Interaction-aware Prediction of Urban Traffic Scenarios

Andreas Philipp[1] Daniel Goehring[1]

***Abstract*— This work presents a novel rule-based interaction-aware multi-modal prediction method for urban traffic scenarios. The method takes into account the most common classes of traffic participants and handles all relevant types of motion behaviors. The potential trajectories of the traffic participants are rolled out resulting in multi-modal probability distributions for the states of all agents for each prediction time step. The analysis of collision risks between these trajectories is the basis for the interaction-awareness. The prediction is fully interaction-aware by considering also the interactions between the obstacles. The system is able to predict complex urban scenarios with numerous different agents in real-time. The approach is evaluated using real-world scenarios and in a simulated environments.**

I. Introduction

Predicting traffic scenarios is an indispensable prerequisite for autonomous driving, since the car has to cooperate with many other traffic participants. The main difficulties arise from the unknown intentions and the high velocities of the agents navigating in limited space, which requires long prediction horizons. This work presents a novel method to create a fully interaction-aware traffic scenario prediction, which is innovative in the following ways:

- All typical motion behaviors of vehicles, as car following, lane changing, lane merging, intersection crossing etc. are handled by an unified model.
- The unified model takes into account all types of traffic participants for interaction evaluation, as passenger cars, trucks, bicycles and pedestrians.
- The potential conflicts between all agents are detected and analyzed independently of predefined conflict zones. The required measures to avoid these conflicts are constraints for the subsequent predictions of motion behavior.
- Conflict resolution is based on application of traffic rules and any violation of them is made explicitly.
- The predicted behavior of the agents is fully explainable by the underlying model and this model may iteratively be refined.
- Complex scenarios with up to 50 agents are predicted for 10 seconds at 10 Hz.

An overview over physics based, maneuver based and interaction-aware prediction approaches is given in [1]. A very recent survey over 200 papers about traffic prediction is presented in [2].

This work is mainly inspired by the following approaches:

[1]DCLMR, Computer Science Institute, Freie Universität Berlin, Germany {andreas.philipp | daniel.goehring} @fu-berlin.de

The Intelligent Driver Model (IDM) [3], presented by Treiber and Kesting, calculates the acceleration of a vehicle in presence of a preceding car in single lane traffic and was initially developed to simulate and analyze traffic flow. The heuristic formula for car-following behavior turned out to match reality so well that it was adopted by many other authors. Subsequent publications enhanced the model for delays, inaccuracies and anticipation [4], lane changes [5], traffic light approaching [6] and stochasticity [7]. But IDM doesn't cover intersections and behaves poor when approaching speed limits [14, p. 140] or lanes merges [14, p. 142]. This work extends the IDM to be applicable for urban traffic scenarios.

Schreier presents in [8] and [9] a system to predict the traffic scenario and to access the criticality of the current situation. The system is part of an ADAS and its purpose is to generate realistic warnings in potentially dangerous situations. The scenario is structured defining some reasonable standard maneuvers for the dynamic obstacles and the ego vehicle, like car following, lane changing or turning. All other observed behaviors are abstracted into a so-called trash maneuver. A Bayesian network calculates the probability distribution of the maneuvers. Gaussian processes are used to create a long-term prediction for each maneuver. Finally, the evolution of the probability distribution for a collision of the ego vehicle with a static or dynamic obstacle is evaluated using a particle filter. Our work also considers the impact of identified risks and how to mitigate them in subsequent predictions.

Schulz et al. present in [10] an interaction-aware approach to predict the driver-behavior at an urban intersection. They propose a Bayesian network for the intention estimation and an extended IDM version to generate the corresponding trajectories. By evaluating the possible crossing sequences of conflict zones as pass and yield maneuvers, they consider the interaction among the vehicles. The probabilistic inference is implemented using a particle filter. In [11], they propose the usage of a Multiple Model Uncented Kalman Filter (MM-UKF) to overcome the performance problems of the particle filter. In [12], they replace the IDM based trajectory generation by a learning based approach using a deep neural network. But this approach is limited to predefined conflict zones and doesn't cover unexpected behavior. In our work, the interaction is based on collision risks detected at arbitrary locations in Cartesian space.. Moreover, unexpected and unlawfull behavior is modeled by the introducing the trash maneuver.

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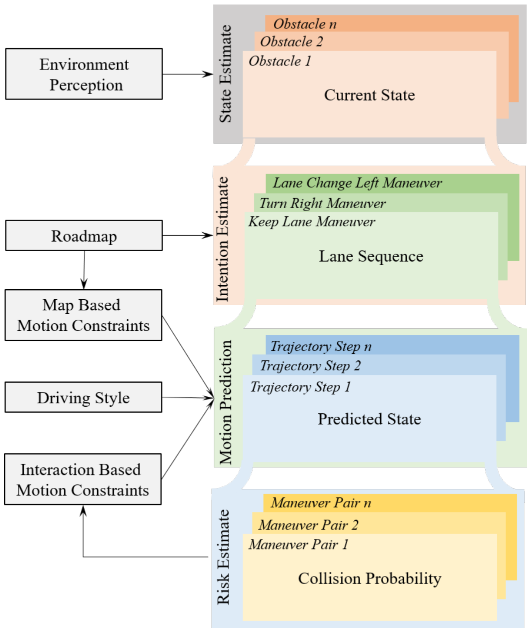


Fig. 1: Major elements of the traffic scenario prediction system.

