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Data-Driven Simulation and Parametrization of Traffic Scenarios for the Development of Advanced Driver Assistance Systems

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***Abstract*—The validation and verification of cognitive skills of highly automated vehicles is an important milestone for legal and public acceptance of advanced driver assistance systems (ADAS). In this paper, we present an innovative data-driven method in order to create critical traffic situations from recorded sensor data. This concept is completely contrary to previous approaches using parametrizable simulation models. We demonstrate our concept at the example of parametrizing lane change maneuvers: Firstly, the road layout is automatically derived from observed vehicle trajectories. The road layout is then used in order to detect vehicle maneuvers, which is shown exemplarily on lane change maneuvers. Then, the maneuvers are parametrized using data operators in order to create critical traffic scenarios. Finally, we demonstrate our concept using LIDAR-captured traffic situations on urban and highway scenes, creating critical scenarios out of safely recorded data.**

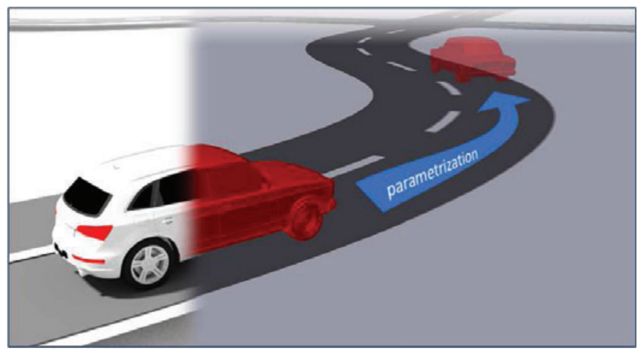


Fig. 1. Our approach consists of recorded sensor data, that is analyzed, parametrized and used for modeling critical traffic scenarios in simulation.

I. Introduction

In the last decades, research in robotics paved the way for the transfer to highly automated driving. Thus, research has basically focused on the intelligent vehicle's cognitive skills sensing the environment, assessing the underlying traffic situation and making an appropriate movement. Beside academic institutions [1]–[3] also industrial groups [4] have shown progress developing more and more complex cognitive skills for intelligent vehicles. Typically these skills are denominated as advanced driver assistance systems (ADAS), supporting the driver in its driving task.

ADAS require different cognitive skills, realized with different kinds of algorithms (machine-learning, control systems,...). The different algorithmic layers of a highly automated vehicle are visualized in Fig. 2. In the first step, the traffic environment is sensed and perceived. Also, the localization of the vehicle itself is estimated. Perception and interpretation algorithms enhance the sensor-sampled information to obtain an enriched and semantic representation of the environment. This extended environment model is used to perform a situation assessment and to plan and execute an appropriate movement of the ego-vehicle.

For the public acceptance of automated driving validation and verification of the cognitive skills is a crucial requirement, especially testing dangerous and critical traffic situations. Therefore, innovative methods for testing and evaluation for ADAS have to be developed [5]. There are three discriminative approaches: Typically, in the early steps integrative simulations are used to verify the functionality. Simulations provide the great advantage of being reliable and repeatable. Then test drives in controlled environments are performed. This enables secure testing with the help of pedestrian dummies, for example. Since it is unfeasible to simulate all possible traffic scenarios, there is still a need for expensive and time-consuming test drives to verify the functionality in the face of unforeseen influences.

In this paper, we demonstrate, how recorded sensor data, e.g. from real test drives, can be exploited in order to create critical traffic scenarios for open-loop testing, see Fig. 1. Our contribution consists of three basic innovations: At first, we demonstrate how reference data is preprocessed in order to derive the underlying time-independent road layout of the recorded drive and the related traffic participant trajectories. This information is needed to derive vehicle maneuvers, exemplary shown for lane change maneuvers, which then can be manipulated using data operators. This approach enables the creation of critical traffic scenarios from observed, non-critical real-world situations, see Fig. 3.

