2018 21st International Conference on Intelligent Transportation Systems (ITSC)
Maui, Hawaii, USA, November 4-7, 2018

Interaction-Aware Long-term Driving Situation Prediction

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***Abstract*— Automated vehicles require a comprehensive understanding of the current traffic situation and their future evolution to perform safe and comfortable actions. To enable reliable long-term predictions of traffic participants the interaction among each other cannot be neglected. This contribution tackles the problem of interaction-based trajectory prediction with limited information of the situation as delivered by most on-board perception systems of nowadays automated vehicles. A *Monte Carlo* simulation based approach which utilizes well-known sensor models in a probabilistic manner to model the interaction between traffic participants is presented. Besides uncertainty in maneuver decisions, the maneuver execution is modeled with a probabilistic model learned from real-world data. Furthermore, the problem of limited information is addressed by a combination of the interaction-aware model with a maneuver classification algorithm providing information on the short-term maneuver. The approach is evaluated on two meaningful simulation scenarios demonstrating the advantages of interaction-based prediction in general and the handling of limited perception capabilities in specific.**

I. INTRODUCTION

Driving in nowadays mixed-traffic with human-driven as well as partially automated vehicles in a safe and comfortable manner is the key challenge to realize fully automated driving. A major concern is the understanding of the current traffic situation, to forecast future driving maneuvers and the prospective evolution in general. For an automated vehicle a prediction of future states of surrounding traffic participants is required to perform decision making and trajectory planning, that fulfills all demands on safety and comfort.

Especially for reasonable decision making a reliable long-term prediction of the behavior of other vehicles in the situation is important information. To achieve such long prediction horizons, the interaction between single participants cannot be neglected in the prediction. The paper at hand presents a novel interaction-based trajectory prediction approach which rests upon a *Monte Carlo* forward simulation of the current traffic situation utilizing probabilistic driver models. Thereby the interaction is considered by the driver models, and the distribution over future states can be approximated by multiple simulation runs. Additionally, the primary drawback of interaction-based approaches, that full information of the traffic scene is required, is addressed.

II. STATE OF THE ART

Following the overview in [1], the prediction of future trajectories for adjacent traffic participants can be divided into physics-based, maneuver-based and interaction-based prediction approaches. The former estimates future states of each vehicle by applying a static or dynamic motion model as for example *Constant Velocity* or *Constant Acceleration* models and is mostly suited for short-term predictions. Maneuver-based approaches first determine the most likely driving maneuver or intention and estimate a trajectory based on this without considering the interaction with other vehicles. One maneuver-based approach is, for example [2], where the authors combine *Dynamic Bayesian Networks* for behavior estimation with Bèzier curves as trajectory models. Schreier et al. [3] also utilize a *Bayesian Network* and couple it with individual trajectory distribution models for each maneuver. In [4] the authors propose a mixture of experts approach to combine *Gaussian Mixture Regression* with a *Random Decision Forest*. The *Decision Forest* is utilized to weight trajectory samples obtained from three regression models, which represent the classes lane change left, lane change right and lane keeping.

In interaction-based trajectory prediction the interplay between traffic participants is directly modeled, and a more reliable long-term prediction is possible. The authors of [5] combine a model-based interaction-aware intention estimation with a maneuver-based motion prediction on the basis of supervised learning to achieve better results for long-term maneuver prediction. The interaction in between the agents and with the road topology is modeled by a potential field, which guides the agents through the traffic situation in an interaction-based manner. A different approach is implemented by the authors of [6], where an approximation of future occupancy by other traffic participants is estimated. Uncertainties in prediction are covered by over-approximating the future occupancy for other traffic participants, where the interaction limits the reachable area. In [7] the authors apply *Inverse Reinforcement Learning* to learn a cost function representing human driving behavior and combine it with a vehicle dynamics based prediction to get the best possible short- and long-term maneuver prediction.

When predicting trajectories of other traffic participants in an interactive manner, the ego vehicle movement can not be neglected. Hence, publications in the field of maneuver planning are also of interest. In [8] the authors perform planning with uncertain maneuver predictions. The problem is formulated as a partially observable Markov decision process where the unknown routes of other traffic participants are hidden variables, which is solved utilizing the Adaptive Belief Tree algorithm.

The paper at hand utilizes well-known driver models to consider the interaction between traffic participants and rolls

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out several simulations in a *Monte Carlo* fashion to capture the most probable evolutions of the situation. The main contributions are

- the application of driver models in a *Monte Carlo* simulation on predicting future trajectories of traffic participants,
- the probabilistic maneuver execution modeling via *Gaussian Processes* learned from real-world data,
- and the handling of incomplete information in an interaction-based prediction.