II. System Overview

This and the following sections describe the scenario prediction system, as it is implemented as part of the MadeInGermany autonomous test vehicle of the Freie Universität Berlin [13]. A more detailed presentation can be found in the dissertation [14]. An accompanying video is attached to this paper or can be found at `https://userpage.fu-berlin.de/andreasp`.

The rule-based multi-modal interaction-aware system models the various objects of a scenario and their hypothetical motion behavior. Figure 1 gives an overview of the most important elements of the system. The environment perception provides the input for the estimate of the current state of all obstacles. Based on the roadmap and the localization of the obstacles in the roadmap, the intention estimate for each obstacle is created and updated. It consists of the lane sequences of all currently feasible maneuvers of each obstacle. The center lines of the lanes are the bases of the predicted paths. In the next step, the motion prediction for each maneuver is created in form of a sequence of trajectory steps. The predicted states of the trajectory steps depend on map based constraints dictated by the infrastructure, as curvature, speed limits, stop signs, etc. Further influence results from the driving style [14, p. 147], which is initially assumed to be neutral. Subsequent updates of the motion prediction, which are performed in receding window fashion, take the interaction based constraints as additional input. These constraints result from the risk estimate, which calculates the collision probabilities for all trajectory steps of a maneuver related to the trajectory steps of all maneuvers of the other agents. The subordinate agent, which is identified by evaluation of the relevant traffic rules, is expected to adapt its motion plan to avoid a collision.

Algorithm 1 gives a high-level overview over the calculation of a scenario prediction. The algorithm Create Scenario Prediction is triggered on arrival of a new set of measurements $\mathcal{Z}$. In the present system, this happens with a frequency of 10 Hz. Further input to the prediction are the sets of objects $\mathcal{O}$, maneuvers $\mathcal{M}$ and trajectories $\mathcal{T}$ as well as the collision matrix $\mathbf{C}$ from the previous prediction. The procedure UPDATEOBJECTS adds newly detected objects, removes old objects and updates the state of preexisting objects. The procedure UPDATEINTENTIONS evaluates the set of currently feasible maneuver intentions and calculates their probabilities. Procedure MAPCONSTRAINTS examines the infrastructure data and establishes constraints resulting from speed limits and intersection properties to be obeyed for a specific maneuver. Procedure INTERACTIONS examines the collision matrix of the previous prediction and infers the type of situation, the applicable traffic rules and the resulting responsibilities. Based on this, the interaction based motion constraints for the next prediction are calculated. The procedures TOFRENET and TOCARTESIAN convert states and trajectories between Cartesian and Frenet coordinates. The procedures ACTION and TRAJECTORYSTEP calculate the predicted trajectory for the next T steps (default 100 steps). Procedure COLLISIONMATRIX finally calculates the collisions risks between any pair of trajectories.

Algorithm 1 Create Scenario Prediction

Require:
$\mathcal{O}_{k-1}, \mathcal{M}_{k-1}, \mathcal{T}_{k-1}\ \mathbf{C}_{k-1}, \mathcal{Z}_k$
Ensure:
$\mathcal{O}_k, \mathcal{M}_k\ \mathcal{T}_k, \mathbf{C}_k$

$\mathcal{O}_k \leftarrow \text{UPDATEOBJECTS}(\mathcal{O}_{k-1}, \mathcal{Z}_k)$
for $i \leftarrow 1$ **to** $|\mathcal{O}_k|$ **do**
  $\mathcal{M}_k^i \leftarrow \text{UPDATEINTENTIONS}(\mathcal{O}_k^i, \mathcal{M}_{k-1}^i, \mathbf{z}_k^i)$
  for $j \leftarrow 1$ **to** $|\mathcal{M}_k^i|$ **do**
    $\mathcal{R} \leftarrow \text{MAPCONSTRAINTS}(M_k^{i,j})$
    $\mathcal{I} \leftarrow \text{INTERACTIONS}(M_k^{i,j}, \mathcal{T}_{k-1}, \mathbf{C}_{k-1})$
    $\mathbf{x}_k^{i,j} \leftarrow \text{TOFRENET}(\mathbf{z}_k^i)$
    for $t \leftarrow 1$ **to** T **do**
      $\mathbf{a} \leftarrow \text{ACTION}(\mathbf{x}_{k+t-1}^{i,j}, \mathcal{R}, \mathcal{I})$
      $\mathbf{x}_{k+t}^{i,j} \leftarrow \text{TRAJECTORYSTEP}(\mathbf{x}_{k+t-1}^{i,j}, \mathbf{a})$
    end for
    $\mathcal{T}_k \leftarrow \mathcal{T}_k \cup \text{TOCARTESIAN}(\mathbf{x}_{k:k+T}^{i,j})$
  end for
end for
$\mathbf{C}_k \leftarrow \text{COLLISIONMATRIX}(\mathcal{O}_k, \mathcal{M}_k, \mathcal{T}_k)$

III. Intention Estimate

The purpose of the intention estimate is to infer the spatial decisions of traffic participants during the next prediction period. The result of the intention estimate is a set of possible intentions and its probability distribution.