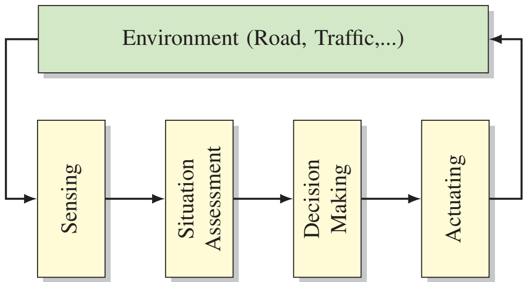


Fig. 2. Information Processing Pipeline of ADAS. Source: [6].

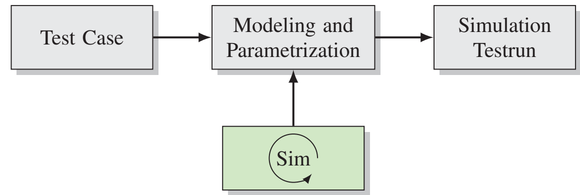
II. Related Work

In general, there are two concepts generating reference data for the development and evaluation of ADAS: Using model-based simulations or empirically collected data with reference sensors. Both approaches are based on the axiomatic assumption, that these reference systems create irrefutable ground truth. Thereby, it seems reasonable to build up a mapping from real, recorded traffic situations to be used in simulations as reference scenarios. Then, realistic test-runs for simulations can be created from test drives and do not have to be modeled manually, which also suffer from human or model imperfection.

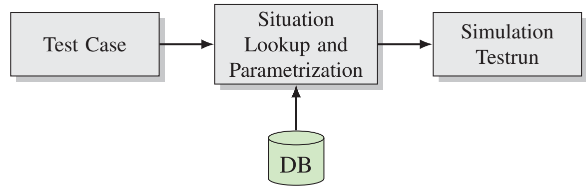
Because of the complexity of traffic situations, for a taxonomy see [7], integrative simulations are deployed for the development and evaluation of ADAS. Every important aspect of a traffic scenario is modeled, like the driver's consitution and behaviour, the vehicle dynamics or the behaviour of traffic participants. Also, for example, the visual mapping process of a camera system can be modeled in simulation. Due to their mathematical or logical founding, models only permit the simulation of a certain aspect of reality. Hence, they lack of the diversity of realism. So, for example in testing vehicles-in-the-loop a model of the vehicle dynamics is replaced by measurements of the real vehicle [8]. In the context of simulating traffic scenarios for ADAS, we can conclude, that we are restricted to a specific traffic participant behaviour, for example. Additionally, the models have to be parametrized appropriately by the human modeler to produce a desired test traffic scenario. Thereby it would be desirable to obtain experienced traffic scenarios as a reference to be used as test cases for subsequent simulations.

In [9] and [10] map-based data has been used to create realistic simulation scenarios in terms of realistic road networks, for example for macroscopic simulations [10]. Also research has focused in creating and evaluating realism by deriving experienced aspects from real drives. For example, in [11], a vision-based technique for the derivation of test runs for subsequent analysis in a realistic 3D-environment simulation, coupled with the simulation engine Virtual Test Drive, is presented. Thereby GPS-traces are matched with a GIS-database to reconstruct the driven trajectory.

As mentioned above, the second possibility to obtain ground truth data is the usage of reference sensors. In [12], [13] recorded data from reference sensors is simply replayed in simulation. There, a LIDAR-based method for detecting and filtering dynamic objects forward and backward is presented to obtain a reliable classification of traffic participants, which can be replayed in a simulation. Nevertheless, there is no indication, how the recorded scenarios can be varied. We have already shown, how simulated vehicles can be integrated into recorded situations in [6]. In this paper, we show a complementary approach, which modifies the recorded sensor data itself in order to create critical traffic scenarios.



(a) Model-based approach to create traffic scenarios in simulation.



(b) Our approach of creating traffic scenarios out of recorded traffic situations.

