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Spatio-Temporal Trajectory Similarity and its Application to Predicting Lack of Interaction in Traffic Situations

Florian Damerow[1], Stefan Klingelschmitt[2] and Julian Eggert[3]

Abstract— **This work addresses two topics. On one hand we study the problem of general measures for spatio-temporal trajectory similarity based on the evaluation of longitudinal and lateral spatio-temporal distance. On the other hand we employ trajectory similarity measures to general situation classification problems for traffic scenarios, which include the well-known problem of lane assignment and driving maneuver recognition.**

We predict situation-specific prototypical trajectories using the interaction-aware Foresighted Driver Model (FDM) and compare the situation-dependent predicted trajectories with the actually measured trajectories resulting in estimations of how good a situation matches the actual behaviors. We then set up a situation classification system, which is able to detect incorrect traffic behavior in terms of *lack of interaction* between two traffic participants when interaction is necessary for a safe behavior.

We evaluate our system using real world and simulated crash cases and show that it is able to warn the driver, that another traffic participant is not considering the own car, about 2 seconds ahead of a crash, which would be sufficient for a suitable evasive behavior.

I. Introduction

Humans in general not only "re-act", but also behave proactively. They are able to look ahead and react to events that they expect will happen but which have not yet occurred. They reflect their intentions and expectations as well as the actual events [1], which makes the prediction of their future behavior and the detection of faulty or unexpected, abnormal behavior a highly complex task.

Especially the breakdown of interaction between traffic participants, is identified to be a major reason for collisions, see e.g. [2]. According to the authors, the most common errors are "faulty interpretations", "observation errors", "misplanning" or "distractiveness" and "inattentiveness".

This paper addresses the problem of situation classification in general and its application to detect that a traffic participant does not interact, when it should interact due to criticality reasons. For this purpose, we propose a situation classification approach, comparing the actually sensed behavior with different expected behavior alternatives, which were predicted under different situation-dependent assumptions. The more an expectation resembles the sensed behavior, the better the considered assumptions of this expectation serve as a suitable model for the considered entities' behavior. The behavior of traffic participants is mainly represented by spatio-temporal trajectories. Therefore, a suitable measure for trajectory similarity is necessary to compare sensed and predicted trajectories. By defining situations in a way that they differentiate between interacting and non-interacting behavior the system for situation classification can be applied to detect the "lack of interaction". This could e.g. be the case when a vehicle does not brake when it should in order to give way to the ego vehicle.

In literature there are multiple measures of trajectory similarity. In [3] those measures are split into four types of error measures, termed "scale dependent", "percentage", "relative" and "scale free". An example of the first type is e.g. the mean absolute error. The authors favor a "scale free" error measure, especially the mean absolute scaled error (MASE) to compare predicted trajectories, because it never returns infinite or undefined values.

In [4] the authors compare different common similarity measures for trajectories, namely the "Euclidean distance", "Haudorff distance", "HMM-based", "Longest Common Subsequence" (LCSS) and "Dynamic Time Warping" (DTW). It could be shown, that LCSS and DTW have very high computational costs and additionally perform relatively poor, because they can not take full advantage of the shape similarity of trajectories in traffic scenarios.

Then there are multiple publications using evidence theory to map different features indicating the similarity of actually measured trajectories and features indicating the similarity of a possible future evolution of trajectories to a maneuver occurrence probability and lane assignment. Such features with predictive character are e.g. the Time-to-Lane-Crossing [5], the angle between vehicle and lane orientation [6], [7], and tangential velocity [8]. It is additionally quite common to use the minimal distance to the lane centerline for probabilistic lane assignment [8]. Especially for lane assignment in highway scenarios the velocity, gap distance and conflict resolution can be used to classify maneuvers such as free, forced and cooperative lane changes [9].

