Classification of Driving Maneuvers in Urban Traffic for Parametrization of Test Scenarios

Lukas Hartjen*, Robin Philipp*, Fabian Schuldt*, Falk Howar† and Bernhard Friedrich‡

Abstract— **This contribution proposes a semantic description of vehicle behavior in urban environments in the form of maneuvers. By detecting these maneuvers in recorded measurement data of test drives, specific scenarios can be identified and evaluated in regards to vehicle behavior on public roads. Characteristics of extracted maneuvers can then in turn be used to describe and differentiate the behavior of traffic participants in test scenarios for automated driving systems. We extend an earlier concept to be applicable for urban vehicular traffic. Furthermore we analyze real-world measurement data of test drives by identifying the maneuvers which are defined in this contribution. We then show exemplary how classified vehicle behavior can be used to formulate a *Logical Scenario* containing parameter distributions. These distributions are then sampled to obtain multiple *Concrete Scenarios* for use in simulation. Finally, we discuss our results and possible future work.**

I. Introduction

In the past years, several research projects have demonstrated automated driving. Safety validation of automated driving is inevitable to bridge the gap from development to release and introduction of the systems on public roads. Calculations such as from Winner et al. [1] have shown that a distance-based validation for automated driving systems is not feasible for economic reasons. Therefore, other methods like scenario-based safety verification and validation are a focus of current research, such as in the German national project PEGASUS[1]. This approach seeks to make a safety statement about an automated driving system by testing it in a set of scenarios.

However, a challenge arises when trying to construct this set of scenarios. When modeling the behavior of another traffic participant in the form of a trajectory, there exists an infinite number of possible permutations, since the temporal and spatial parameters (t, x, y, z) are all continuous variables. As noted in [2], it is therefore difficult for validation engineers to argue for the completeness of a given set of scenarios, since there exists an infinite number of scenarios that are not contained in it.

One possible argument for the use of a finite set of scenarios can be made based on the exposure during the operation of the automated driving system in the field. The exposure is an essential component of the traditional risk assessment of electric and electronic systems [3]. Following this definition, unsafe behavior in more frequently occurring scenarios is considered to be of greater risk than in infrequent scenarios. A part of the overall validation process should therefore focus on scenarios with a high probability of occurrence.

A scenario set could be considered to be suitable for exposure-based testing when it covers an agreed upon percentage of urban traffic during field operation. This can be verified stochastically through measurement data collected during test drives.

In this work, we propose to make a stochastic statement of this kind using maneuvers as a semantic description of urban vehicular traffic. Defined maneuvers are used to recognize recurring behavior of vehicles in recorded measurement data and make statements about their characteristics. These characteristics are expressed in the form of parameter distributions which can then be sampled to obtain representative scenarios for the test of automated driving systems.

II. Related Work

In the past, there have been different contributions on the topic of maneuver-based traffic descriptions and the testing of automated driving systems. In the following, a selection of previous publications is introduced.

Wachenfeld et al. [4] discuss how test-driving can not only be used to test the developed automated driving system itself. The collected data can also aid in modeling the surrounding traffic for scenario-based testing.[2] An example for this approach is investigated in this work.

Bagschik et al. propose a layered approach [6] [7] to describe traffic scenarios for the test and validation process of automated vehicles. Recently, a 6th layer for this scenario model has been proposed in [8] to incorporate digital information as well. In this work, we focus on scenario layer 4, the description of movable objects and their maneuvers during the scenario.

Menzel et al. [9] introduce the terms of *Functional*, *Logical* and *Concrete Scenarios*. *Functional Scenarios* contain a semantic description and can be read and understood by human experts. *Logical Scenarios* exhibit a greater level of detail by modeling parameter ranges and probability distributions, as well as dependencies between the parameters. A *Concrete Scenario* can be derived by sampling these distributions for the individual parameter values. To the best

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[1]For more information see https://www.pegasusprojekt.de/en/home.

[2]This work adopts the definitions of scene and scenario first published by Ulbrich et al. [5]

of our knowledge, the conversion of *Functional Scenarios* into *Logical Scenarios* has not yet been investigated for urban traffic.