The remainder of the paper is organized as follows. First, the problem of trajectory prediction in a situation with several agents is described. In section IV the interaction-aware prediction framework is presented and in the following section adjustments in the implementation to the limitations imposed by the available sensor setup are addressed. The developed framework is evaluated in section VI for two exemplary scenarios. Section VII concludes the paper.

III. PROBLEM FORMULATION

This work focuses the prediction of future movements for all vehicles in the direct surrounding of the ego vehicle in an interactive manner as depicted in Fig. 1.

Given a set of K agents in the current driving situation $\mathcal{N} = \{N_0, N_1, ..., N_K\}$, where N_0 represents the ego vehicle and each agent having a state $\mathbf{x}^{(k)}(t) \in \mathbb{R}^4$ at time t, the goal is to estimate the future states of all agents $\mathbf{x}^{(k)}(\tau)$ for $k \in \{1, 2, ..., K\}$ and $\tau \in [t, t_p]$ within the prediction horizon t_p. The agents are located in an arbitrary traffic scene $\mathcal{S}$ describing the road geometry and additional context regarding driving decisions, e.g. traffic signs or signals. The scene is not restricted to a fixed representation but may originate from onboard sensors as well as from digital maps. To move within the scene each agent applies a longitudinal acceleration $a_x^{(k)}(\tau) \in [-a_{max}, a_{max}]$ and performs a lateral maneuver $m^{(k)}(\tau) \in \mathcal{M}$ at time τ, where $\mathcal{M}$ is the set of possible maneuvers. From the lateral maneuver, an execution path through the traffic situation is derived which leads to a lateral acceleration to follow the path. With a given longitudinal and lateral acceleration the transition of state $\mathbf{x}^{(k)}(t)$ to the following one is defined by a transition model $\mathbf{x}^{(k)}(t + \Delta t) = f(\mathbf{x}^{(k)}(t), \mathbf{a}^{(k)}(t)) : \mathbb{R}^{4\times 2} \rightarrow \mathbb{R}^4$, where $\mathbf{a}^{(k)} = [a_x^{(k)}, a_y^{(k)}]^{\mathrm{T}}$. Longitudinal accelerations, as well as the lateral maneuver decision and execution, are based on individual preferences and driving behaviors of the respective drivers and the current traffic situation and such subject to uncertainties. Thus, the longitudinal acceleration and lateral maneuver are modeled with their respective distributions

$$a_x^{(k)}(\tau) \propto P(a^{(k)}(\tau)|\mathbf{x}^{(k)}(\tau), \mathcal{N}, \mathcal{S}) \tag{1}$$

$$m^{(k)}(\tau) \propto P(m^{(k)}(\tau)|\mathbf{x}^{(k)}(\tau), \mathcal{N}, \mathcal{S}, m^{(k)}(\tau - 1)) \tag{2}$$

which depend on the agents current state, the other agents within the traffic situation and their interactions.

IV. INTERACTION AWARE PREDICTION

The presented approach aims to deliver a valid estimate of the future evolution of the current traffic situation by predicting the trajectories for all traffic participants. Hereby the interaction between them, meaning how the maneuvers of agent N_i influence the behavior of agent N_j, is considered. One example of such interactions can be seen in Fig. 1, where two possible evolutions of the situation are depicted.

Three kinds of uncertainties have to be considered within trajectory prediction for human agents:

1) The unknown maneuver decision which may vary within one situation depending on the driver type.
2) The uncertainty in maneuver execution which also varies with the driver.
3) The uncertainty in initial state estimation imposed by sensor noise.

While the former two are explicitly considered in the presented approach, the latter can easily be incorporated as described in section V-B. The presented approach approximates the distribution over the future states of all agents in the current traffic situation

$$P(\mathbf{x}^{(k)}(\tau)) \text{ with } k \in \{1, 2, ..., K\}, \tau \in [t, t_p]$$

by repeatedly simulating the evolution of the situation n_m times utilizing probabilistic driver models. An overview of the complete procedure is presented in algorithm 1 later on. The following sections represent single steps and refer to their respective part in the overall algorithm.