Instead of using several different features indicating the future trajectory similarity, we use kinematic short term prediction models and directly evaluate trajectory similarity on the spatio-temporal distance level. This is a more general approach which allows the incorporation of more complex kinematic predictions for trajectory similarity. In Fig. 1, the past trajectory similarity is indicated by the green equi-time connections, whereas the blue connections indicate future

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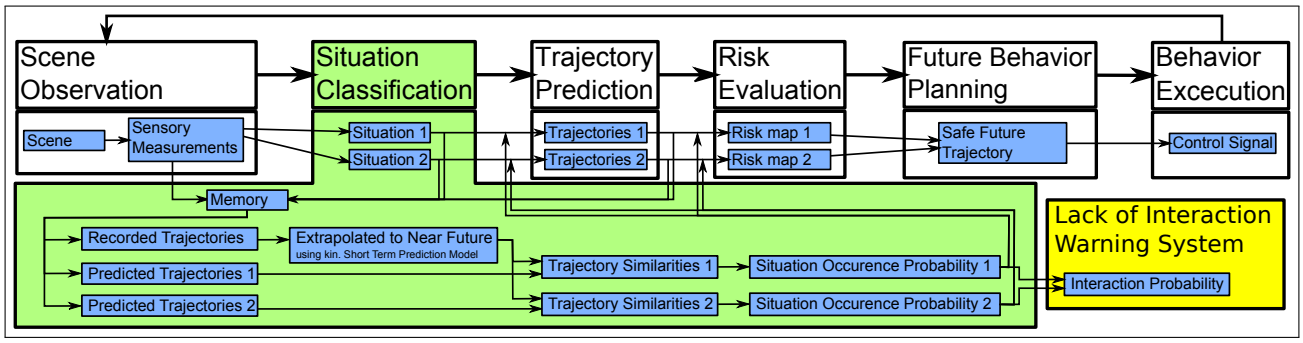


Fig. 2: Framework for situation based risk evaluation and behavior planning with the integrated approach for situation classification based on the trajectory similarity evaluation (green)

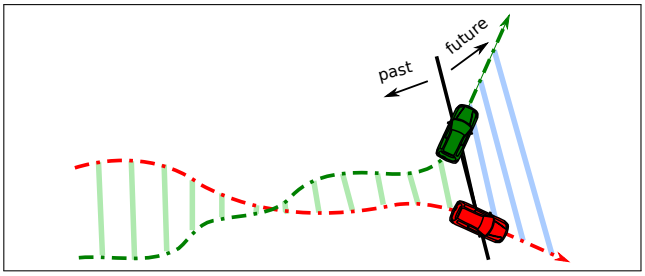


Fig. 1: Past (green) and future (blue) similarity of spatio temporal trajectories.

trajectory similarity.

Other publications propose learning-based approaches to classify different maneuvers. E.g. in [10] the authors use a probabilistic framework for maneuver recognition and trajectory prediction based on training a set of HMM's and comparing their output with current measurements. Similar approaches tackling the detection of interaction in terms of difference between expectation and intention of certain drivers are [11], [12], where contextual features such as lateral distance to centerline, longitudinal distance to car ahead/following car and relative velocities are used to incorporate interaction between the involved cars.

The contribution of this paper lies **on one hand** in the modeling of a general measure for trajectory comparison resp. trajectory similarity based on the decomposition of scaled, mean, lateral and longitudinal spatial prediction error and its time derivatives. In our approach there is no need for features indicating the future trajectory similarity, as we explicitly extrapolate the measured trajectories to evaluate not only past, but also future trajectory similarity. Thus our approach can be applied to any kind of scenario requiring different features of future trajectory similarity, simply by incorporating kinematic short term prediction models.

On the other hand we propose a model-based approach for situation classification using the measure for trajectory similarity. We explicitly use this system to detect the lack of interaction between traffic participants, which is especially important for cases where interaction is necessary to avoid upcoming risks, such as car-to-car collisions.

We show that our approach is able to cope with the spatio-temporal varieties of traffic trajectories and as a consequence, situations with or lacking interaction can be reliably distinguished.

II. Approach

In [13], [14] a framework for situation-based risk evaluation and behavior planning is introduced. The framework consists of the 6 steps shown in Fig. 2 executed repetitively. In the first step, the system aquires all relevant data of the current scene from sensor measurements. The following step performs a situation classification to determine situations relevant for the ego vehicle's behavior, for which the third step then predicts prototypical state evolutions. Based on those predictions, we estimate the future risk, e.g. car-to-car collsion risk and plan the ego behavior in a risk-aversive way.