In order to model the behavior of movable objects in *Functional Scenarios*, a semantic description in the form of maneuvers can be used. Dickmanns [10] defines a maneuver as the temporal progression of control signals that transfer a system from one state to a new one. This definition is also used by Schuldt et al. [11]. However, it does not cover state preserving maneuvers such as *Lane Following* or *Following* a lead vehicle, where a vehicle's state does not change but is preserved through control inputs.

Reschka [12] describes nine basic maneuvers that he deems necessary to participate in urban vehicular traffic. Namely, those are *Driveaway*, *Following*, *Approach*, *Passing*, *Lane Change*, *Turn*, *U-Turn*, *Parking* and *Safe Stop*. Schuldt et al. [11] describe a framework to recognize the occurrence of basic maneuvers from measurement data on German highways. Based on the definitions by Reschka [12], they formulate a set of basic maneuvers for highway traffic. Secondly, they implement classifiers for the maneuvers *Halt*, *Driveaway*, *Follow*, *Approach Leader*, *Passing*, *Lane Change* and *Fall Behind*. Since the focus of their work is the analysis of highway traffic, the applicability of their framework for urban vehicular traffic was not investigated.

Mauritz et al. [13] investigate the test of a lane change assistant using an abstract semantic domain description. Using this abstract domain, they are able to differentiate test scenarios from each other and thereby estimate the achieved test coverage over time. To the best of our knowledge, the transfer of the methodology to urban vehicular traffic has not been investigated up to date.

In a publication by Roesener et al. [14], they describe how the extraction of semantic behavior elements, such as lane changes, from measurement data can help to validate an automated driving system. By classifying these elements in time-series data, they compare the behavior of an automated vehicle to the behavior of the recorded human drivers. In this work, we do not make a comparison of the extracted maneuvers to those performed by the automated driving system. Instead, the data is used to establish a parameter space from which test scenarios can be sampled, a *Logical Scenario*.

Erdogan et al. [15] discuss the extraction of test scenarios for automated vehicles from measurement data by using various classification methods. They compare rule-based approaches to supervised and unsupervised machine learning techniques. The data-driven modelling of driving maneuvers for validation is purposes is also presented by Krajewski et al. [16]. In their approach, they employ machine learning techniques such as generative adversarial networks (GANs) and variational autoencoders to model lane change maneuvers previously recorded on highways.

Another approach for the classification of driving maneuvers at intersections is presented in [17]. They aim to recognize maneuvers for the purpose of scene understanding and object prediction at intersections. The generation of test scenarios is not a focus of their work. To this end, Althoff [18] et al. presented a methodology for the automatic generation of critical scenarios for an automated vehicle. Their work focuses on safety critical test cases and is not concerned with the representativeness of the generated scenarios.

Past research has encompassed the definition of basic maneuvers for vehicular traffic [12] [11]. While the feasibility of recognizing basic maneuvers in highway measurement data has been demonstrated, the application to urban traffic has not been investigated to date. This work therefore aims to transfer the methodology to urban traffic and evaluate its applicability. Extending the previous work [11], the recognized maneuvers are used to convert two selected *Functional Scenarios* into *Logical Scenarios* by deriving its parameter distributions from measurement data.

III. DEFINITIONS AND CONCEPT

Based on earlier definitions [11], we define a traffic maneuver as follows.

Definition 1. Maneuver *A maneuver is the intentional transfer of a traffic participant from one defined state into the next, which can also be identical.*

This extends earlier maneuver definitions to include state preservation, such as lane keeping or standstill, as well as state changes. Maneuvers are defined as object movements based on internal decisions. They can be used to specify vehicle behavior for scenario-based testing in the form of instructions. Using maneuvers as semantic labels for object movements helps to reduce the complexity of traffic participant behavior in large databases. By dividing time-series data of object movements into discrete semantic units similar behavior can be identified and compared.

Following this concept, we propose to structure urban vehicular traffic into three distinct categories of basic maneuvers. The categories and the maneuvers are described in the following subsection.