Fig. 3. Our concept is based on a database with classified situation aspects, which can be parametrized, instead of defining a test run by multiple traffic participant maneuvers.

III. Concept

The process chain of our method consists of several algorithmic steps, see Fig. 4, namely the sensor recordings during real test drives, the traffic participant maneuver classification and modification and the exemplary coupling to an integrative simulation environment. This approach is completely contrary to the parametrization of simulation models for traffic scenarios. In contrast, our approach is based on the parametrization of observed traffic situations for the simulation of traffic scenarios in subsequent simulations (Fig. 3). We present this concept using the example of detected lane change maneuvers and their manipulation in order to create critical scenarios out of safe traffic situations. In the following the different steps are explained in detail:

A. *Logging of Reference Sensor Data*

Two very basic situation aspects are necessary in order to create realistic driving scenarios with respect to test cases regarding exteroceptive ADAS: the global ego-position of the measuring vehicle as well as the relative positioning of the surrounding traffic participants in order to reconstruct trajectories. Due to their properties, reference systems for environmental perception are predestinated to record reference scenarios from recording drives. For a detailed explanation of environmental perception reference systems, we refer to [14].

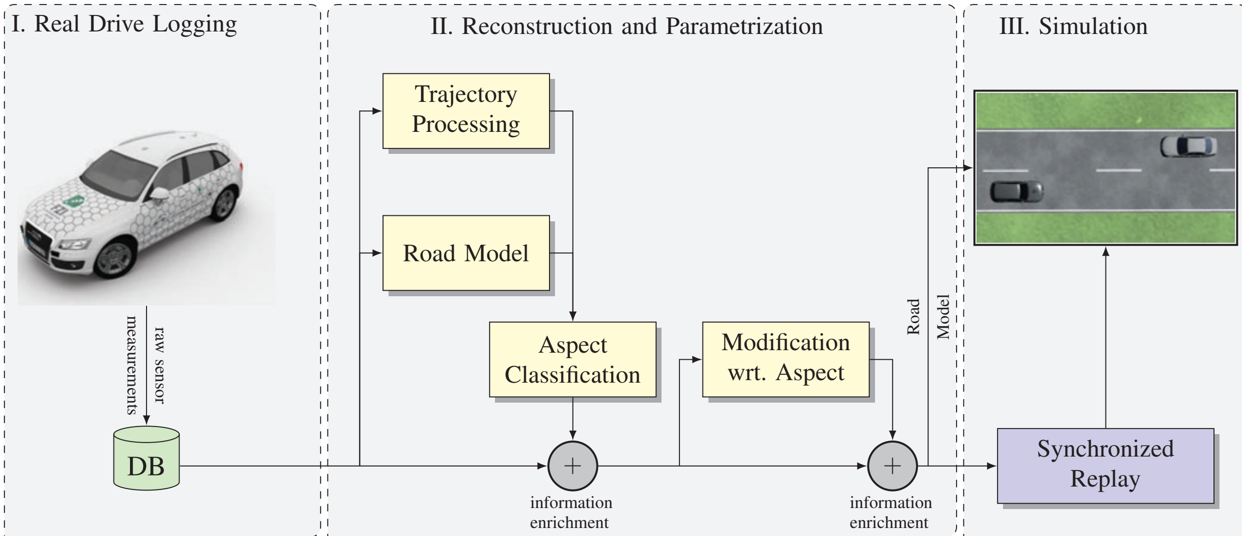


Fig. 4. Our approach consists of three basic steps: Sensor data is logged during a real drive. Then the road layout is reconstructed, vehicle trajectories and maneuvers are detected and parametrized for the subsequent simulation runs. Finally, simulation runs can be performed to develop some ADAS' functionality.