Lane Bound Intention Classes					Trash
Turn Left	Lane Change Left	Keep Lane (Forward)	Lane Change Right	Turn Right	(Phys. Laws)

Maneuver Intention Classes

A. Lane Bound Intention Classes

In the case of vehicles, it makes sense to consider the lanes that can be reached in the near future as a spatial alternatives. The considered spatial decisions in this work are keep lane, turn left or right and lane change left or right. Only the next upcoming spatial decision of each class is taken into account. This system could be extended including additional behaviors, as parking or U turns, or by defining sequences of decisions during the prediction horizon, like double lane changes.

The intended path of a vehicle is defined by a lane sequence. A lane sequence is a sequence of consecutive lanes from the roadmap. At the start of the prediction, the current lane of the vehicle becomes the first lane of the lane sequence. Additional lanes are added to the lane sequence, until the total length of the lane sequence covers the maximal driving distance during the prediction time-span. The maximal driving distance is calculated using the current speed limit for the lane plus some surcharge for traffic rule violators.

B. Trash Intention Class

Every agent in the system may execute a trash maneuver. For vehicles, it serves as fallback, if the observed motion cannot be explained by some of the standard intention classes. Examples are taking a U turn or leaving the road for a parking lot. For pedestrians and other non-vehicle objects on the road, the trash maneuver is the only alternative. The same holds for any object moving off-road. The purpose of the trash maneuver is also to cover cases, where drivers do not adhere to traffic laws during lane bound maneuvers, e.g. running a red light or a stop sign.

The trash maneuver is used to allow some basic motion prediction for all these cases. Typical implementations of the trash maneuver are constant velocity model (CV), constant acceleration model (CA) or constant turn rate and velocity (CTRV). The prediction quality of the physical motion models is good for short-term predictions (1-3 seconds) and should leave the chance for an emergency reaction.

C. Maneuver Life Cycle

A maneuver is the combination of a path intention, its predicted trajectory and the estimated probability of the maneuver. A maneuver has a unique id during its life time, which serves as reference to the maneuver. The predicted trajectory and the probability of the maneuver are updated on each subsequent prediction.

Whenever a new obstacle is detected, all feasible maneuvers for this obstacle are evaluated. For each obstacle, there is always a Trash maneuver. A vehicle on a lane has also at least a keep lane maneuver. Turn and lane change maneuvers are only added, if the required lanes appear on the roadmap in front of the vehicle within the maximal prediction horizon (given in meters).

In subsequent predictions for an obstacle, the path intentions of the existing maneuvers are checked for validity based on the new position of the obstacle. If that position is no longer on the lane sequence of the maneuver, e.g. the diverge region has been passed and the turn is no longer feasible, the maneuver is discarded. The lane sequences may be updated by discarding lanes, which are now behind the current vehicle position. Since the horizon of the maneuver moves forward, new lanes may be added at the end of the lane sequence. When extending the keep lane maneuver, new occasions for lane changes or turns may become visible and new turn or LC maneuvers are created, if not already existing. An detailed example is shown in [14, pp. 113-114].

D. Maneuver Probability Calculation

A Hidden Markov Model is used to calculate the probability distribution of the maneuver intention at time step k M_k:

$$M_k \in \{TUl,\ LCl,\ KL,\ LCr,\ TUr,\ TR\} \tag{1}$$

The maneuver intention probability is modeled as a hidden state, which emits 3 observables:

- Dynamic state $\mathbf{x}_k \in \mathbb{R}^6$: lateral and longitudinal position, velocity and acceleration. The dynamic state is taken as input data from the perception system. The state is used in Cartesian coordinates for the trash maneuver and in Frenet coordinates for all other maneuvers.
- Turn signal state $S_k \in \{left, right, none, both\}$. It is the main indicator for an imminent turn or lane change.
- Lane change incentive $l_k \in \mathbb{R}$. The lane change incentive measures the potential preference for a discretionary lane change based on comparing the trajectory length of the LC maneuver with that of the keep lane maneuver. The lane change incentive for left and right is asymmetric to support the German law, which requires to drive in the right lane, whenever possible.

The three observables are assumed to be conditionally independent of each other given the maneuver intention. The probability distribution is initialized by some prior $p(M_0)$ and forwarded on subsequent predictions by the following recursion:

$$\begin{aligned} p(M_k|\mathbf{x}_k, s_k, l_k) = \eta\ \mathbf{\Pi}_{i,j} \times p(M_{k-1})\ p(\mathbf{x}_k|M_k) \\ p(S_k|M_k)\ p(l_k|M_k) \end{aligned} \tag{2}$$

with η as a normalization constant, transition matrix $\mathbf{\Pi}_{i,j}$, dynamic state likelihood $p(\mathbf{x}_k|M_k)$, turn signal probability $p(S_k|M_k)$ and lane change incentive density $p(l_k|M_k)$ [14, p. 114-117]

IV. Motion Constraints

For each maneuver and it's associated lane sequence, a predicted trajectory is rolled out. The rollout is created using an extended, probabilistic Intelligent Driver Model (IDM) [3], which is detailed in subsection V-B.