Here, we introduce an approach for situation classification that nicely fits into this framework (see Fig. 2, green part). We utilize the acquired sensor data, such as the current road structure and dynamic entities including their current states, to generate a set of situation hypotheses based on the different possible behavior alternatives of the involved entities. A situation represents a specific assumption how the entities possibly behave, e.g. if an entity does give way to another entity or not. For each of those situations we perform a trajectory prediction to get situation-dependent prototypical future state evolutions, more precisely future trajectories of the considered entities. We continuously store the sensed trajectories, as well as the situation-dependent expected or predicted trajectories in combination with the considered situation-dependent assumptions.

To evaluate the likelihood that a certain situation applies to the current scenario, we check which situation-specific prediction fits best to the actually recorded trajectories of the present entities. This is done by calculating the trajectory similarity of each situation's predicted trajectories with the recorded trajectories and estimating the occurrence probability of each situation based on this similarity measure. To increase the predictive capability of our situation analysis, we naturally incorporate future trajectory similarity indicators (e.g. current driving orientation) by means of kinematic short term prediction models to extrapolate the recorded trajectories into the near future.

By defining situations such that they differentiate between interacting and non-interacting behavior and an interaction-aware trajectory prediction approach, the situation classification can be applied to detect situations lacking interaction,

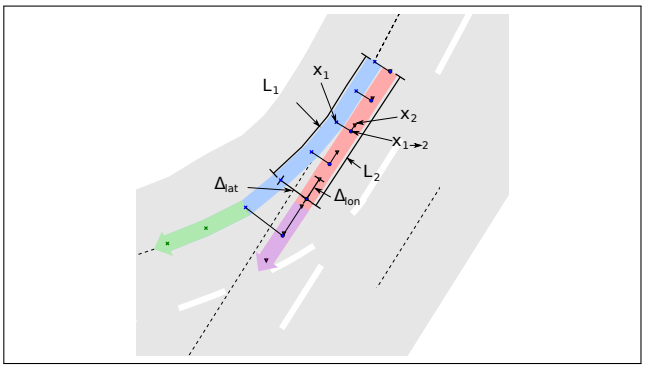


Fig. 3: Calculation of longitudinal and lateral distances between two trajectories $\mathbf{x}_2$ (red) and $\mathbf{x}_1$ (blue). The blue crosses and red triangles denote points of the corresponding trajectories at the same moment in time starting from the top right. The blue circles denote the projected points $\mathbf{x}_{1\to2}$ of $\mathbf{x}_1$ onto $\mathbf{x}_2$. Δ_{lat} and Δ_{lon} are exemplarily indicated for the 5th point in time. The blue and red trajectories are for the past time interval $[t-T_p,t]$ and as extrapolation the green trajectory continues the blue and the purple trajectory the red into the future for the time interval $[t:T_f]$.

e.g. the violation of right-of-way (see Fig. 2, yellow part). Here, for the trajectory prediction, we perform a forward simulation of the given situation hypothesis by modeling each entity as a Foresighted Driver Model [15], which is an interaction-aware, microscopic driver model.

III. Trajectory Similarity and Situation Classification

A. Trajectory Similarity

The target of this section is to derive a similarity measure for spatio-temporal trajectories. Let us assume to have two spatio-temporal trajectories $\mathbf{x}_1(s)$ and $\mathbf{x}_2(s)$, e.g. one measured and one predicted trajectory (see Fig. 3).

$$\mathbf{x}_{1/2}(s) \mid s \in [a,b], \tag{1}$$

where s denotes the time and $[a,b]$ a certain time interval.

First, we calculate the length of the trajectories the entity traveled in the time interval $[a,s]$ as a function of time s. This is done by calculating the length of the curve segment (trajectory) parametrized by the time s' for the considered time interval.

$$L_{1/2}(s) = \int_a^s \left| \frac{\mathrm{d}}{\mathrm{d}s'} \mathbf{x}_{1/2}(s') \right| \mathrm{d}s', \tag{2}$$