Our concept requires two kinds of reference sensors for the recording of traffic situations: First, a D-GPS/INS-Sensor is needed, which typically provides an accuracy of $\pm 2\text{cm}$ of the current position of the ego-vehicle in the global geographic coordinate system. This localization information can be referenced to a global euclidean coordinate system using an UTM-conversion with a fixed origin, obtaining a metric ego-position $\vec{x} = (x, y)$. Secondly, an abstract object sensor is needed, which provides information about the surrounding traffic participants. This can be a camera with a vision-based vehicle detector or also LIDAR-based object classifier [12]. Typically, an abstract object sensor of any kind of physical measurement principle and feature classification provides information about the objects, like geometrical dimensions or estimated velocity.

So, at each time step t, we obtain a list of currently seen obstacles $O(t)$ from the abstract object sensor. Thereby, each of the perceived objects at time step t, $o_i(t)$, is represented by estimated features, forming a feature vector:

$$o_i(t) = (id, x_{\text{rel}}, y_{\text{rel}}, v_{\text{lat}}, v_{\text{lon}}, \text{type}, \dots)$$

In order to relate the observed vehicle states to global frame in space and time, both the internal localization sensor system and the object sensor system have to be synchronized to a system-wide timestamp.

B. Filter Design

The central road geometry filter estimates the layout of the road in a global coordinate system. Beside the detection of lane changes, it can also be used to generate digital maps.

The D-GPS/INS-Sensor already gives a very precise estimation of the ego vehicle's position. On a single lane road, this information can directly be used to estimate the road geometry similar to the way OpenStreetMap data is usually created from GPS-tracks. On a multi-lane road this approach cannot be accomplished, due to possible lane changes of the ego-vehicle. Therefore, we want to estimate the ego-vehicle position relative to the road by evaluating environmental traffic participants given by the abstract object sensor.

In order to derive a representation of a multi-lane road, the filter operates in the ego-vehicle trajectory coordinate system, but observations are aggregated over time: At each time slice all tracked vehicle's are transformed to the global coordinate system using the ego vehicle's position estimation. Then, the global object positions are aggregated over time. This way, at each point of the road, all observations are aggregated, that can be origined from different time slices. After this temporal fusion all object observations are processed spatially along the ego-vehicle's trajectory: Every observation is transformed into the vehicle trajectory coordinate system (Fig. 5).

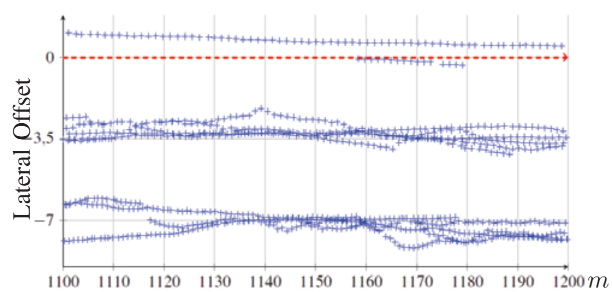


Fig. 5. Position measurements (in ego-vehicle trajectory coordinate system) of an abstract object sensor over 100 metres of a highway drive. These observations are used to reconstruct the road model with a particle filtering approach. The red trajectory indicates the driven ego-trajectory.

Now, we use a Particle Filter that operates on the vehicle trajectory coordinate system using the aggregated observations from other timeslices to estimate the ego vehicle's current lateral position on the road. Using Monte Carlo Sampling, Particle Filters are a very generic way to implement a Bayesian filter without restrictions, like Gaussian distributions etc. The application-specific parts of the Particle Filter are the particle space itself, the motion model and the sensor model.

Our road model consists of these parameters: the number of lanes n_l with their center points c_j and respective width b_j ($j \in \{1, .., n_l\}$). These parameters can be estimated by the particle filter, but are also available through maps or terms of reference, like the RAA for German highways [15]. We assume, that both parameters are known and constant for the spatial extent of the traffic situation. Under this assumption, we can create traffic scenarios for most street sections on highways and rural roads, except points of discontinuities between different street types. The center lines c_j can be seen as lateral coordinates in the road coordinate system (Fig. 6). We assume the road coordinate system's origin being in the most-right lane ($c_0 = 0$).