The extended IDM takes a number of motion constraints into account.

A. Map Based Motion Constraints

Map based motion constraints are any restriction on an agent's motion, which arise from the infrastructure and that are assumed to be annotated in the roadmap. The constraints only apply to lane-bound maneuvers. These constraints may force the agent to decelerate and they are independent of the presence of other traffic participants.

There are two classes of constraints: Speed limits and intersection properties.

1) Speed Limits: There are three types of map based speed limits: Legal speed limits, curvature speed limits and visibility speed limits:

- Legal speed limits are indicated by traffic signs or are valid for certain road types (highway, urban, ...).
- The curvature speed limit is calculated from the curvatures of the drive splines of the maneuver lanes. The speed limit for the curve is calculated as $v = \sqrt{a_c \ r_{min}}$ with a_c the maximal desired centripetal acceleration of the driver and r_{min} the minimum radius of the curve. The curvature speed limit should be reached before the start of the curve to avoid braking in the curve and is valid until the end of the curve.
- Visibility speed limits apply due to scarce visibility when approaching a pedestrian crossing or an unsignalized intersection. The visibility speed limit starts at an imaginary line of sight and the maximal speed at the line of sight is calculated as $v = \sqrt{2 \ b \ d_{ls}}$, with the desired constant deceleration of the driver b and the distance d_{ls} between the line of sight and the stop line.

2) Intersection Properties: During a lane bound maneuver, an object may have to approach one or more intersections which may force the target to decelerate, independent of the presence of any other object. The relevant properties of these intersections are:

- Conflict type: Crossing one or more other lanes or only merging with one other lane (on turn left or right).
- Priority: Yes or no. If two lanes intersect having the same priority, the right-before-left rule is applied.
- Stop Type: GiveWay, Stop or FourWayStop.
- Traffic light: Yes or no. If a traffic light applies to the lane and it is operational, it supersedes all other rules.

B. Interaction Based Motion Constraints

The interaction based motion constraints have to be determined, if the maneuver is involved in one or more collision risks. The collision risk between two trajectories is estimated using the approach in[15]. The estimate is always calculated for the trajectories of the previous prediction. Therefore, no risks are available, when the first trajectory of a new maneuver is rolled out. The following steps are required to determine the interaction based motion constraints:

- Select risks to be considered
- Establish type of the risk
- Evaluate responsibility for risk mitigation
- Provide parameters for risk mitigation

The potential risks are all risks from the collision risk analysis, which belong to a maneuver with a certain probability and which exceed a certain accumulated collision risk until the end of the prediction horizon. Risks below this threshold are ignored for the time being.

The type of the risk depends on the current traffic situation, especially on the relationship between the two traffic participants. The following risk types are considered [14, pp. 120-136]:

- Single Lane Car Following
- Multi Lane Traffic with Lane Changes
- Lane Merge / Round About
- Intersection Crossing
- Pedestrian Crossing
- Other Risks

The type of risk determines the traffic rules to apply. The traffic rules normally decide, who of the two agents has to mitigate the risk during the prediction horizon.

In this system, only two methods for risk mitigation are considered: braking or postponing a planned lane change. Accelerating is not considered for risk mitigation, since it is assumed, that the agents already drive as fast as possible and therefore further acceleration would violate traffic rules or be uncomfortable. Moreover, this system does not yet consider swerving to evade an obstacle. Instead, in cases of blocked lanes, it will always predict a full stop or a lane change.

If a conflict situation has been handled correctly, the collision risk disappears during the next evaluation. Nevertheless, the corresponding motion constraint must be forwarded to the next predictions to avoid oscillations in the system.

V. Motion Prediction

The motion prediction generates one probabilistic trajectory for each maneuver of an agent. The trajectory of the trash maneuver is created by predicting the future states in Cartesian frame using the constant velocity model without any regard of the roadmap, traffic rules or obstacles. Other physics based models, like constant acceleration, may be used. For the lane bound maneuvers the longitudinal components of the predicted states in Frenet frame [14, p. 137] are calculated using an extended Intelligent Driver Model (IDM). The center line of the lane is used as reference path for all maneuvers except lane change.

The predicted actions at each time step are the continuous longitudinal and lateral acceleration values. The trajectory data includes the acceleration, velocity and position of the object, as well as their covariance matrix. It is assumed that any driver wants to reach its goal as quickly as possible under the constraints of safeness, comfort, economy and traffic rules.

A. Basic Intelligent Driver Model (IDM)

The Intelligent Driver Model (IDM) [3] calculates the longitudinal acceleration a_{idm} of a vehicle as a function of the current speed v, the desired speed v_0, the preferred acceleration a and deceleration b of the target vehicle as well as an eventually required interactive deceleration b_{kin}:

$$a_{idm} = \dot{v} = a \left[1 - \left(\frac{v}{v_0} \right)^{\delta} \right] - \frac{b_{kin}^2}{b} \quad (3)$$

The left part is the free driving part, which accelerates or decelerates the vehicle to the desired velocity v_0. The right part is the interaction part, which implements the Intelligent Braking Strategy [3] based on the required braking b_{kin} and the preferred braking b. The standard IDM model defines only one brake reason, a preceding car, for which the required deceleration is calculated using a heuristic with Δs as actual and s_0 as minimal distance to the preceding car, Δv as velocity difference and T as time gap:

$$b_{kin} = \frac{\sqrt{ab}}{\Delta s} \left(s_0 + \max \left(0, vT + \frac{v \Delta v}{2\sqrt{ab}} \right) \right) \quad (4)$$

B. Extensions to the IDM

To be usable for the prediction of urban traffic scenarios, the IDM must be extended in several ways. Some extensions to overcome the deficiencies of the model have already been proposed in [16], but these are not sufficient.

