collision avoidance is achieved by requiring, through the constraints of an optimization problem, that the distances between the circle centers and the obstacle polygons are greater than or equal to the circle radii. In this work, our system slightly differs from [12], since we use one circle per discrete time instant only which is placed around the vehicles mass center according to figure 3a. Since this circle does not cover the whole vehicle shape, we virtually resize the preceding vehicle by $r$, according to figure 3b. To obtain the same "push-away" effect as in [12], we append a virtual triangle at the preceding vehicles rear as shown in 3. Figure 4 illustrates how a rear-end collision can be avoided in this way.

![Diagram](image-url)
In addition to the constraints explained so far, further constraints are added to make sure, that the quadratic absolute acceleration stays within dedicated bounds \([12]\). Further, spatio-temporal constraints, which guarantee safety in intersection scenarios (cmp. Section III-2), are applied. The constraints vector is then composed of five parts and can be written as follows:

\[
    h(\xi) = [h_{fb}(\xi)^T, h_{fs}(\xi)^T, h_{dyn}(\xi)^T, h_a(\xi)^T, h_{s}(\xi)^T]^T \leq 0.
\]  

(2)

With the component due to the left free space boundary \(h_{fb}(\xi)\), the right free space boundary \(h_{fs}(\xi)\), dynamic obstacles \(h_{dyn}(\xi)\), the spatio-temporal constraints \(h_s(\xi)\) and the absolute acceleration \(h_a(\xi)\) respectively. The constraints \([12]\) together with the cost functional \([1]\) are finally summarized to one overall optimization problem formulation. This problem plays a central role within the architecture of our system and we will refer to it as the "central optimization problem" throughout the remaining paper. Each trajectory that gets forwarded to the vehicle controller corresponds to a solution of this problem. What now remains to be clarified is the computation of the behavior trajectory \(x_b\). In the following, we explain how to compute \(x_b\) for different scenarios and maneuvers.

2) Longitudinal Traffic: The longitudinal traffic mode (LTM) is the default driving mode and implements free driving and car following functionality. In addition, this mode is able to cope with intersections and roundabouts. The behavior trajectory generation in the LTM mode is achieved through the incorporation of driver models. We’d like to briefly explain the corresponding model equations of the intelligent driver model (IDM):

\[
    \dot{s} = v
\]

\[
    \dot{v} = a \left[ 1 - \left( \frac{v}{v_{\text{target}}} \right)^\zeta - \left( \frac{s_{\text{target}}(v, \Delta v)}{\Delta s} \right)^2 \right].
\]

(3)

(4)

The longitudinal position on the ego lane is denoted by \(s\) and the longitudinal velocity by \(v\). The value \(s_{\text{target}}\) corresponds to the desired distance to the vehicle in front and depends on the ego vehicle’s velocity \(v\) and the relative velocity \(\Delta v\) between the vehicles. The current distance to the preceding vehicle is denoted by \(\Delta s\). The parameter \(a\) is the maximum acceleration and \(\zeta\) the acceleration exponent. Since the road curvature is not considered by the equations, the target velocity \(v_{\text{target}}\) is extracted from a precomputed velocity profile (cmp. \([24]\)).

In our implementation we use an extension of the IDM, the "Enhanced Intelligent Driver Model" (EIDM), which builds on the equations above and provides improved braking behavior. Further explanations may be found in the related literature \([25], [26]\).

Accordingly, behavior trajectories \(x_b\) utilized in following and free driving scenarios are directly generated using the EIDM. However, in intersection scenarios multiple maneuver options have to be regarded. Therefore, different behavior trajectory candidates are generated and subsequently, the behavior trajectory representing the best maneuver option is passed to the central optimization problem. Especially in merging scenarios, it is further necessary to regard vehicles of different lanes, which is not viable by directly using car-following driver models. Therefore, a virtual leading vehicle is modeled on the ego lane which represents a real vehicle on another lane in order to be able to generate smooth merging behavior by following the virtual leader. As a consequence, smooth merging as well as free driving, following and stopping behavior can be directly generated utilizing the EIDM in intersection scenarios. For further details regarding the generation of trajectory candidates and the modeling of the virtual leader, the interested reader is referred to one of our previous works \([27]\).