Then, using linear referencing, we project the spatio-temporal trajectory $\mathbf{x}_1(s)$ onto $\mathbf{x}_2(s)$ using (2) (see Fig. 3)

$$\mathbf{x}_{1\to2}(s) = \mathbf{x}_2(L_2^{-1}(L_1(s))), \tag{3}$$

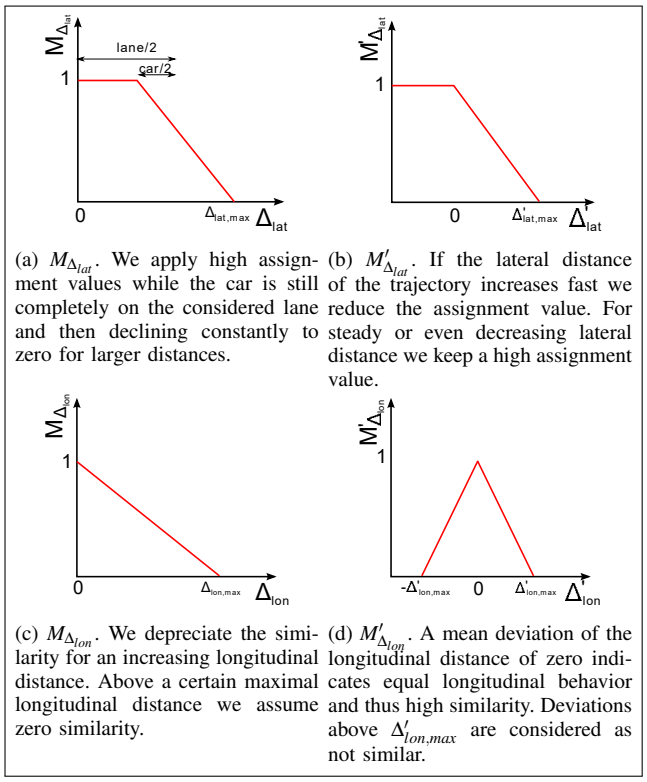
where L_2^{-1} is the inverse function of L_2 such that

$$L_2^{-1}(L_2(s)) = s. \tag{4}$$

In a next step, as shown in Fig. 3, we derive the longitudinal and lateral[1] distances between two trajectory points,

$$\Delta_{lat}(s) = ||\mathbf{x}_{1\to2}(s) - \mathbf{x}_1(s)|| \tag{5}$$

[1]Here "lateral" does not mean "orthogonal", but quantifies the difference between the original trajectory points and the corresponding points projected onto the other trajectory, as formulated in (5). See Fig. 3 for a more detailed explanation.



(a) $M_{\Delta_{lat}}$. We apply high assignment values while the car is still completely on the considered lane and then declining constantly to zero for larger distances.

(b) $M'_{\Delta_{lat}}$. If the lateral distance of the trajectory increases fast we reduce the assignment value. For steady or even decreasing lateral distance we keep a high assignment value.

(c) $M_{\Delta_{lon}}$. We depreciate the similarity for an increasing longitudinal distance. Above a certain maximal longitudinal distance we assume zero similarity.

(d) $M'_{\Delta_{lon}}$. A mean deviation of the longitudinal distance of zero indicates equal longitudinal behavior and thus high similarity. Deviations above $\Delta'_{lon,max}$ are considered as not similar.

Fig. 4: Assignment functions. a) assigns similarity depending on lateral distance to the considered lane, b) how fast the lateral distance increases, c) the longitudinal distance and d) how fast the longitudinal distance increases. The mean similarities a) and c) mainly cope for spatial similarity, whereas the derivatives b) and d) cope for velocity similarity. The used parameters are $\Delta_{lon,max} = 50m$, $\Delta_{lat,max} = 9.6m$, $\Delta'_{lon,max} = 5m/s$, $\Delta'_{lat,max} = 5m/s$, $lane = 3.2m$, $car = 2m$.

and[2]

$$\Delta_{lon}(s) = ||\mathbf{x}_{1\to2}(s) - \mathbf{x}_2(s)|| \tag{6}$$

Based on those distances, we calculate the following mean similarities as the mean longitudinal/lateral similarity of the trajectories

$$M_{lat/lon} = \frac{1}{b-a} \int_a^b M_{\Delta_{lat/lon}}(\Delta_{lat/lon}(s))\mathrm{d}s \tag{7}$$

and the mean similarity of the derivative of lateral/longitudinal distance

$$M'_{lat/lon} = \frac{1}{b-a} \int_a^b M'_{\Delta_{lat/lon}}(\Delta'_{lat/lon}(s))\mathrm{d}s \tag{8}$$

The single similarity values $M_{lat/lon}$ and $M'_{lat/lon}$ are derived by applying nonlinear weighted assignment functions to the lateral/longitudinal distances and their derivatives, as shown in Fig. 4. Those weighting functions are designed specifically for road traffic scenarios but hold for any kind of scenario, such as intersections or lane changes.