A. Motion Model

The current state of agent $N^{(k)}$ is defined as $\mathbf{x}^{(k)} = [x, y, \dot{x}, \dot{y}]^{\mathrm{T}}$ describing the position and velocity of the agent. To estimate the state in the following time step, a state transition model (line 14 in algorithm 1), which describes the movement of a vehicle with sufficient accuracy and does not exhibit large computational effort, is required. With common onboard sensors and in the absence of inter-vehicle communication no internal states as steering wheel angle and rate of other agents rather than the ego vehicle are available. Thus, a point mass model is chosen as it offers sufficient accuracy with a low computational burden. Mathematically it is defined as

$$\dot{\mathbf{x}}^{(k)} = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \mathbf{x}^{(k)} + \begin{bmatrix} \frac{\Delta t^2}{2} & 0 \\ 0 & \frac{\Delta t^2}{2} \\ \Delta t & 0 \\ 0 & \Delta t \end{bmatrix} \begin{bmatrix} a_x^{(k)} \\ a_y^{(k)} \end{bmatrix}, \tag{3}$$

where $a_x^{(k)}$ and $a_y^{(k)}$ are the longitudinal and lateral acceleration of agent N_k, respectively.

B. Longitudinal Acceleration Model

To generate a suitable longitudinal acceleration for each agent, the interaction between traffic participants has to be considered. This includes the assumption that each driver rather performs a braking maneuver than causing a collision. This behavior is implemented by the intelligent driver model [9]. It is a collision-free model, which is widely

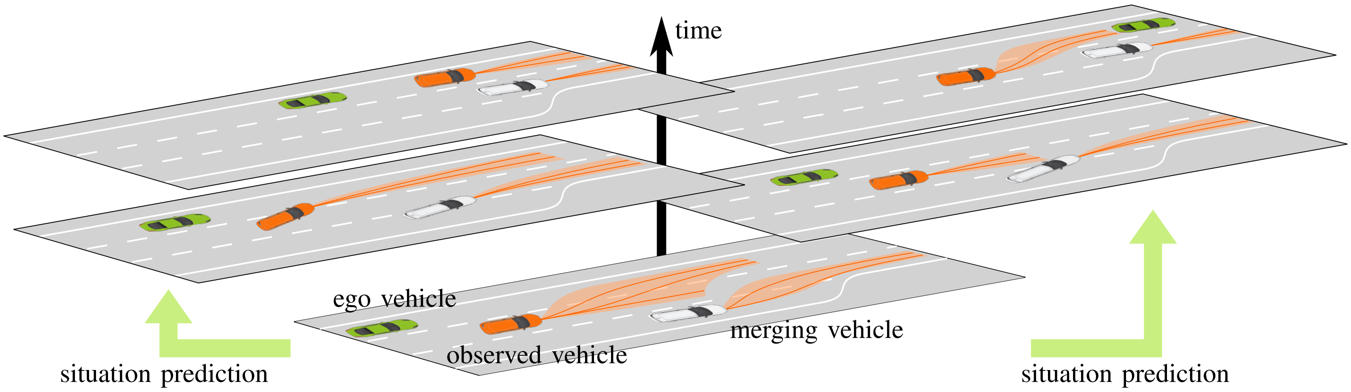

Fig. 1: Driving scenario with three vehicles on three lanes, where the most right one is ending. Two possible evolutions of the situation arise. On the left side, the observed vehicle changes to the leftmost lane due to the merging vehicle and is the new leader of the ego vehicle. In general, the situation could also evolve as shown on the right side, where the observed vehicle first decelerates to generate the required space and changes to the left lane afterward. Both possibilities have to be captured by an interaction-based prediction framework.

utilized in microscopic traffic simulation tools. The equations for longitudinal motions are

$$a_x^{(k)} = a_{max}\left[1 - \left(\frac{v^{(k)}}{v_{des}^{(k)}}\right)^{\delta}\right] - a_{max}\left(\frac{s^*(v^{(k)}, \Delta v^{(k)})}{s^{(k)}}\right)^2 \quad (4)$$

$$s^*(v^{(k)}, \Delta v^{(k)}) = s_0 + v^{(k)}T^{(k)} + \frac{v^{(k)}\Delta v^{(k)}}{2\sqrt{a_{max}b}} \quad (5)$$

with the parameter a_{max} for maximum acceleration, the comfortable deceleration b, s_0 for minimal distance to the leading vehicle, $T^{(k)}$ denotes the gap time and $v_{des}^{(k)}$ the desired velocity, respectively. δ is an additional tuning parameter and is commonly set to 4. All parameters of the longitudinal driver model are aggregated in θ_{long}. For observed vehicles these parameters cannot be measured but largely influence the driving behavior. In general, the model is divided into two parts: the free flow behavior and the behavior at congested traffic. For the free flow behavior, the desired velocity has significant influence not only for the longitudinal acceleration but also for lane change decisions as it is pointed out in section IV-C. To cover a large variety of possible driving maneuvers in the presented work $v_{des}^{(k)}$ is modeled as a uniform distribution based on the current velocity