1) Multiple Brake Reasons: In real traffic scenarios, multiple brake reasons have to be kept in mind. A simple example is a lane changing vehicle, which has eventually to brake for the preceding car in the old lane and for another one in the destination lane.

Equation 3 is modified to use the maximum brake value calculated for the set of potential brake reasons R.

$$b_{kin} = \max_{r \in R}(\{b_{kin,r}\}) \quad (5)$$

2) Braking for Reduced Speed Limit: When generating a trajectory, various kinds of speed limits may have to be observed (see Subsection IV-A.1). Speed limits are handled in standard IDM by manipulating the desired speed v_0. But this results in unrealistic decelerations. In [16], the Improved Intelligent Driver Model (IIDM) has been proposed, which mitigates the problem. But even with IIDM, the deceleration starts only at the point, where the speed limit comes into effect, and not when approaching it.

When driving with speed v and approaching a speed limit v_{limit} with $v_{limit} < v$ in distance $s_{limit} > 0$, the required kinematic deceleration is calculated as:

$$b_{kin} = \frac{v^2 - v_{limit}^2}{2\, s_{limit}} \quad (6)$$

3) Braking for Crossing Obstacles: Another brake reason not properly covered by the IDM are obstacles crossing the lane of the target vehicle. This may be a vehicle on a priority lane at an unsignalized intersection or a pedestrian crossing the road at an arbitrary position. Most planning and prediction algorithms solve this kind of conflict by scheduling a full stop in front of the conflict zone. But human drivers are able to anticipate the point in time, when the obstacle will have left the conflict zone and will try to avoid a full stop.

When driving with speed v and approaching a lane crossing conflict zone in distance s_{crssng}, which is expected to be cleared at time $t_{crssng} > t$, the required kinematic deceleration is

$$b_{kin} = \begin{cases} \frac{2\,(v\,(t_{crssng} - t) - s_{crssng})}{(t_{crssng} - t)^2} & s_{crssng} > \frac{v\,(t_{crssng} - t)}{2} \\ \frac{v^2}{2\, s_{crssng}} & \text{otherwise full stop} \end{cases} \quad (7)$$

4) Braking while Approaching Intersections: Even if no collision risk is present, approaching an intersection may require braking. In case of a stop sign or a red traffic light, Equation 4 is used, while line of sights are handled using Equation 6.

5) Lane Change Decision: Braking for leading vehicles in the source and destination lane is done using Equation 3.

The required front gap Δs to the new leader before starting the LC is checked by (see [16] P. 249):

$$\Delta s > \frac{s_0 + \max \left(0, vT + \frac{v \Delta v}{2\sqrt{ab}} \right)}{\sqrt{1 + \frac{b}{a}}} \quad (8)$$

The required rear gap to the new follower is calculated by Equation 8 using the velocity of the new follower as v.

6) Braking for Lane merges: In [16], the authors claim that merge situations can be handled like lane changes by Equation 8 when taking the difference of the distances to the merge point as Δs. But this holds only if the merging car has not the priority. The present system solves the problem by using Equation 7 to handle the access to the conflict zone in combination with Equation 4 for the subsequent car following situation.

7) Lateral Trajectory Prediction: Lateral motion occurs in case of lane changes or when a car has to return to the center of the lane. The lateral position $d(t)$ in Frenet frame during a lane change left with $t = k \Delta t$ and a lane width of w_l for both lanes is given by:

$$d(t) = \frac{w_l}{2}\,(\tanh(\beta\, t) + 1) \quad (9)$$

The steepness factor β decides about the lateral acceleration of the lane change and therefore about the abruptness of the maneuver. For calculation of factor β and the influence of limited steering angles see [14, pp. 142-145]. The lateral velocity v_{lat} and acceleration a_{lat} are given by the first and second derivative of Equation 9.

8) Probabilistic Trajectories: To be able to calculate the collision risk between the trajectories of two obstacles [14, p. 149], the uncertainty of the predicted states must be estimated. The above algorithms calculate the future states $[s, d, v_{lon}, v_{lat}]^T$ as a result of applying the predicted actions $[a_{idm}, a_{lat}]^T$.