[2]For a trajectory $\mathbf{x}_2$ with strong curvature a more accurate way of calculating is $\Delta_{lon}(s) = |\Delta L(s)|$ with $\Delta L(s) = L_1(s) - L_2(s)$. Here we only use the absolute value $|\Delta L(s)|$, but in general $\Delta L(s)$ can be utilized to distinguish which trajectory has traveled a longer distance at time s, e.g. for $\Delta L(s) > 0$ trajectory $\mathbf{x}_1(s)$ has traveled a longer distance than $\mathbf{x}_2(s)$.

The resulting measure for trajectory similarity is derived as the combination of the mean similarities as,

$$M_{sim} = M_{lat} \cdot M'_{lat} \cdot M_{lon} \cdot M'_{lon}. \tag{9}$$

For two identical trajectories we then get a value of $M_{sim} = 1$. For highly unequal trajectories the similarity value tends to $M_{sim} \to 0$.

B. Trajectories

The target here is to find a suitable model for each involved entity's future behavior. Thus, we generate under different assumptions on how each entity i could behave a set of expected trajectories. Additionally, we record or estimate the actually driven trajectories.

For the recorded past trajectories of each involved car i, (here, we consider only the ego and another car) we get

$$\mathbf{x}(s,t,i) \quad | \quad s \in [t - T_p, t], \tag{10}$$

where t is the current time and $[t - T_p, t]$ the considered past time interval. We then extrapolate the trajectories into the future as shown in Fig. 3 using e.g. a simple "constant velocity, constant orientation"-model,

$$\mathbf{x}(s,t,i) \quad | \quad s \in [t, t + T_f]. \tag{11}$$

In the following, we group one behavior assumption per involved entity in a situation h (as explained in section IV) and get for each situation, in the set of all considered situations $h \in \mathbb{H}_{cons}$, one predicted (or expected) trajectory per entity, where the prediction is initialized with the vehicle states at the past time $t - T_p$ and an overall prediction horizon of $T_p + T_f$,

$$\hat{\mathbf{x}}(s,t,i,h) \quad | \quad s \in [t - T_p, t + T_f]. \tag{12}$$

C. Situation Classification

For each entity i in each situation h, we then calculate the trajectory similarity between the recorded trajectory $\mathbf{x}(s,t,i)$ and the (under the situation's assumptions) predicted trajectory $\hat{\mathbf{x}}(s,t,i,h)$ according to (9), as $M_{sim}(t,i,h)$.

Based on those trajectory similarities, we calculate the situation's occurrence probability as

$$P(t,h) = \frac{M_{sim,total}(t,h)}{\sum_{h' \in \mathbb{H}} M_{sim,total}(t,h')}, \tag{13}$$

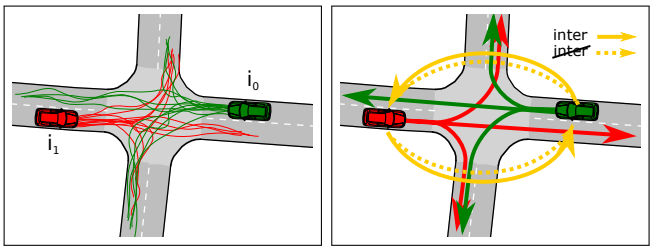
with

$$M_{sim,total}(t,h) = \sum_{i \in I(h)} M_{sim}(t,i,h)$$

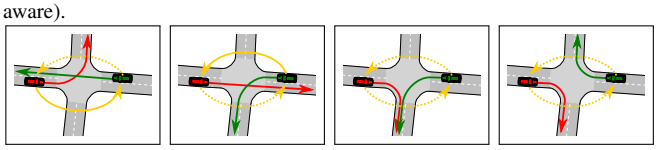
where $M_{sim,total}(t,h)$ is a situation's assigned prediction similarity (considering all involved entities $I(h)$).