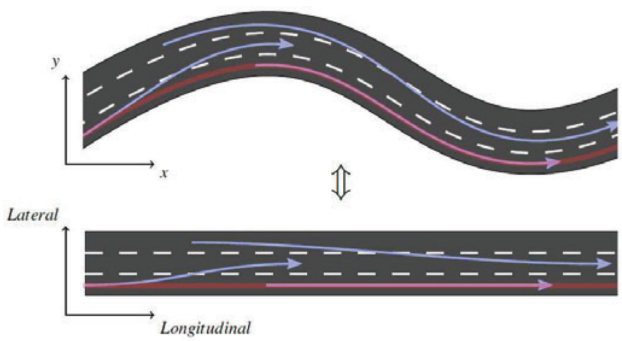


Fig. 6. Global Coordinate System (top) and Road Coordinate System (bottom)

The particle space of the Particle Filter is one-dimensional and represents the lateral offset Δy of the road coordinate system to the ego-vehicle's trajectory.

We introduce two different sensor models: For the observed objects an evaluation function is used, that respects the location of the lanes on the road (Fig. 7): A particle is evaluated positively, if its road hypothesis fits to most of the observed vehicles. For the ego-vehicle itself, we introduce an evaluation function that does not have a bias towards lanes (Fig. 8). While it preserves the ego vehicle to be on road, lane changes of the ego-vehicle do not affect the road offset estimation.

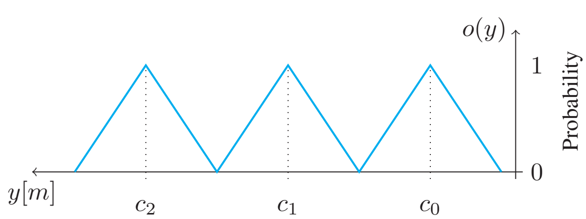


Fig. 7. A concatenated triangle function is used to evaluate road offset hypotheses according to vehicle observations.

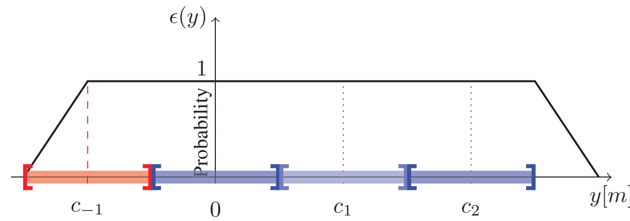


Fig. 8. A separate evaluation function weightens the particles according to the ego vehicle's position. The road lanes are visualized using coloured intervals. A virtual fourth lane is included, so that we can already estimate the highway road model while entering the highway on the acceleration lane.

The motion model of the Particle Filter is modeled as Gaussian noise. Additionally an estimation of the lateral movement of the ego-vehicle can be integrated.

The result of the particle filter is the offset between the road model and the ego-vehicle's trajectory. Using the precise ego-vehicle trajectory and the offset, the road layout is now transformed into a global road geometry and can be persisted in a digital map. For example, OpenDrive, OpenStreetMap or derived description languages, like Lanelets [16] are suitable formats. Nevertheless, for subsequent simulations the map description language has to be determined with respect to the format support of the simulation environment of choice.

C. *Modification of Classified Vehicle Maneuvers*

In this paper, we modify vehicle maneuvers, which are suitable in order to create test cases for a congestion assistant or forward collision warning system, for example. Generally, our concept is expandable to different situation aspects (e.g [17]), which are affected by the underlying road layout. The more complex decision-making algorithms of ADAS have to be tested, the more situation aspects have to be observed or annotated manually and classified in the recorded sensor data. For this, observed interaction patterns between different elements of a traffic situation (road, participants, traffic lights,...) have to be classified in order to manipulate them in a further step using data operators.