A. Urban Vehicle Maneuver Catalog

The basic maneuvers are structured into three categories of maneuvers regarding the vehicle state itself, maneuvers regarding the infrastructure and maneuvers regarding relations to surrounding traffic participants. Vehicle State Maneuvers describe changes or preservations of a vehicle's velocity state. At all times a vehicle is either performing an *Accelerate*, *Keep Velocity*, *Decelerate* or *Reversing* maneuver. *Driveaway* is a special case of *Accelerate* maneuvers and is performed when a vehicle starts to move. *Standstill* is a special case of *Keep Velocity* and describes the vehicle while not moving at all. *Halt* is a special case of *Decelerate* maneuvers and is performed when a vehicle comes to a halt by braking.

Infrastructure Maneuvers denote state changes or preservations with respect to the surrounding road infrastructure. Maneuvers in this category can happen simultaneously with maneuvers regarding a different infrastructure element. When

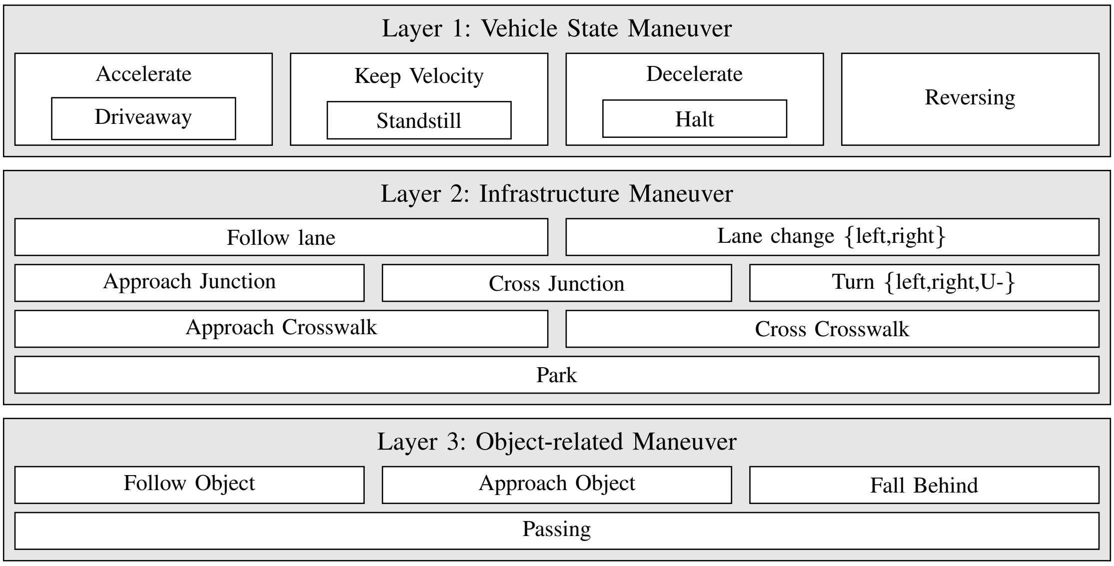

Fig. 1. Layered maneuver model for urban vehicular traffic

lanes are present, a vehicle is either performing a *Follow Lane* maneuver or a *Lane Change*. Vehicles can approach junctions (*Approach Junction*) and afterwards either cross them (*Cross Junction*) or perform a *Turn Left*, *U-Turn* or *Turn Right* maneuver. A crosswalk is approached at first (*Approach Crosswalk*) and then crossed (*Cross Crosswalk*). When a vehicle is parking, a *Park* maneuver is executed. The maneuver set presented here regarding infrastructure elements is not exhaustive as we do only consider lanes, junctions, crosswalks and parking spaces as maneuver-relevant infrastructure elements in this work.

Object-related maneuvers describe interactions with other traffic participants. Regarding the existence of a lead vehicle[3], different cases are considered. When the referenced vehicle is driving faster than its lead vehicle, the vehicle is approaching it (*Approach Object*). When both vehicles are driving with the same velocity, the referenced vehicle follows its lead vehicle (*Follow Object*). A *Fall behind* maneuver is performed when the referenced vehicle is driving slower than its lead vehicle and is also decelerating. When a vehicle is driving past another vehicle in a neighboring lane, a *Passing* maneuver is executed.

The maneuvers are summarized in Fig. 1. At most, one maneuver of a row (cf. Fig. 1) can be performed at a time with the exception of Vehicle State maneuvers where exactly one of the maneuvers is performed at any time. Thereby not every combination of simultaneously executed maneuvers can occur. Valid combinations of simultaneously executed maneuvers are implicitly defined by the just mentioned logic operations between the subsets. Such combinations can be used to detect certain scenarios in test drives where each of these maneuvers are classified.