The situation occurrence probability is then an indicator for how good the situation-dependent assumptions on the involved entities' behavior did fit to the actually sensed trajectories and can then be utilized to further predict the evolution of the current traffic scenario.

We consider particularly the other entity's behavior alternatives, because we want to estimate if the other entity interacts with the ego entity in scenarios where it should due to traffic rules and criticality reasons.



(a) Left: Sampling of possible future trajectories of the ego car i_0 (green) and another car i_1 (red). Right: Clustering of sampled trajectories into prototypical behaviors defined by prototypical spatial paths and prototypical longitudinal behavior options (here interaction-aware and non-interaction-aware).



(b) Possible situations. Each situation is defined by one prototypical spatial path for each entity and one prototypical longitudinal behavior. The longitudinal behavior is determined here by the interaction pattern, meaning that in the interaction-aware case the risk of the other traffic participant will be explicitly considered for the own driving behavior.

Fig. 5: From trajectory sampling to situations.

IV. Situation Modeling, Generation and Trajectory Prediction

To be able to utilize the derived trajectory similarity measure for situation and interaction classification, we shortly give an explanation of how we define a situation and how they are generated. Additionally, we explain the situation-specific prediction of future trajectories, such that they can be used to distinguish between interaction and the lack of interaction.

A. Situations

Sampling-based approaches for trajectory generation (see e.g. [16]), use dynamic models of traffic participants and randomly sample over the parameter space to provide a large amount of possible trajectories, as shown in Fig. 5(a). If we now want to determine which are the most likely trajectory constellations of a certain traffic scenario this ends up in a highly combinatorial problem.

Thus, we group similar trajectories to reduce the complexity of the problem, as shown in Fig. 5(b). Each cluster is then represented by prototypical trajectories, in this case one for each traffic participant.

We distinguish trajectories of different spatial appearance and trajectories of different longitudinal behavior. For inner-city traffic scenarios the spatial separation of possible trajectories can be determined in a straightforward way by the given road structure and the resulting possible paths of the involved entities. For the longitudinal behavior we separate interactive and non-interactive behavior[3], which will be explained later in more detail.

Following [17], situations separate possible behavior alternatives of traffic scene entities, such that in one situation each

[3]Here, with interactive behavior of the other entity, we mean that the other entity considers the ego entity in its behavior to avoid a potentially upcoming crash, e.g. by braking and giving way.

entity follows one prototypical behavior, defined by its spatial path and longitudinal behavior. In such a way, we directly predict the prototypical trajectory for each cluster instead of randomly sampling a large amount of possible trajectories and then clustering them into prototypical trajectories.

The possible spatial paths can easily be determined if we have access to the current road structure. For this purpose, as shown in Fig. 6 we map the current position of the entity to the center line of the road structure element (e.g. lane or lane junction) and determine possible future paths from the geometry of the road structure.

The different longitudinal behavior options are defined by an interaction matrix indicating which entity considers which other entity for interaction. The actual prototypical trajectories are then generated by a forward simulation of the situation, as explained further in IV-B.

The representing situation parameter h contains all information needed to perform a forward simulation of the situation, in terms of a set of spatial paths Ξ (one path χ for each entity), an interaction matrix A indicating which entity considers which other entity for interaction and a set of static model parameters P_{FDM}.

$$h = (\Xi, A, P_{\mathrm{FDM}}), \tag{14}$$

with

$$\Xi = [\chi_0, ..., \chi_N], \tag{15}$$

$$A = \begin{bmatrix} a_{0,0} & ... & a_{0,N} \\ ... & ... & ... \\ a_{N,0} & ... & a_{N,N} \end{bmatrix}, \tag{16}$$