In this step, the observed vehicle measurements are transformed into vehicle trajectories with the help of a unique identifier from the abstract object sensors. These trajectories are compared with the road layout. The road layout gives indications on which lane the observation took place. Thereby two exemplary classes of vehicle maneuvers can be inferred: A lane change behaviour always takes place, if the vehicle movement of the traffic participant passes the transition between two adjacent lanes. We also can detect a vehicle-following behaviour, if the other traffic participant as well as the ego-vehicle have been on the same lane of the road layout. This information is persisted in an index structure.

In order to parametrize the experienced traffic situation by modifying the trajectories, which have been classified as lane-change maneuvers, we define the following data operators. They facilitate shifting the vehicle maneuvers in space or time, with respect to the lateral and longitudinal street coordinate system:

- Spatial Translation: The original trajectory f is manipulated by adding a constant path length difference Δs longitudinally or laterally:

$$\tilde{f}: T \times V \rightarrow \mathbb{R}^2, (t, v) \mapsto f(t) + \Delta$$

$$\text{with } \Delta = (\Delta s, 0), \text{or } \Delta = (0, \Delta s)$$

- Temporal Translation: The driven trajectory now is manipulated by adjusting the domain of the mapping. Thereby the maneuver is shifted in time with a time difference Δt:

$$\tilde{f}: T \times V \rightarrow \mathbb{R}^2, (t, v) \mapsto f(t + \Delta t)$$

  Thereby the trajectory remains the same, but the vehicle appears sooner or later.

D. Simulation

Finally, the created and parametrized traffic scenarios can be used in subsequent simulation runs to develop or evaluate the performance of ADAS, especially higher decision control algorithms. Therefore, integrative simulation environments are well-suited platforms, so that algorithmic components of ADAS can be tested with the use of virtual sensors, for example. Within our concept, we assign two data-driven models to the subsequent simulation run: the derived road layout and the vehicle's trajectories including parametrization.

These steps basically depend on the specific simulation environment. In the case of the IPG CarMaker [18], the road model is extracted from the observed trajectories, smoothed and converted into the appropriate test run description in a preprocessing step, see Fig. 4. Then a set of traffic objects is defined. These traffic objects are represented by a 3D-model in the virtual environment. Instead of defining traffic participants' maneuvers a priori, their position and orientation is updated online during the simulation run according to the observed behaviour from the recording including any parametrization. In the case of CarMaker this is done using the application online interface and a time-synchronizing mechanism, where the recorded trajectories are synchronized with the timestamp of the simulation environment. This ensures the repeatability of the simulation runs.

An important aspect is, that the virtual ego-vehicle model has to coincide with the behaviour of the real representation in order to obtain spatial-temporal smoothness. This means, that the recorded trajectories - consisting of space-time points - are still plausible in the absence of the real vehicle and presence of the virtual counterpart. Generally, two approaches are conceivable:

- The 3D-model of the ego-vehicle can also be used as an avatar without any model of the vehicle dynamics. Thereby, the recorded trajectory of the ego-vehicle is simply replayed, but this approach lacks of testing ego-vehicle's functionality closed-loop.
- In order to integrate a complex control algorithm, a complete mapping of the real vehicle, including its perception and decision algorithms, can be modeled in the simulation. Then the movement of the ego-vehicle has to be parametrized this way, that it coincides with the recorded ego-trajectory in the space-time environment of the traffic situation under test.

After the mapping of such a traffic situation to a traffic scenario in simulation, we can obtain, for example, simulated sensor views or object lists to evaluate and develop ADAS. It is also possible to evaluate different sensor principles for the same present traffic scenario. Due to possible error propagation from recording to re-simulating a traffic situation, we assume that reference sensors and algorithms have been used for perception and object recognition tasks.