[3] A lead vehicle is a vehicle driving in front of the referenced vehicle.

B. Maneuver Extraction

In order to parameterize the formulated maneuvers for simulation or proving-ground tests of automated vehicles, their occurrence is detected in real-world measurement data. The database contains measurements of ego states, surrounding objects and map information. The process architecture for the maneuver classification is shown in Fig. 2.

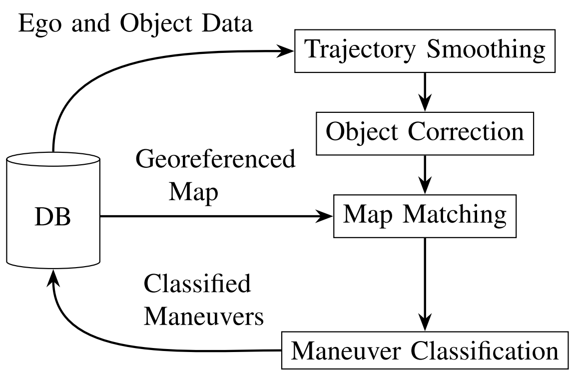

Fig. 2. Process overview showing the classification of driving maneuvers from a measurement database (DB)

After the ego and surrounding object data have been extracted from the database (DB), they are first reprocessed to improve the quality. This includes general smoothing of sensor noise using a Gaussian[4] filter, as well as object classification and dimension estimation. By evaluating the full history of classification and dimension measurements, it is possible to improve the accuracy of the live recordings. Afterwards, object positions are matched onto a georeferenced map for a subsequent classification of infrastructure-related maneuvers such as lane changes. The map is also contained in the same database as the object and ego data. Afterwards

[4] Carl Friedrich Gauß (1777-1855), German Mathematician and Physicist

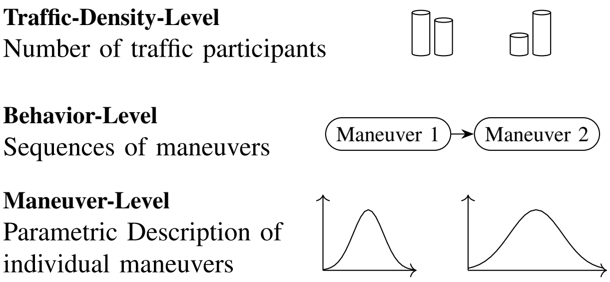

Fig. 3. Layers of analysis for traffic participants in an urban traffic scenario

a rule-based classification of the maneuvers from Fig. 1 is performed to recognize them in the data. The detected maneuvers are then stored in the database as well, along with a reference to the drive in which they occurred. After the maneuvers have been classified, the resulting semantic database can be analyzed on several levels to obtain scenarios from it, as shown in Fig. 3. For instance, it is then possible to query the database for all *Left Turn* maneuvers performed by the Ego vehicle. The introduced levels of analysis can be used to gradually determine the exposure of traffic scenarios. On the *Traffic-Density-Level*, the number of other traffic participants in the scenario is analyzed. For example, the average numbers of surrounding vehicles and pedestrians during *Left Turn* maneuvers can be used to model common urban traffic scenarios at junctions. The *Behavior-Level* describes consecutive maneuvers that are carried out by each object and their correlations. Common, recurring maneuver sequences such as *Lane Change* and *Passing* are identified on this level. In the testing process, they can be applied to formulate common behavior patterns and the associated exposure. Lastly, the parametric description of each individual maneuver (such as the chosen velocity) is taken into account on the *Maneuver-Level*. In this work, we focus on extracting data about the *Maneuver-Level*, while the number of traffic participants and their maneuver sequences are defined by the chosen *Functional Scenario*. For a seamless validation process, the exposure needs to be considered on all three levels of analysis.

IV. Initial Application

In this section we examine the applicability of our proposed concept and the maneuver extraction process. We show how we extract maneuvers out of measurement data which include captured vehicle movements and then subsequently estimate distributions of defined parameters for the extracted maneuvers.