where N denotes the number of involved entities. Here,

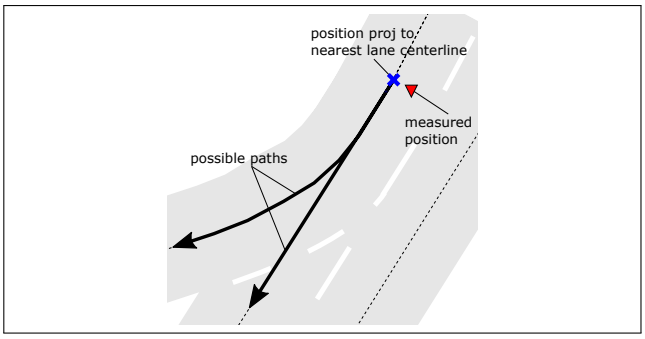


Fig. 6: Map-based estimation of possible spatial paths. To determine possible spatial paths we first project the measured position of the vehicle onto the centerlines of the surrounding reachable lanes.

$a_{u,w} = 1$ indicates that entity u considers entity w for interaction, whereas $a_{u,w} = 0$ indicates no interaction. In Fig. 5(b), exemplary situations are illustrated. For the most left situation, Ξ_1 and A_1 have the following form,

$$\Xi_1 = [\chi_0^s, \chi_1^l], \tag{17}$$

$$A_1 = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \tag{18}$$

where χ_0^s is the "going **s**traight path" of the ego car and χ_1^l the "turning **l**eft path" of the other car.

Considering N entities i where each entity has N_χ^i possible spatial paths and N_q^i possible longitudinal behavior options, we obtain the entire set of situations $\mathbb{H}$ in the current scene by simply determining all variations of the combinatorical set, resulting in

$$N_{\mathbb{H}} = N_\chi^0 \cdot N_q^0 \cdot ... \cdot N_\chi^N) \cdot N_q^N) \tag{19}$$

possible situations.

A highly relevant question for traffic scenarios is to estimate if another car possibly violates a right-of-way situation of the ego car. Thus, in the following we consider bilateral situations including only the ego car i_0 and one other car i_1.

For simplification we assume right-of-way *for the ego car* and thus only non-interacting longitudinal behavior and a known path resulting in $N_\chi^0 = 1$ and $N_q^0 = 1$ and the reduced set of situations of length

$$N_{\mathbb{H}} = N_\chi^1) \cdot N_q^1). \tag{20}$$

Situations where interaction is considered by the other entity $a_{1,0} = 1$ are combined in the set $\mathbb{H}_{inter}$, whereas situations with $a_{1,0} = 0$ in $\mathbb{H}_{\cancel{inter}}$. Similarly, we combine all situations with the same other entity's path χ in the set $\mathbb{H}_\chi$.

B. Interaction-aware Trajectory Prediction using FDM in Forward Simulation

A situation h contains all the information needed to predict the evolution $\hat{\mathbf{X}}(s,t,h)$ of the situation by a forward simulation using the predicted time s and the current state of the scene $\mathbf{X}(t)$. The evolution of the entire situation is a combination of one behavior evolution $\hat{\mathbf{x}}(s,t,i,h)$ per involved entity i.

$$\hat{\mathbf{X}}(s,t,h) = \bigcup_{i \in I(h)} \hat{\mathbf{x}}(s,t,i,h) \tag{21}$$

$$= \mathrm{FSIM}(s, \mathbf{X}(t), h), \tag{22}$$

$$\text{for } s \in [t,T]. \tag{23}$$

Here FSIM denotes the forward simulation for future times $t+s$ according to the situation parameters[4] h.

The evolution $\hat{\mathbf{x}}(s,t,i,h)$ of each entity's prototypical behavior is predicted using a Foresighted Driver Model (FDM). The FDM [15] is a highly general, interaction-aware, microscopic driver model, which is able to provide realistic, long term stable prediction of traffic scenes, including intersection scenarios. It determines the velocity change by a gradient-decent on a cost function combining a simplified risk evaluation and utility costs.

During the forward simulation of a situation assuming interaction, the evolution of each interaction-aware entity is dependent on the evolution of other entities. For situations where none of the entities considers any other entity for interaction the trajectories of each entity $\hat{\mathbf{x}}_i(s,t,h,i)$ can also be predicted independently of each other (e.g. the two right hand situations in Fig. 5(b)).