$$P\left(v_{des}^{(k)}\right) = \mathcal{U}(v^{(k)} - \sigma_{des}v^{(k)}, v^{(k)} + \sigma_{des}v^{(k)}), \quad (6)$$

where σ_{des} is a parameter describing the range of possible desired velocities. While it could be determined by recorded data, it is empirically set to 0.2 in this paper. To enable variability in congested traffic the gap time $T^{(k)}$ is modeled as a uniform distribution around the calibrated value in [10]. All other parameters are kept fix and are chosen according to the suggested values in [10]. Currently only cars are considered in the prediction framework but it could be easily extended to trucks or other vehicles by changing the drivermodel parameters accordingly (e.g. less acceleration for trucks). The longitudinal model implements the function ACCELERATIONMODEL in algorithm 12.

C. Lane Change Model

To get valid prediction results lateral maneuvers also have to be considered. On highways mainly three maneuvers are possible: lane change to the left, lane keeping and lane change to the right, such that for the presented approach $\mathcal{M} = \{LCL, LK, LCR\}$. Obviously, more complicated maneuvers as for example overtaking or cut-in and cut-out maneuvers are possible but can always be decomposed into a sequence of the basic maneuvers. Consequently, the task of the lane change model is to find the most likely maneuver for each agent in the current traffic situation based on measured vehicle states. During the *Monte Carlo* simulation the lane change model is executed in each prediction step to enable a sequence of maneuvers being executed. Since the aim is to estimate a reliable long-term prediction, the lane change model should consider the interaction between agents as well as the influence of traffic signs and road topology.

In general, a wide range of lane change or lane selection models are available from research in microscopic traffic simulation or even learning based models are possible. However, the model has to fit several requirements to be suitable for prediction. It has to be computationally inexpensive to ensure real-time capability. It should have as few parameters as possible since most parameters describe specific driving behavior and thus are not measurable by any sensor. Finally, the model should be suited for German highway driving, considering the specific characteristics as high relative velocities and the so-called *Rechtsfahrgebot*, meaning that a vehicle has to drive on the right lane if it is free. For this purpose, the lane change model MOBIL [11] is chosen, which aims to minimize the overall braking induced by a lane change. It has very few parameters since it mainly rests on accelerations estimated by a car following model as described in IV-B. It is formulated for symmetric and asymmetric traffic and also has reasonable computational effort. It defines a so-called

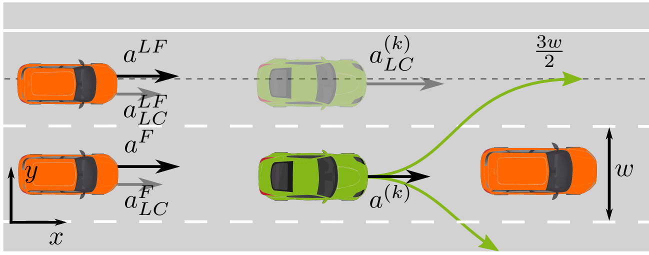

Fig. 2: Visualization of the accelerations of follower on current and left lane with and without a lane change of the ego vehicle.

safety criterion

$$a_{LC}^{TF} \geq -b_{\text{safe}}, \tag{7}$$

where a_{LC}^{TF} is the deceleration induced by a potential lane change of agent N_k on the new follower on the target lane and b_{safe} is a model parameter for agent N_k. Hence, equation (7) describes the maximal deceleration of the new follower which is accepted by agent N_k when performing a lane change. Similar to the safety criterion the lane change decision is estimated based on a possible gain in acceleration resulting from a lane change. For asymmetric traffic the criterion for lane changes to the left is

$$a_{LC}^{(k)} - a^{(k)} + \rho^{(k)}(a_{LC}^{LF} - a^{LF}) > \Delta a_{th} + \Delta a_{\text{bias}} \tag{8}$$

and for lane changes to the right

$$a_{LC}^{(k)} - a^{(k)} + \rho^{(k)}(a_{LC}^{F} - a^{F}) > \Delta a_{th} - \Delta a_{\text{bias}}, \tag{9}$$

while $a_{LC}^{(k)}$ denotes the acceleration of agent N_k after a prospective lane change and $a^{(k)}$ without a lane change, respectively (see Fig. 2). a_*^{LF} is the resulting acceleration of the vehicle on the left lane and a_*^{F} on the current lane. $\rho^{(k)}, \Delta a_{th}$ and Δa_{bias} are model parameters. For a detailed description of the criteria, the reader is referred to [11]. All parameters for the lateral driver model are aggregated in θ_{lat}.