In an exemplary application we focus on a scenario with fixed infrastructure at the Volkswagen factory grounds in Wolfsburg. In this scenario the vehicle under test (Ego) is performing an unprotected left turn on a three way intersection. The behavior of oncoming vehicles can either be a *Right Turn* onto the connecting road or the crossing of the T-intersection (*Cross Junction*) and therefore staying on the major road. For both cases we define a separate *Functional*

Functional Scenarios
'Left Turn I' and 'Left Turn II'

Base road network:
Three-way intersection in urban area
Tempo limit of 30 km/h
Connecting road:
Two lanes in each direction
Crosswalk in front of intersection
Major road:
One lane in each direction
Crosswalk on one side of intersection

Movable objects:
Ego vehicle:
Left Turn (onto connecting road)
Oncoming vehicle:
I: *Cross Junction* (stays on major road)
OR
II: *Right Turn* (onto connecting road)

Fig. 4. Description of the Functional Scenarios 'Left Turn I' and 'Left Turn II' on layer 1 and 4 following [6]

Scenario (cf. Fig. 4). A visualization of the two scenarios can also be seen in Fig. 5.

Unprotected left turns pose a challenge for automated vehicles in urban areas. The movement of oncoming vehicles has to be correctly captured and possible future trajectories have to be considered to ensure safe behavior by the system [12]. Therefore there is great interest in testing such scenarios with realistic and representative traffic participant behavior.

Our initial application is structured into four parts. First, all occurrences of both *Functional Scenarios* and their maneuvers in our database are extracted. Then the parameters for the basic maneuvers *Right Turn* and *Cross Junction* are defined. Subsequently, by analyzing the extracted scenarios, the parameter distributions for the defined parameters are derived. Finally a set of *Concrete Scenarios* is sampled which can be used to test automated driving systems.

A. Extraction of Scenarios and Maneuvers

The measurement data used as a basis for scenario and maneuver extraction is captured during test drives at the Volkswagen Factory Grounds. An OpenDRIVE [19] map is used as a georeferenced map to correctly assign the ego vehicle and surrounding vehicles to their respective lanes. Based on the resulting scenario representation, we detect executed basic maneuvers for every observed vehicle. To extract all scenarios that fit to our *Logical Scenario*, we look for left turns performed by the ego vehicle and subsequently extract all simultaneous maneuvers from the surrounding vehicles that performed a *Right Turn* or *Cross Junction*. Both maneuvers are recognized by detecting the points in time when a vehicle enters or exits a junction polygon defined by OpenDRIVE [19]. For our examined junction, a *Cross Junction* maneuver is defined as the vehicle entering and exiting the junction with an absolute difference less than a predefined threshold value in its global heading. Accordingly, *Right Turns* and *Left Turns* are classified as complementary maneuvers and differentiated based on the sign of the heading difference. These thresholds should be modified for different junctions as junction topology and therefore the spatial course of *Cross Junction* and *Turn* can vary. All detected occurrences are stored and form the basis for our analysis process.

B. Definition of Parameters

When generating test scenarios for an unprotected *Left Turn* at an intersection, the behavior of surrounding vehicles which can lead to a conflict with the ego vehicle is focused. Therefore, the maneuvers *Right Turn* and *Cross Junction* are examined. First, we define the corresponding parameters which can be diversified to generate an approximation of the observed occurrences of these maneuvers. Both maneuvers are modeled as Bézier[5] curves. A Bézier curve is specified by n control points which define the course of the curve in a multidimensional space. Following Equation 1 where $n > 0$ and the control points $\boldsymbol{b_0}, \boldsymbol{b_1}, ..., \boldsymbol{b_n}$ describe a spatial polygon.

$$\boldsymbol{b}(t) = \sum_{i=0}^{n} \binom{n}{i} t^i (1-t)^{n-i} \boldsymbol{b_i}, 0 \le t \le 1 \qquad (1)$$