To choose the best behavior trajectory \(x_b\) in intersection scenarios, these are rated according to a cost function inspired by the MOBIL model \([28]\). The idea is to consider the ego costs and the costs of other vehicles arising through the ego behavior. The behavior trajectory which minimizes the overall costs for the ego vehicle and other vehicles is passed to the central optimization problem. As a consequence, the cost functional enables social compliant and courteous behavior. In general, the costs for a behavioral trajectory \(x_b\) are defined as

\[
    J_b = w_e j_e(x_b) + w_o \sum_{\iota \in \mathcal{O}} \sum_{k \in \mathcal{K}} P(x_{\iota}^{\iota,k}) j_{\iota,k}(x_b, x_{\iota,k}),
\]

(5)

where \(w_e\) and \(w_o\) represent cost weights. In order to estimate \(j_e\) the negated average ego acceleration of the regarded behavior trajectory is utilized. Costs for other vehicles are represented by \(j_{\iota,k}\). Thereby, for each vehicle \(\iota \in \mathcal{O}\), multiple trajectory hypotheses \(x_{\iota,k}\) and their according probabilities \(P(x_{\iota,k})\) are considered. These hypotheses account for different behavior options \(k \in \mathcal{K}\) of other vehicles in intersection scenarios. To determine \(j_{\iota,k}\) the vehicle \(\iota\) using trajectory hypothesis \(k\) is regarded. The costs are derived from the acceleration deviation due to the estimated reaction on the ego vehicles trajectory. As a result, strong reactions to the trajectory of the ego vehicle are penalized encouraging courteous behavior towards other traffic participants. The reactions are modeled using the IDM, which enables a computationally efficient cost evaluation. For further details the reader is referred to \([27]\).

In general, the optimization of longitudinal driving is subject to acceleration constraints as well as free space boundaries and collision constraints. In addition, to guarantee safety in intersection scenarios and to make sure the optimized trajectory will stay in the vicinity of the behavior trajectory, spatio-temporal constraints according to expression \([4]\) are employed. These are derived based on the intersection geometry and the predictions of the vehicles, which are expected to occupy the intersection before and after the ego vehicle. In general,
maximum and minimum distances are determined, which have to be traveled in a given time in order to enter and leave the intersection on time. Consequently, safety distances to the other vehicles are ensured while the deviation of the optimized trajectory to the behavior trajectory is limited.

3) Lane Changing: In our previous work [29], we implemented lane change functionality by numerically integrating the IDM on the reference line to obtain the behavior trajectory. Subsequent minimization of the cost functional (1) results in a transition to the target lane. To improve lateral guidance, we extend this procedure by additionally using a kinematic singletrack model. The model equations are given by:

\[
\begin{align*}
\dot{x} &= v \cos(\theta) \\
\dot{y} &= v \sin(\theta) \\
\dot{\theta} &= \frac{v}{l_r + l_f} \frac{\delta}{u_1} \\
\dot{v} &= \frac{a}{u_2},
\end{align*}
\] 

For determining the steering angle \( u_1 = \delta \), we use a pure-pursuit steering controller [30]. For the sake of completeness, we’d like to briefly explain the control principle by the help of figure 5. First, the “look ahead position” on the reference line must be computed. This corresponds to the one position on the reference line, whose distance to the mass center corresponds to the “look ahead distance” \( L \), which has to be chosen in dependence of the velocity. Subsequently, the steering angle \( \delta \) is chosen such, that the mass center moves towards the look ahead point on a circular arc. Obviously, smooth lateral guidance and low lateral accelerations can be obtained by increasing the look ahead distance. For more information and further details the reader is referred to [30]. The acceleration \( u_2 = a \) is computed by numerically integrating the EIDM equations on the reference line of the target lane.

4) Emergency: The emergency mode is used in safety critical situations to compute full braking and evasive trajectories. Since the EIDM was not designed for safety critical situations, we use an optimization based approach to compute the behavior trajectory in such situations. To guarantee real-time capability, two convex quadratic optimization problems for the longitudinal and lateral movement are formulated and sequentially solved. The problem formulations are very similar to the ones in [31]. As this work focuses on non-safety critical scenarios, further details are omitted.

5) Decision Making: To benefitfully connect the described operational modes and to obtain an overall motion planning system, we implemented a decision making module which can be divided into a situation assessment and a finite state machine. The main task of the situation assessment consists in determining boolean state transition variables for the state machine. Therefore, the model ”MOBIL”, which is based on the IDM, is used to decide whether lane changes are desirable [28]. By this model, the current traffic situation is compared with the hypothetical situation that the ego vehicle is located on a candidate lane. In both situations, the current and the hypothetical one, the accelerations of all relevant surrounding entities as well as the one of the ego vehicle itself is computed using the EIDM/IDM. If in the hypothetical situation the overall acceleration is increased compared to the current situation, a lane change is assessed as incentive. To obtain high consistency between decision making and the computation of the behavior trajectory, we use the EIDM within MOBIL. However, lane changes may only be performed, if there are no roundabouts, intersections or road sections of high curvature in reach. To identify safety critical situations and to determine whether the emergency mode has to be activated, the distance and the relative velocity between the ego vehicle and its leader is checked. If braking with a constant acceleration threshold is not sufficient to avoid a rear-end collision, the situation is assessed as critical and the emergency functionality gets active. As mentioned already, the longitudinal traffic mode is the default operational mode and always active, provided no lane change or emergency maneuver needs to be performed. The overall structure of the motion planning system is also depicted in Figure 7.