Since these parameters are not measurable, a variety of drivers should be described by the lane change model. Similar to section IV-B the parameter with most influence to the driving behavior is modeled by a distribution while the other ones are set fixed. In case of MOBIL Δa_{th} and Δa_{bias} are set to the values suggested by [11] and the politeness factor $\rho^{(k)}$ is modeled as

$$P(\rho^{(k)}) = \mathcal{U}(0,1). \tag{10}$$

Based on the road topology, the other agents and the drawn parameter the lane change model estimates in each simulated time step a maneuver for agent N_k (see line 9 in algorithm 1).

D. Maneuver Execution

To execute the estimated maneuver a path $\mathbf{p}_m^{(k)}$ is generated, which is followed by the agent for the current simulation rollout. As stated before, the available maneuvers are either a lane change or lane following. For the latter, the best prediction is represented by the center of the lane. To account for orientations of agents, a third order polynomial is applied with boundary conditions corresponding to the current state as start condition and center of the current lane with orientation along the road as goal condition. Similarly, a lane change path is represented by a third order polynomial with goal condition on the target lane as shown in Fig. 2.

TABLE I: *GP* hyper-parameters after maximization of the log likelihood.

	l_1	$\sigma_{f,1}$	l_2	$\sigma_{f,2}$
Lane Change	199.99	0.01	46.77	0.46
Lane Keeping	1881.5	0.30	97.81	0.34

To additionally account for different maneuver execution depending on the driver type to each path a random sample of a Gaussian Process model ξ_{GP} is added, similar to the approach in [12]. A Gaussian Process (*GP*) is defined as a collection of random variables, where a finite set is always Gaussian distributed and is shortly outlined here. A more detailed mathematically description can be found in [13]. The process $f(x) \propto GP(m(x), k(x, x'))$ can be fully described by the mean

$$m(x) = \mathbb{E}[f(x)] \tag{11}$$

and the covariance function

$$k(x, x') = \mathbb{E}[(f(x) - m(x))(f(x') - m(x'))]. \tag{12}$$

For modeling different maneuver executions the sample of the *GP* represents deviations from the estimated maneuver path. Hence, the mean function is set to zero, and the sample is added to the path later on. The covariance function regulates the amount of change for the underlying function and is defined by the function-type as well as its parameters, so-called hyper-parameters θ_H. For the covariance function, a combination of squared exponential functions is chosen, since it offers smoothness in the generated samples and shows reasonable variability

$$k(x, x') = \sum_{i=1}^{n_{\text{GP}}} \sigma_{f,i}^2 \exp\left(\frac{-(x - x')^2}{2 l_i^2}\right). \tag{13}$$

$\sigma_{f,i}$ denotes the maximum variance for component i of the function and l_i the corresponding length scale. In general, for a small l_i the function is more likely to change within constant distance. The hyper-parameters θ_H can be estimated from recorded data by maximizing the log marginal likelihood. Once the parameters are learned a sample of the *GP* can be generated as described in [13].

For both maneuver types, a covariance function with $n_{\text{GP}} = 2$ components is utilized, and the parameters are estimated on recorded lane keeping and lane change data, respectively. The resulting parameters can be found in table I. Results of the generated paths including *GP* samples $\mathbf{p}^{(k)} = \mathbf{p}_m^{(k)} + \xi_{GP}$ are depicted in Fig. 3 and implement the function GENERATEPATH in algorithm 1. The vehicle is located in the right lane, and three samples for lane keeping maneuvers (solid lines) as well as three examples of lane change maneuvers to the left are drawn (dashed lines). It

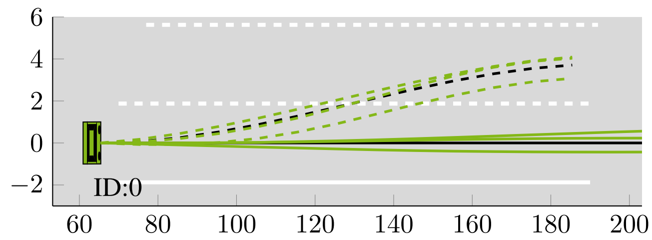

Fig. 3: Derived paths for *Monte Carlo* simulation rollouts. Black lines denote the maneuver without any modeled uncertainty, and green lines show various maneuver executions. Dashed lines represent lane changes to the left and solid lines lane keeping, respectively.

shows, that the application of *GP* not only adds a realistic deviation from lane center during lane following, what can be observed for nearly every human driver, but also mimics the fact, that a lane change maneuver does not always end up in the center of the target lane.