We describe the spatio-temporal course of *Right Turn* maneuvers at the examined junction as a Bézier curve of third order. This curve is specified by four three-dimensional control points which contain two-dimensional positions and a velocity value. The first and last control point are defined by starting position, starting velocity and end position and end velocity of the vehicle executing the *Right Turn*. The two inner control points enable the possibility to describe how the right turn is executed in regards to the spatio-temporal course. The *Right Turn* parameterization consists of four control points $(x_{r_i}, y_{r_i}, v_{r_i})$, $i \in [0, 3]$ which add up to twelve values. As a 13th value, we include the timing and therefore the start of the right turn maneuver. This is modeled relative to the ego vehicle position by measuring the distance d_{Ego} from the ego vehicle to the lane center of the junction the moment the maneuver of the oncoming vehicle starts. This parameter can be directly used in OpenSCENARIO [20] to create a distance trigger condition for the maneuver.
As with the *Right Turn* maneuver, the spatial course and the velocity profile of the examined *Cross Junction* maneuvers are modeled as a Bézier curve of third order. The *Cross Junction* parameterization again consists of four three-dimensional control points $(x_{c_i}, y_{c_i}, v_{c_i})$, $i \in [0, 3]$ which add up to twelve values. As with the *Right Turn*, another parameter d_{Ego} is added to model the timing of the oncoming vehicle leading to a total of 13 parameters.

Both maneuver parameterizations are summarized in Fig. 5 and Fig. 6. As these models represent a first proposal for parameterizations of *Right Turn* and *Cross Junction* maneuvers which are suitable for the examined junction, there might be a need for modeling enhancements in the future to handle more complex infrastructure.

[5]Pierre Bézier (1910-1999), French Engineer and Mathematician

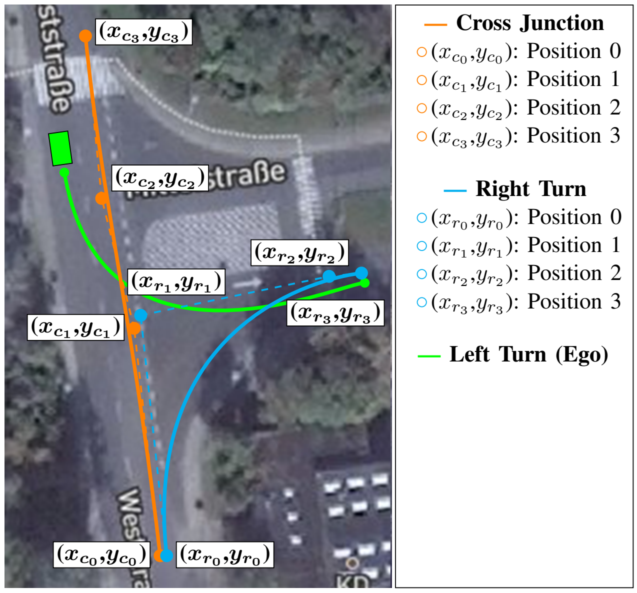

Fig. 5. Spatial parameterizations of the maneuvers *Cross Junction* and *Right Turn*. Satellite image is taken from OpenAerialMap [21].

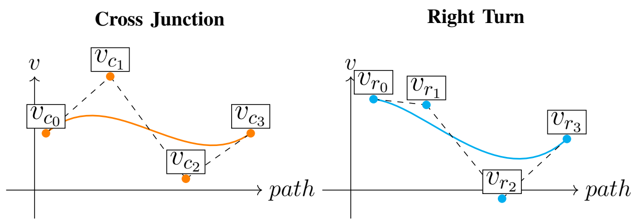

Fig. 6. Temporal parameterizations of the velocity v during the maneuvers *Cross Junction* and *Right Turn*. v_{c_i} and v_{r_i} are control points of cubic Bézier curves.

C. Estimation of Parameter Ranges

To generate a *Logical Scenario*, a distribution is calculated for each introduced parameter. We assume the parameter values to adhere to a normal distribution defined by its mean μ and the standard deviation σ. We detected 5 occurrences of our functional scenario *Left Turn I* and 6 occurrences of our functional scenario *Left Turn II*. Expectation values μ and standard deviations σ for each parameter of both scenarios are shown in Table I.