The initial covariance matrix P_0 of the trajectory is initialized from the observed state of the perception system. Since the longitudinal and lateral motion are predicted independent of each other, the corresponding parts of the covariance matrix are forwarded separately. In this work, the covariances for the longitudinal motion are propagated using an Extended Kalman Filter. This requires calculating the Jacobian matrix for the system function:

$$\mathbf{J}(s_k, v_{lon,k}) = \begin{bmatrix} \frac{\partial f_s(s,v_{lon})}{\partial s} & \frac{\partial f_s(s,v_{lon})}{\partial v_{lon}} \\ \frac{\partial f_v(s,v_{lon})}{\partial s} & \frac{\partial f_v(s,v_{lon})}{\partial v_{lon}} \end{bmatrix} \tag{10}$$

with the system function given by::

$$f_s = s + v\Delta t + \frac{1}{2}\Delta t^2 \; a_{idm}(s, v) \quad \text{(position forwarding)} \tag{11}$$

$$f_v = v + \Delta t \; a_{idm}(s, v) \quad \text{(velocity forwarding)} \tag{12}$$

The function a_{idm} is independent of the current longitudinal position s, therefore the Jacobian becomes:

$$\mathbf{J}(v) = \begin{bmatrix} 1 & \Delta t + \frac{1}{2}\Delta t^2 \; \frac{\partial a_{idm}(v)}{\partial v} \\ 0 & 1 + \Delta t \; \frac{\partial a_{idm}(v)}{\partial v} \end{bmatrix} \tag{13}$$

with $a_{idm}(v)$ given by Equation 3.

$$\frac{\partial a_{idm}(v)}{\partial v} = -a \; \delta \frac{v^{\delta - 1}}{v_0^{\delta}} - \frac{2 \; b_{kin}(v)}{b} \frac{\partial b_{kin}(v)}{\partial v} \tag{14}$$

Since there are different equations for $b_{kin}(v)$ (Equations 4, 6 and 7), the partial derivative gets:

$$\frac{\partial b_{kin}(v)}{\partial v} = \begin{cases} \frac{\Delta v}{2\,\Delta s} + \frac{T}{\Delta s} & \text{car following} \\ \frac{v}{s_{limit}} & \text{speed limit} \\ \frac{2}{t_{crssng} - t} & \text{crossing slow} \\ \frac{v}{s_{crssng}} & \text{stop before crossing} \end{cases} \tag{15}$$

The covariance matrix for the longitudinal state P_{lon} is forwarded by:

$$\mathbf{P}_{lon}^{k+1} = \mathbf{J}(v) \times \mathbf{P}_{lon}^{k} \times \mathbf{J}(v)^T + \begin{bmatrix} 0.5 \; \Delta t^2 \\ \Delta t \end{bmatrix} \times \sigma_a^2 \times \begin{bmatrix} 0.5 \; \Delta t^2 \\ \Delta t \end{bmatrix}^T \tag{16}$$

The acceleration noise σ_a is assumed to be 0.1 m/s^2 (see [16] P. 216). It covers the uncertainty about the driving style and other parameters, like $\Delta v, \Delta s$ and t_{crssng}.

Concerning the lateral motion, [8] P. 158 proposes to model the deviation from the reference trajectory by a continuous-time Ornstein-Uhlenbeck process. This results in forwarding the lateral variance by:

$$P_{dlat}^{k+1} = e^{-2\frac{\Delta t}{T_c}} P_{dlat}^{k} + \sigma_{dlat}^2 (1 - e^{-2\frac{\Delta t}{T_c}}) \tag{17}$$

with time constant $T_c = 1.5$. The variance σ_{dlat} results from the assumption that a driver of a vehicle with width w_v will stay inside the lane width w_l with a probability of 3σ:

$$\sigma_{dlat} = \frac{1}{3} \frac{(w_l - w_v)}{2} \tag{18}$$

The standard deviation for the lateral velocity is estimated to be constant with $\sigma_{vlat} = 0.1 \frac{m}{s}$ and the lateral covariance between position and velocity with 0.5 $\sigma_{vlat}\sqrt{P_{dlat}^t}$. Thus, the lateral covariance matrix becomes:

$$\mathbf{P}_{lat}^{k+1} = \begin{bmatrix} P_{dlat}^{k+1} & 0.5 \; \sigma_{vlat}\sqrt{P_{dlat}^{k+1}} \\ 0.5 \; \sigma_{vlat}\sqrt{P_{dlat}^{k+1}} & \sigma_{vlat}^2 \end{bmatrix} \tag{19}$$

VI. Evaluation

Evaluation is done by comparing the prediction results of four different methods:

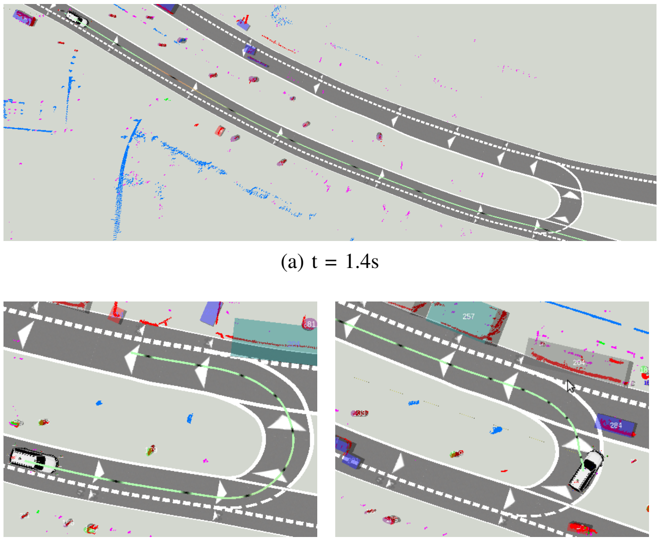
- Physical prediction model, using constant velocity,
- Uni-modal prediction based on the roadmap without considering maneuvers (Road follower),
- Multi-modal maneuver-based prediction (Non interaction-aware),
- Multi-modal maneuver-based prediction (Interaction-aware).