From the generated path the lateral acceleration can be estimated utilizing a path following controller, controlling the error of a look ahead point to the path (LATACCFROMPATH off algorithm 1).

V. IMPLEMENTATION

A. Constraints Imposed by Sensor Setup

While the general approach described in section IV can be utilized with a wide range of sensor setups some adjustments have to be made for specific configurations. In the paper at hand no digital maps are available for the ego vehicle, and hence the road topology has to be detected by onboard camera sensors and consequently is only available for several meters ahead of the car. Furthermore, ending or opening lanes, which have significant impact on lane change decisions, are not known in advance from a digital map but have to be detected by the camera. This clearly limits the performance of any prediction algorithm because such situations are hard to predict without this knowledge.

Another issue when considering interactions between agents is the limited view range and the fact that some sensors are partially blocked by nearby vehicles and thus cannot detect objects behind those. As a consequence, the interactions between these agents are not considered in the prediction. To adequately compensate the limited perception capabilities vehicle-to-vehicle communication would be required, which can not be assumed in nowadays traffic. Hence, a different approach utilizing maneuver prediction techniques is applied to ensure correct short-term predictions. This is explained in the following section.

B. Initial Driving Maneuver and Initial State

Lane changes imposed by a slower leading vehicle are often hard to predict in an interaction-based manner if the observed vehicle is driving directly in front of the ego vehicle. Since the observed vehicle covers the on-board sensors, the leader is not detected, and no interaction is modeled. To overcome this issue, a maneuver classification algorithm is utilized to estimate the probability distribution of the maneuver set $\mathcal{M}^{(k)}(t)$ for agent k at time t. This also combines the advantages of a maneuver-based trajectory prediction in short-term accuracy with the benefits of interaction-based prediction. In the presented work a classifier similar to the one in [14] is applied to all agents in the situation to acquire class wise probabilities. For each *Monte Carlo* simulation, the initial maneuver is then sampled from the predicted distribution $P(\mathcal{M}^{(k)}(t))$ and a maneuver path is planned using techniques from section IV-D. This implements the function INITIALMANEUVER in line 4 of algorithm 1.

In addition to the initial maneuver the current state is also subject to uncertainty. To include this into the prediction the initial state of the agent k can be sampled from the state distribution given by the applied perception framework in each *Monte Carlo* simulation rollout.

C. Trajectory Clustering

Each *Monte Carlo* rollout of the traffic situation generates one trajectory per agent, which is impractical to handle throughout following algorithms as for example decision making or trajectory planning. Thus, a more compact way to represent the trajectory distribution has to be found. For this purpose the resulting trajectories of each agent are clustered by their respective end points at $t_e = t + t_p$ utilizing the *DBSCAN* algorithm [15]. Each cluster is then represented by a sequence of Gaussian distributions for each state and an associated cluster probability defined as

$$p_c = \frac{n_c}{n_m}, \tag{14}$$

where n_c denotes the number of trajectories associated to the respective cluster (see CLUSTERTRAJECTORIES in algorithm 1).

The overall algorithm is implemented in C-Code to enable real time hardware application. The function DRAWPARAMETER draws random parameters for the driver models described in section IV-B and IV-C. Without any parallelization the algorithm runs with 10 Hz on a Windows computer with an Intel(R) Core i7-4770 processor and 16 GB ram. The performance clearly can be boosted by parallel computing the simulation rollouts and the update steps for each agent in the situation.

VI. EVALUATION

To demonstrate the capabilities of the presented approach, it is evaluated in two exemplary scenarios utilizing the simulation environment presented in [12]. The simulation enables realistic modeling of camera and radar sensors including occlusion of objects and lane information. Furthermore, human-like driving behavior for all vehicles can be generated in various highway scenarios. In the first scenario limitations imposed by the perception system are neglected and it is assumed that a digital map is present to show the full potential of interaction-based prediction. In a second scenario limited perception capabilities as they are present in most nowadays automated vehicles are simulated. Thus, the