D. Sampling of Concrete Scenarios

In a next step *Concrete Scenarios* for the test of automated vehicles are sampled based on the estimated parameter ranges. These scenarios can then be executed in a simulation environment or recreated on a proving ground. Since the sample size of the observed maneuvers was too small to obtain a meaningful covariance matrix, the correlations between the parameters are not accounted for during this initial application. To demonstrate the applicability of the methodology, the calculated distributions of the *Logical Scenarios* are sampled at random to obtain 100 *Concrete Scenarios* for each of them. The 200 sampled trajectories

TABLE I
EXPECTATION VALUES AND STANDARD DEVIATIONS OF THE MANEUVER PARAMETERS IN THE ANALYZED DATASET

Cross Junction

[m]	μ	σ	[m]	μ	σ	[m/s]	μ	σ
x_{c_0}	619787.4	0.22	y_{c_0}	5810521.4	1.10	v_{c_0}	10.91	1.29
x_{c_1}	619780.9	2.97	y_{c_1}	5810563.1	15.36	v_{c_1}	9.9	3.14
x_{c_2}	619781.3	2.97	y_{c_2}	5810564.5	6.29	v_{c_2}	3.0	8.71
x_{c_3}	619776.4	1.05	y_{c_3}	5810593.6	1.53	v_{c_3}	10.2	2.38
d_{Ego}	53.1	21.97						

Right Turn

[m]	μ	σ	[m]	μ	σ	[m/s]	μ	σ
x_{r_0}	619787.7	0.88	y_{r_0}	5810521.9	0.73	v_{r_0}	9.4	0.44
x_{r_1}	619789.7	3.09	y_{r_1}	5810549.1	3.70	v_{r_1}	8.9	1.47
x_{r_2}	619803.9	4.97	y_{r_2}	5810552.7	1.16	v_{r_2}	7.2	2.39
x_{r_3}	619822.2	1.67	y_{r_3}	5810559.8	0.85	v_{r_3}	8.1	2.23
d_{Ego}	53.2	12.00						

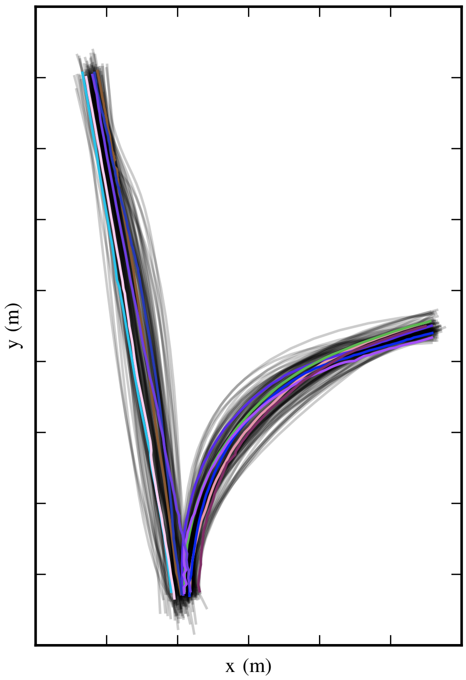

Fig. 7. Trajectories (black) sampled from the Logical Scenarios *Left Turn I* and *II* and the original measured trajectories (randomized colors)

are shown in black in Fig. 7, with the recorded trajectories overlayed in randomized colors.

In an additional step the sampled trajectories are converted into OpenSCENARIO [20] files. To this end the trajectories are implemented as an action that is triggered by the sampled distance condition parameter d_{Ego}. Fig. 8 shows the execution of one of these scenarios in a simulation environment for automated driving systems.

V. DISCUSSION

As demonstrated, the process of maneuver classification and subsequent parametrization can be used to obtain re-

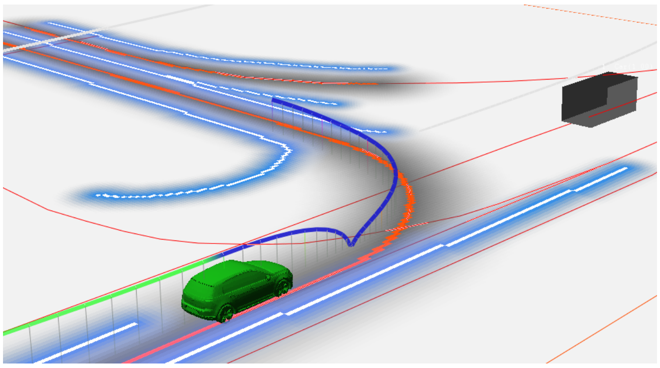

Fig. 8. Simulation of a sampled scenario *Left Turn I* for the *Cross Junction* maneuver of the oncoming vehicle. The vehicle displayed in green is the ego vehicle, the oncoming vehicle is colored in black.

alistic test scenarios for automated vehicles. It is possible to quantify the exposure of specific behavior on layer 4 of the scenario description model as the occurrence of defined maneuvers. In contrast to replay approaches, where a recorded trajectory is used to define simulated behavior, this work abstracts from the raw data of positions and timestamps by introducing parameterized maneuvers. Depending on the sample rate, these maneuvers generally contain fewer parameters than the recorded trajectories and can facilitate the systematic variation of a scenario during the testing process of automated driving.