The first evaluation uses real world ROS bag files recorded during test drives of the MadeInGermany [13]. The prediction results of the ego-vehicle trajectories are compared to the ground truth measured by the D-GPS with Float RTK correction data of the test vehicle. For each prediction method, the position error and the position likelihood [14, p. 151] over the whole prediction horizon starting at different points in time is evaluated.

In this scenario, the target drives on the Thielallee in Berlin Dahlem and makes a U-turn to the reverse direction. During that turn, it has to merge the lane with an oncoming vehicle.

The first Picture 2a, taken at $t = 1.4s$, shows the target approaching the turn, but the most probable trajectory is still that of the keep lane maneuver. The Diagram 3 shows the probabilities of the keep lane and turn maneuver, the only feasible lane bound maneuvers at the start of the scenario.

The position error of the 10s prediction starting at $t = 1.4s$ (see Figure 4a) is in the beginning quite low, but grows for the multi-modal predictions with time, even more than for the simpler road follower and constant velocity predictions. The reason for this is that the target drives at $12m/s$, while $14m/s$ are allowed and therefore, the multi-modal methods predict an acceleration. In contrast, the likelihood is much better for the multi-modal methods due to the characteristics



(a) t = 1.4s

(b) t = 11.0s (c) t = 20.7s

Fig. 2: Turn maneuver with subsequent lane merge, showing the predicted 10s trajectory of the ego-vehicle.

of the covariance matrix. The longitudinal variances are much higher than the lateral ones and the prediction error occurs almost entirely in longitudinal direction. The constant velocity model assumes symmetric uncertainties, while the road follower predictions do not provide any probabilistic information.

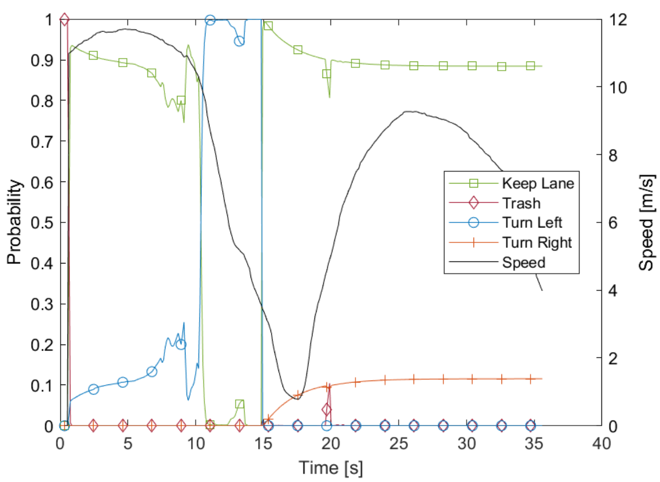


Fig. 3: Evolution of maneuver probability over time for the turn and merge scenario. Current speed is shown in black. Turn left becomes the most probable maneuver at $t = 11s$ and is completed at $t = 14s$.

At $t = 11s$ (see Picture 2b), the turn maneuver becomes the most probable. The vehicle is still about $25m$ away from the start of the turn lane and has so far no lateral deviation from the forward lane. But due to the deceleration of the target, the evidence fits much better to the turn maneuver. There is no obstacle ahead of the vehicle on the forward lane, which could explain the deceleration.

The position error of the prediction at $t = 11s$ (see Figure 4b) for the multi-modal interactive prediction remains very low during the whole prediction horizon, while it increases up to almost $100m$ for non-modal methods, which predict going straight at that time. The multi-modal non-interactive prediction is worse than the interactive one since it is a mixture in which the constant velocity model has a significant weight. The likelihood is at least until $t = 17s$ significantly better for the multi-modal predictions.

At about $t = 14s$, the turn maneuver has been executed, i.e., the target is not anymore on the forward lane. The turning lane becomes now the new lane for the keep lane maneuver, turning left becomes unfeasible (see Figure 3). The probability of a turn right maneuver at the next intersection (not shown) starts to increase.

At $t = 20.7s$ (see Picture 2c), the turn is almost completed and the target could re-accelerate. But is has to slow down to let pass the oncoming vehicle #284, which has the right of way. The interactive prediction (see Figure 4c) recognizes this and has therefore at least until $t = 28s$ a very low position error. All other models predict at least constant velocity, which would yield to a crash with the obstacle. The likelihood evolves correspondingly.

For further evaluations of real-live scenarios see [14, pp. 150-174].