IV. Proof-of-Concept

For the data acquisition, we use recorded reference sensor data from the FZI's experimental vehicle Cognitive Car (CoCar). It is equipped with different environmental sensors, like laserscanners, PMD sensors and stereo camera systems. Additionally, gas, brake and steering actuators are integrated, which enables to drive fully automated. A high precision D-GPS/IMU sensor system provides a high detailed localization. In order to gather information about the surrounding traffic participants during test drive, we have collected the object lists obtained from a set of three IBEO LUX laserscanner and a fusion ECU. The fusion ECU classifies and estimates attributes of the observed traffic participants, like estimated position, orientation, velocity and dimensions for example. In Fig. 9 the sensor setting of the experimental vehicle is visualized.

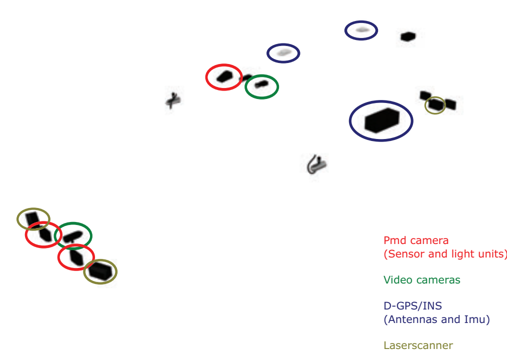


Fig. 9. Sensor setting of the FZI's experimental vehicle CoCar. Adapted from [1].

As a proof-of-concept, we demonstrate our concept creating a critical traffic scenario, where a vehicle moves into our lane. Therefore, we have recorded drives on the German highway A5 between Karlsruhe and Rastatt. On these recorded drives lane change maneuvers have been detected. As an exemplary maneuver, the lane change maneuver in Fig. 10a has been used. Using the proposed data operator for spatial translation, the vehicle maneuver is pulled to the front of the ego-vehicle, see

Fig. 10b for the visualized application. The derivation of the road layout is also applicable for urban scenarios by adapting the expected number of lanes and their width in the particle filter, see Fig. 11.

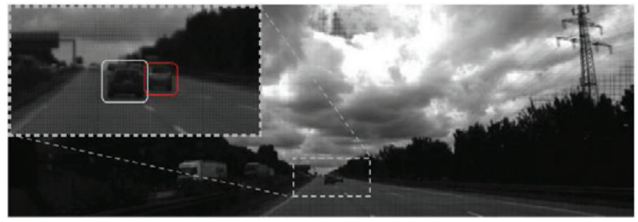
The original and parametrized trajectories can now be used to move the vehicles in the simulation. The derived road layout thereby enables the usage of a vehicle dynamics and a driver model. Hence, the ego-vehicle can coincide with the trajectory of the real vehicle in that subspace in space and time, for which the parametrization of the trajectory aggravated the recorded traffic situation. Different snapshots of this resulting traffic scenario are visualized in Fig. 10c to 10e. The usage of a vehicle dynamics and a driver model facilitates the testing of plugged-in-algorithms, like an emergency braking algorithm. This algorithm, for example, can be stimulated with virtual sensors, see Fig. 10c to Fig. 10e in the top-left corner of the visualization. Hence, the effect of the algorithm-under-test can be tested closed-loop, which means, that its reaction towards the critical scenario can be observed in simulation. Though, we lack of closed-loop behaviour of the environment, which means, if the ego-vehicle brakes other traffic participants with recorded and trajectories will ride over the ego-vehicle.

V. Conclusions and Future Work

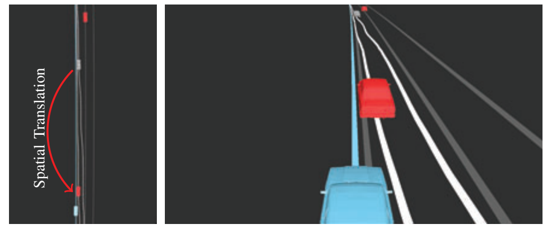
In this paper a data-driven concept for the derivation and parametrization of traffic scenarios out of recorded sensor data is presented. Our approach can be seen as reenacting and aggravating an experienced traffic situation in simulation. Thereby, reference sensor data is used to reconstruct the road layout of the test drive, as well as traffic participant maneuvers are detected. Then, the trajectories of the traffic participants are modified in order to create critical scenarios. These test scenarios can be used in subsequent integrative simulation environments in order to evaluate and test ADAS' components. In this paper, the IPG CarMaker has been used. The proposed data-driven concept hence is a completely contrary approach to parametrize traffic scenarios with simulation models.