IV. Experiments

Experiments are carried out on our experimental vehicle which is shown in figure 1. The luggage space contains two usual consumer computers and a MicroAutoBox by the company dSpace, which serves as a real-time capable control system. The algorithmic processing chain is implemented on the consumer PCs using ROS [32], which is already proven to work as a middleware for autonomous driving (see e.g. [33]). Figure 7 illustrates the hardware arrangement and shows which software components are implemented on the devices. The sensor setup consists of LiDARs, RaDARs, Cameras and an ADMA [3]. The ADMA contains a DGPS system and allows the determination of the vehicle position accurately with errors only up to a few centimeters. Sensor data is first passed to the perception PC and object information is extracted by the object detection modules [34]. This information is then passed to the tracking algorithm where the detections are fused and filtered using a Labeled Multi-Bernoulli Filter to estimate the states of all surrounding dynamic obstacles [35]. The ego motion module fuses data from the ADMA together with information from other sensors (e.g. odometry) to determine the ego vehicles state as accurately as possible. This information is passed to the motion planner which is running on the application PC. Information of the static environment is retrieved from an HD digital map stored on the application PC. The controller

\[ \text{Robot Operating System } [32]. \]

\[ \text{Automotive Data Motion Analyzer by the company GeneSys.} \]
on the MicroAutoBox requires a trajectory represented by \( N = 60 \) support points over a temporal horizon of \( T = 2.95 \) s (cmp. [4]). The target state is then extracted from the trajectory and used together with the ego state for the computation of controls by the trajectory controller. To test our algorithms, we have chosen a test track close to the university which leads through the district of Ulm called “Lehr”. The test track is \( \approx 4 \) km long and contains an intersection, an acceleration strip, a pedestrian crossway, a roundabout, zones of various speed limits, and thus provides a challenging opportunity to test our algorithms in public road traffic. Figure 8 shows a bird’s-eye-view of the test track. The blue line represents the vehicles path which was recorded during an automated drive. Even though our vehicle is capable of driving long routes autonomously, it does not reveal much about the driving behavior and the capability of the vehicle to behave socially. Therefore, we show some representative scenarios in more detail below.

### A. Lane Change

The first demonstration scenario corresponds to a lane change maneuver. The recorded data is shown in figure 9. The first row shows the drivers perspective by camera images for three dedicated time instants and the second row shows the according ROS-RViz display and thus, corresponds to what the vehicle perceives. In order to relate these two perspectives to each other, the trajectory itself is mapped from the RViz-display into the camera images. Beside the trajectory, the center line for each lane is visualized and the blue boxes correspond to the ego vehicle, whereas red boxes represent other vehicles in the scene. Thereby, the trajectory originates in the gravity center of the ego vehicle. The third row corresponds to the measured velocity, acceleration and steering angle during the maneuver.

The three images show a transition from the right to the left lane. Whereby the lane change gets triggered shortly after ① and executed at ②. At ③, the vehicle has already arrived at the target lane. Even though the reader has not the possibility to...
take a test drive himself, a view on the measured values shows that the acceleration as well as the steering wheel angle remain small and don’t change rapidly during the scenario. This indicates comfortable driving behavior, which was experienced when the data was recorded.

B. Roundabout

The second experiment corresponds to a roundabout scenario. According evaluations and pictures are shown in Figure 10. Besides the center line of the ego vehicle, possible center lines for other vehicles in the roundabout are visualized in the ROS-RViz display.

Initially, there are two other vehicles involved in the scenario. Therefore, the ego vehicle first has to reduce the velocity while approaching the roundabout. At $\mathcal{O}$, the velocity is adapted for smooth merging behavior behind the other vehicle into the roundabout using the approach presented in [III-2]. At $\mathcal{O}$ the vehicle merged successfully. Qualitatively, the driving experience during this scenario can be described as natural and human-like.

C. Intersection

The third experiment demonstrates a left turn scenario. The corresponding scene is visualized in Figure 11. First, the vehicle approaches the intersection and reduces the velocity. In general, there are two other vehicles involved. One is approaching the left and one approaching from the right, both are prioritized over the ego vehicle. Using the approach presented in [III-2], the vehicle remains in standstill up to $\mathcal{O}$ as driving in front of the other vehicles is rated as too aggressive and, consequently, not feasible in this scenario. Driving off shortly after $\mathcal{O}$ implements courteous behavior as the vehicle approaching from the left is already predicted to take a right turn and therefore, it does not interact with the ego vehicle. Thus, the ego vehicle is able to smoothly merge behind the vehicle approaching from the right.