Algorithm 1 Interaction aware trajectory prediction

Require: $\mathcal{N}_i$: Initial set of agents, $\mathcal{S}$: Traffic scene, $\mathcal{M}$: Initial maneuver distribution, n_m: Number *Monte Carlo* simulations, t_p: Prediction time

for $i = 1$ to n_m **do**
  $\mathcal{N} \leftarrow \mathcal{N}_i$
  for each agent k **do**
    $m_0 \leftarrow$ INITIALMANEUVER($\mathcal{M}[k]$)
    $\mathbf{p}[k] \leftarrow$ GENERATEPATH($m_0, \mathcal{S}$)
    $\theta_{lat}[k], \theta_{long}[k] \leftarrow$ DRAWPARAMETER($\mathcal{N}[k]$)
  for $\tau = 0$ to t_p **do**
    for each agent k **do**
      $m[\tau] \leftarrow$ LANECHANGEMODEL($\mathcal{N}[k], \theta_{lat}[k]$)
      if $m[\tau] \neq m[\tau - 1]$ **then** ▷ New maneuver
        $\mathbf{p}[k] \leftarrow$ GENERATEPATH($m[\tau], \mathcal{S}$)
      $a_{long} \leftarrow$ ACCELERATIONMODEL($\mathcal{N}, \theta_{long}[k]$)
      $a_{lat} \leftarrow$ LATACCFROMPATH($\mathbf{p}[k]$)
      $x[i, \tau, k] \leftarrow$ MOTIONMODEL($x[i, \tau - 1, k], a_{long}, a_{lat}$)
for each agent k **do**
  $P(\mathbf{x}[k]) \leftarrow$ CLUSTERTRAJECTORIES($x[\cdot, \cdot, k]$)
return $P(\mathbf{x})$

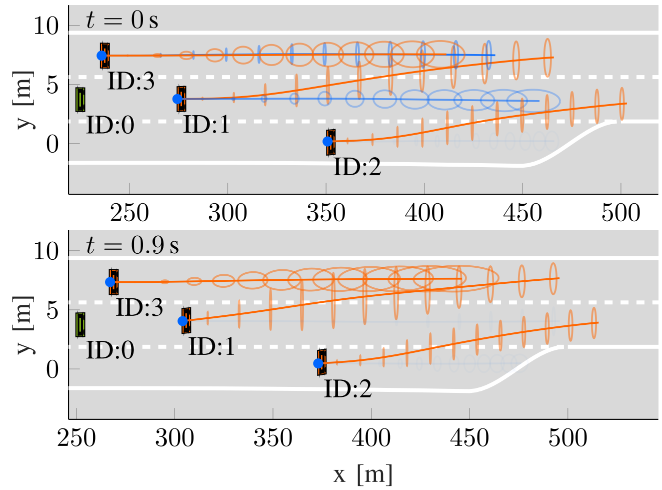

Fig. 4: Simulation scenario with an ending lane on the right side. Vehicle 2 has to change to the middle lane which directly effects possible trajectories of vehicle 1 and 3. Solid lines represent the predicted means with ellipses denoting the respective 95% confidence ellipse. Matching colors represent a specific predicted evaluation of the situation. More probable classes have higher opacity.

scenario demonstrates the ability of the presented approach to handle these limitations and generate reasonable predictions.

A. Closing Lane Scenario

The first scenario is similar to the situation in Fig. 1. On a three-lane highway, the most right lane ends within some distance such that vehicle ID:2 has to perform a lane change to the left to maintain driving. Besides the ego vehicle (ID:0) two other vehicles are driving in front of the ego on the middle (ID:1) and the left lane (ID:3), respectively (see Fig. 4). The three observed agents are driving with $v_{\text{ID:1}} \approx 32\,\text{m/s}$, $v_{\text{ID:2}} \approx 25\,\text{m/s}$ and $v_{\text{ID:3}} \approx 34\,\text{m/s}$ at time $t = 0\,\text{s}$. As the lane ending is known from some external source in this scenario (e.g., digital maps) vehicle 2 is predicted to perform a lane change maneuver to the left at $t = 0$. Ellipses visualize the uncertainty originating from variances in maneuver execution. The lane change affects the predicted trajectories for agent 1 in a way that two possible maneuvers arise. Either decelerate or keeping the velocity and change to the most left lane. On the other hand, this results in an interaction with agent 3, which has to decelerate in case of a lane change of agent 1. The interaction is correctly predicted by the approach as it can be seen in the trajectories in Fig. 4 at $t = 0.9\,\text{s}$, where the two orange ones in front of vehicle 1 and 3 represent the case where vehicle 1 performs a lane change and the blue ones for the lane keeping case, respectively. At this time both possibilities have nearly the same probability.

Roughly one second later vehicle 1 is still driving with the same velocity of $v_{\text{ID:1}} \approx 32\,\text{m/s}$, such that the probability for a lane change maneuver is higher. This also means that vehicle 3 has to decelerate to maintain a safe distance to the new leader. Since the distance considered as save is subject to the longitudinal vehicle model in section IV-B, the varying parameters for every simulation rollout result in a larger longitudinal uncertainty denoted by the error ellipse.