Another advantage of the resulting distributions in the form of the *Logical Scenarios* is the fact that they allow engineers to perform exposure-based testing. For example, to arrive at a finite set of scenarios, only an agreed upon confidence interval of the distribution could be taken into account when sampling test scenarios. Engineers could also decide to sample parameter intervals with high exposures with a higher sampling rate and thereby increase testing efforts for scenarios that are more likely to occur under real world traffic conditions.

The analyzed *Functional Scenarios* of a *Left Turn* with oncoming traffic were chosen for their apparent simplicity to show a proof of concept of the methodology. The oncoming vehicle only executes one defined maneuver in each of the scenarios. In spite of that, the parameterized *Logical Scenarios* contain 13 parameters respectively. This constitutes a high-dimensional search space of possible *Concrete Scenarios* that could be sampled from this distributions. In order to limit this search space to a certain extent by focusing on the most likely scenarios, the correlations between different parameters should be taken into account. Strategies for sampling and testing such a *Logical Scenario* were not a focus in this work and should be investigated in the future.

The analyzed dataset was too small to obtain a robust, statistically valid set of parameter distributions for each of the investigated maneuvers. The presented values should rather be viewed as a proof of concept of the overall methodology. They are not expected to be representative for vehicle behavior at this intersection in general, nor has their applicability to other junction topologies been investigated.

The parameterization of the maneuvers as Bézier curves constitutes a significant abstraction from the observed physical behavior. This abstraction was made to reduce the number of variables in the resulting *Logical Scenario* and to obtain a uniform set of parameters to model all occurrences of the maneuver at the investigated junction. The reproduction of the parameterized maneuvers in simulation and a quantification of the deviation from the recorded behavior should be investigated in detail in the future to verify the model accuracy of the chosen parameter set.

Another subject of debate raised by the initial application is the abstraction level of *Functional Scenarios* which is also addressed in [9]. On one hand, when investigating a narrow scenario as in this work, less parameters are needed to model the observed behavior. For example, by focusing on one intersection, the road curvature does not need to be modeled as an influencing factor since it is constant for all observed *Right Turn* maneuvers. On the other hand, in datasets collected for general purposes, there will generally be less data matching a narrow scenario description than a coarse one. This can result in less reliable parameter distributions being derived for the chosen *Logical Scenario*. This fundamental tradeoff between many, narrowly defined and fewer, more coarsely modeled *Functional Scenarios* will be a key challenge to solve for the data-driven testing of future automated driving systems.

VI. Conclusion and Future Work

In this paper, a catalog of basic maneuvers for vehicular traffic in urban environments is introduced. These maneuvers are separated into three distinct categories which relate to the vehicle state, the infrastructure and surrounding objects of the vehicle, as can be seen in Fig. 1. We then demonstrate the extraction of maneuvers from a measurement database for the generation of representative scenarios for automated driving systems. To that end, two *Functional Scenarios* are defined which describe a *Left Turn* at a three-way intersection with oncoming traffic. Occurrences of these *Functional Scenarios* are detected in our database by recognizing the specified combinations of maneuvers. In a next step, extracted maneuvers are analyzed to generate *Logical Scenarios* with parameter distributions. For this reason, we parameterize the maneuvers *Cross Junction* and *Right Turn*. Ultimately, we sample 200 test scenarios for an automated vehicle based on the analysis that took place. In the future, we would like to complete the maneuver catalog for urban environments and show its applicability regarding the testing of automated vehicles. This includes both the definition and the parameterization of further traffic maneuvers which is needed to diversify vehicle behavior. Another topic of future research could be to consider all layers of analysis shown in Fig. 3 to estimate the exposure of traffic scenarios.

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