V. CONCLUSION AND FUTURE WORK

We presented a motion planning system that is capable of computing comfortable trajectories in real-world scenarios by using model knowledge in combination with continuous optimization. Thereby, the main task of the behavior generation consists in computing a maneuver specific behavior trajectory for the central optimization problem. Therefore, the EIDM equations are used to compute the longitudinal motion along the lane’s reference line. If lane changes are to be performed, a single track model is additionally used to also describe the lateral motion. The resulting behavior trajectory mainly influences the pose of the global optimum of the central optimization problem and therefore, the optimal solution and the corresponding final maneuver. Due to the problem constraints, it is ensured that collisions with the static free space boundaries, as well as with dynamic obstacles, are avoided.

This paper corresponds to a continuation of our previous works and shows beside some theoretical extensions also the practical deployment. We have described how a level 4 motion planning system can be built and demonstrated the functionality by real-world results in public road traffic. However, even though the vehicle is able to cope with a variety of daily traffic situations, there is no possibility to obtain a driving behavior that differs substantially from something than can be generated using the EIDM/IDM. This becomes an issue, for instance, when driving in urban environments, with cyclists and pedestrians crossing the road. In such situations, more advanced approaches, like e.g. machine learning techniques could be utilized to compute the behavior trajectory.

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Fig. 9: Lane Change scenario for three dedicated time instants: The first row shows the drivers perspective by camera images. The second row shows recorded as well as processed data in top view. The third row depicts measured values during the maneuver, where the velocity, the longitudinal (blue) together with the lateral (red) acceleration, and the steering wheel angle are shown over time. Note that the peak in the lateral acceleration at $t \approx 3.8\, \text{s}$ is due to measurement noise.

Fig. 10: Roundabout scenario, for three dedicated time instants: The first row shows the drivers perspective by camera images, with vehicles emphasized by red bounding boxes. The second row shows recorded as well as processed data in top view. The third row depicts measured values during the maneuver, where the velocity, the longitudinal (blue) together with the lateral (red) acceleration, and the steering wheel angle are shown over time.
Fig. 11: Left turn scenario, for three dedicated time instants: The first row shows the drivers perspective by camera images, with vehicles emphasized by red bounding boxes. The second row shows recorded as well as processed data in top view. The third row depicts measured values during the maneuver, where the velocity, the longitudinal (blue) together with the lateral (red) acceleration, and the steering wheel angle are shown over time. Note that the peak in the lateral acceleration at $t \approx 4.5 \, \text{s}$ is due to measurement noise.

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Maximilian J. Graf received his B. Sc. degree in 2014 and his M. Sc. degree in 2016, both from the University of Ulm/Germany in the field of electrical engineering. From 2016 until 2020 he was a research assistant and PhD student at the institute of Measurement, Control and Microtechnology at the University of Ulm and since 2021 he is with the ZF Group Friedrichshafen. His main research interests include motion planning for autonomous driving and vehicle motion control.

Oliver M. Speidel received the Master’s degree in computer science with distinction from Ulm University, Ulm, Germany in 2017. Currently, he is a research assistant at the institute of Measurement, Control and Microtechnology of Ulm University, where he is working towards the Doctoral degree. His main research interests include the areas of decision-making and motion planning with a focus on applications for autonomous vehicles.

Jona O. Ruof received his M. Sc. degree in media informatics with distinction in 2019 from Ulm University, Ulm, Germany. Since 2019, he is a research assistant at the institute of Measurement, Control and Microtechnology of Ulm University, working towards the Doctoral degree. His current research interests encompass, decision-making, motion planning, and learning control for automated vehicles.

Klaus Dietmayer (M’05) was born in Celle, Germany, in 1962. He received the Diploma degree (equivalent to M.Sc. degree) in electrical engineering from the Technical University of Braunschweig, Germany, in 1989, and the Dr.-Ing. degree (equivalent to Ph.D. degree) from the University of Armed Forces, Hamburg, Germany, in 1994. In 1994, he joined Philips Semiconductors Systems Laboratory, Hamburg, as a Research Engineer. In 1996, he became a manager in the field of networks and sensors for automotive applications. In 2000, he was appointed to a Professorship at Ulm University in the field of measurement and control. He is currently a Full Professor and the Director of the Institute of Measurement, Control and Microtechnology, School of Engineering and Computer Science, Ulm University. His research interests include information fusion, multi-object tracking, environment perception for advanced automotive driver assistance, and E-mobility. He is a member of the German Society of Engineers VDI/VDE.