B. Free Flow with Sensor Limitations

In the second scenario the lane markings are only visible within a limited camera range and might be occluded by other vehicles as it can be seen in Fig. 5. Furthermore, in the beginning vehicle 2 is not visible for the perception system since vehicle 3 is driving in the direct line of sight (see Fig. 5 $t = 0\,\text{s}$). The vehicles move with an initial velocity of $v_{\text{ID:1}} \approx 30\,\text{m/s}$, $v_{\text{ID:2}} \approx 20\,\text{m/s}$ and $v_{\text{ID:3}} \approx 25\,\text{m/s}$. This means, to maintain their speed agent 3 has to overtake agent 2 and agent 1, therefore, has to switch to the most left lane to overtake vehicle 3. However, due to the undetected vehicle 2 no interaction can be modeled and thus no lane change is predicted. This is clearly a drawback of all interaction-based approaches and arises as soon as information on the surrounding is incomplete. As described in section V-B the presented approach utilizes a maneuver classification algorithm which estimates the distribution of possible driving maneuvers to overcome this issue. 1.5 s later the probability for a initial lane change left maneuver raises to 29% and one part of the predicted trajectory distribution is on the middle lane (see Fig. 5 $t = 1.5\,\text{s}$). This again causes an interaction with vehicle 1, which either could keep the lane or change to the left. After two seconds lane change left becomes the most probable maneuver for agent 3 and thus also the lane change maneuver of agent 1 becomes more probable. Finally, after 3.6 s vehicle 2 is detected by the sensors of the ego vehicle and the interaction between all three traffic

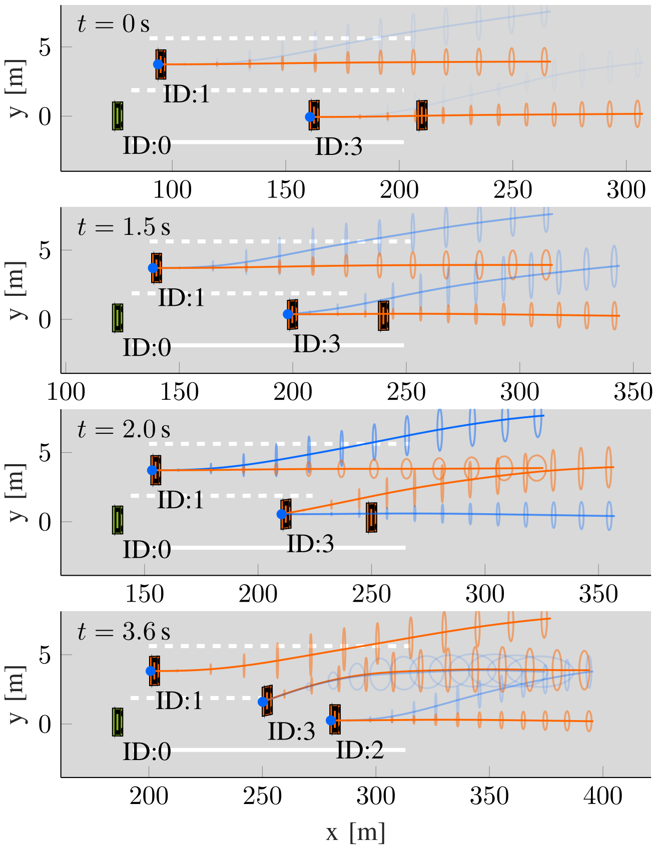

Fig. 5: Simulation scenario with incomplete information of the traffic situation in terms of road geometry and participants.

participants can be modeled. Note, that for vehicle 2 the maneuver classification estimates a lane change to the left with some probability, which leads to two possible actions of vehicle 3, either maintain its speed in case of no lane change or decelerate if a lane change is performed.

VII. CONCLUSION

The paper at hand presents a novel approach for interaction-based trajectory prediction on highways. It rests upon a *Monte Carlo* simulation utilizing driver models to model interaction between agents within a traffic scene in a probabilistic manner. Furthermore, the main drawback of interaction-based approaches resulting in poor performance for incomplete information of the traffic situation is addressed and solved by combining the approach with a state of the art maneuver classifier. The strength of reliable long-term prediction is demonstrated on two meaningful scenarios.

In future work the performance of the presented approach will be evaluated on data recorded by a test vehicle and the runtime will be improved applying parallel execution.

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