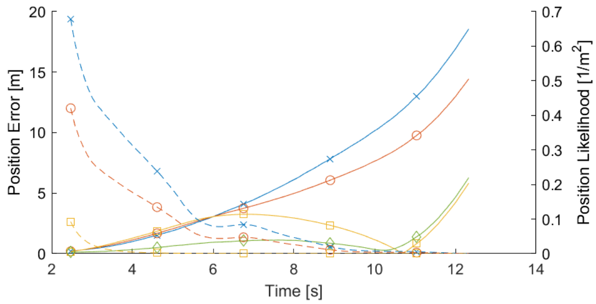
The second type of evaluation is done using a simulator, which allows to consider complex and potentially dangerous scenarios [14, pp. 182-191]. The simulator takes the predicted $10s$ trajectories and converts them to motion plans. In the example scenario. the vehicles have to cross an unsignalized multi-lane intersection (see Figure 5) with priority in east-west direction.

The result of the evaluation in Figure 6 shows the efficiency, indicated by the average speed, and the safety/comfort, indicated by the number of emergency brakes, of the generated motion plans. The interactive method is the most efficient one by allowing about twice the average speed as the non-interactive methods. While there were no collisions during the evaluations, the constant velocity method shows an unacceptable number of emergency brakings (deceleration $< -5m/s$).

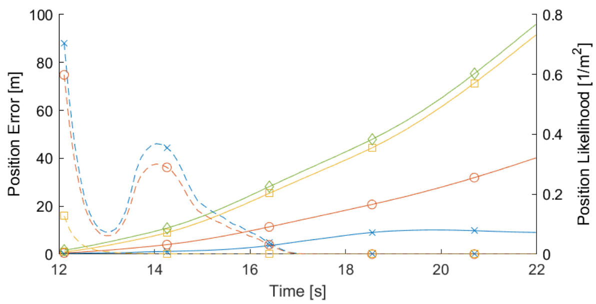
VII. Summary

This work has presented a new method to predict traffic scenarios involving up to 50 moving objects with a horizon of 10 or more seconds at a frequency of 10 Hz in real-time. It does so by analyzing the feasible maneuvers of all perceived traffic participants and rolling the trajectories out into the future. By evaluating the collision risks between all trajectories, the interaction constraints for the next prediction are established. The system not only detects and avoids conflicts between the ego-vehicle and the obstacles, but also the conflicts among the obstacles. Only in this way, a realistic forward projection of a dense urban traffic situation is achievable.

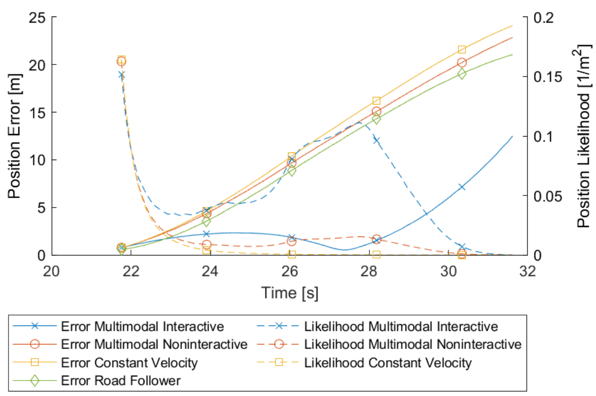
The evaluation using real-world traffic scenarios proves that the multi-modal interaction-aware prediction system is



(a) Position error and likelihood t = 1.4s



(b) Position error and likelihood t = 11.0s



(c) Position error and likelihood t = 20.7s

Fig. 4: Position error and position likelihood over time for the predictions at t=1.4s, t=11.0s and t=20.7s during the turn and merge scenario.

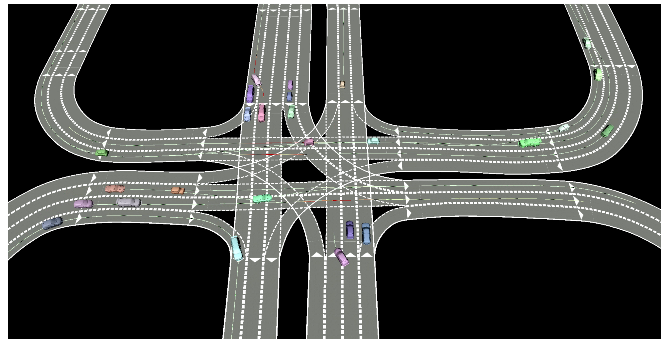
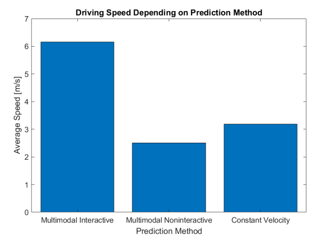
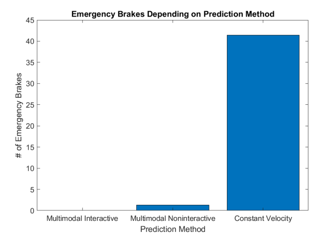


Fig. 5: Example traffic situation at intersection. Several cars on the subordinate road have to await priority traffic.



(a)



(b)

Fig. 6: Efficiency and safety/comfort for different prediction methods in intersection scenario.

able to predict complex urban traffic scenarios. The simulation results also show that the predictions can be used as a basis for an interaction-aware motion planning.

All details about the method and the evaluations are given in [14, pp. 79-191].

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