Altough we have shown, that it is possible to evaluate ADAS components closed-loop w. r. t. the ego-vehicle's reaction, we are limited to the fixed, derived and parametrized vehicle maneuvers. Our concept is also based on the basic premise, that small modifications can be applied on the recorded vehicle trajectories so that the plausibility and consistency of the original scene are still preserved. Then, this approach is more realistic than modeling traffic situations using parametrizable and limited models. This has to be verified and limitations have to be identified in further steps.

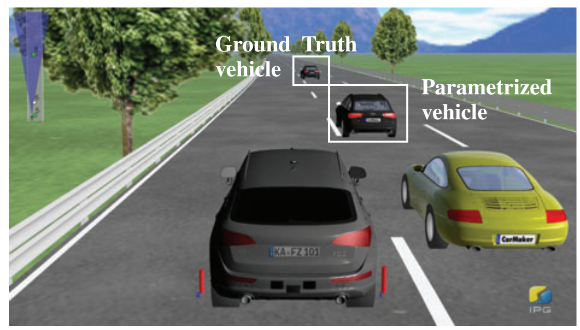
Our work indicates, that there are many future research aspects: We will focus on deriving more complex road layouts, like highway entries or intersections. In this paper, we've focused on lane change maneuvers, due to their criticality for a highway pilot, for example. So, further research will focus on classifying more complex situation aspects and appropriate data operators, which modify situations with plausible implications. Interactions between multiple traffic participants will have to be considered to create a reactive environment.



(a) Recorded *ground truth* traffic situation.



(b) Usage of data operator: Pulling the lane change in front of the ego-vehicle by modifying the recorded trajectory.



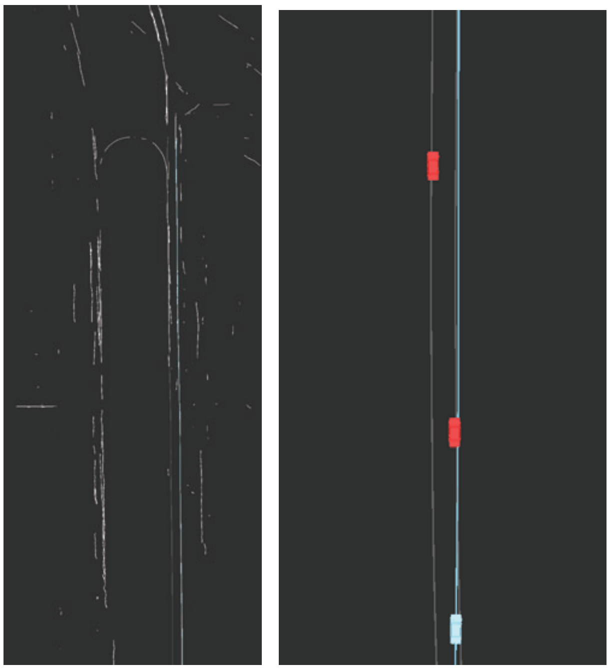
(c) The black car and its modified mapping initiate their lane change,

(d) move to our lane

(e) and are detected by our virtual sensor (top-left corner).

Fig. 10. The lane change maneuver is pulled in front of the ego-vehicle.

(a) *Ground Truth* of the recorded urban scenario.



(b) Aggregated object positions, which have been measured by the laserscanner ECU.

(c) Top-down view on reconstructed road center lines with the two vehicles in front of the ego-vehicle.

Fig. 11. The laserscanner ECU delivers object positions at every timestep. They can be aggregated over time in order to obtain evidences for road lanes. These measurements are used as input for the Particle Filter.

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