[4]It can be seen, that the consideration of situations assuming prototypical behaviors heavily reduces the combinatorial complexity, compared to approaches which perform an intensive sampling of possible trajectories.

C. Situation Pre-Selection

Since the number of situations can get quite large, we define a simple rule-based filter, which reduces the entire set of situations to a subset of situations important for the ego car's behavior. As stated in [18], a proper situation selection approach takes the situation occurrence probability as well as the potentially upcoming risk into account. Thus, we reduce the total set of situations based on a worst case risk estimation. Assuming the distance-based risk measure introduced in [15], the highest possible risk along two spatial paths, is where they get closest. Additionally, taking the vehicle dynamics, especially the maximal acceleration/deceleration into account, we can estimate an upper bound for risk r_b, representing the maximal possible risk, which the ego entity can encounter if both (ego and other car) act in the worst possible way (get closest under consideration of their vehicle dynamics). Thus, we build the subset of situations of generally low car-to-car risk,

$$\mathbb{H}_{r_{low}} = \{h \in \mathbb{H} | r_b(h) \leq b_{risk}\} \tag{24}$$

where b_{risk} is a risk threshold defining when a situation is considered as being "of low risk" and can be set conservatively, filtering only situations of very low risk. r_b can be estimated according to [15]. As interaction in situations of low risk plays a minor role, we remove those situations from the set of considered situations

$$\mathbb{H}_{cons} = \{h \in \mathbb{H} | h \notin \mathbb{H}_{r_{low}} \vee h \in \mathbb{H}_{\cancel{inter}}\}. \tag{25}$$

As a result, we get a set of situations which are important to understand a scene and thus important for the own future behavior.

V. Situation Classification for Interaction Detection and Lane Assignment

We defined situations which differ in terms of their involved entities' possible drivable paths and longitudinal behaviors, here especially considering the alternatives that the other entity interacts with the ego vehicle to give way or that it does not interact.

To calculate the probability for interaction/non-interaction, we sum up the occurrence probabilities of all situations, according to (13), where interaction was assumed/was not assumed in the prediction of the other entity as

$$P(t, \mathbb{H}_{inter}) = \sum_{h \in \mathbb{H}_{inter}} P(t,h) \tag{26}$$

$$P(t, \mathbb{H}_{\cancel{inter}}) = \sum_{h \in \mathbb{H}_{\cancel{inter}}} P(t,h) = 1 - P(t, \mathbb{H}_{inter}) \tag{27}$$

Similar, for lane assignment, we sum up the occurrence probabilities of all situations in $\mathbb{H}_\chi$ for a certain other entity's path alternative χ as

$$P(t, \mathbb{H}_\chi) = \sum_{h \in \mathbb{H}_\chi} P(t,h) \tag{28}$$

VI. Interaction Detection applied to Real World Crash Scenarios

A. Evaluation of a Multi-Lane-Intersection

To illustrate the general procedure of our system, we evaluate a complex intersection scenario with multiple crossing lanes, as shown in Fig. 7. The examined scenario is taken from the real world crash database GIDAS-PCM (German In-Depth Accident Study - Pre-Crash-Matrix [19]), which contains the reconstructed trajectories of the entities involved in an upcoming crash. In this crash case a violation of right-of-way and thus a lack of interaction was identified as the main cause.

Our system is not only able to estimate if another vehicle does not interact with the ego vehicle, it can also determine how likely it is, that the other entity will choose a certain spatial path. To show this combined estimation of "which path will the other entity choose" and 'how will the other entity behave along that path" we evaluate the intersection in Fig. 7(a). Furthermore, four possible situations in this scenario are illustrated in Fig. 7(b). For the ego car, we assume the spatial path as well as the longitudinal behavior to be known. The resulting situations arise from the other entity's path and behavior alternatives, namely turning right on the right lane (situation 0 and 1), turning left on the left lane (situation 2 and 3), as well as interaction-awareness (situation 0 and 2) or non-interacting behavior (situation 1 and 3).

The assigned longitudinal prediction similarities of all situations in Fig. 7(c) start with a value close to one, because the prediction model for interaction and no-interaction both predict that keeping the velocity constant is an appropriate behavior, which also fits well to the actually measured behavior of the other car. At around $t = -3s$ ahead the crash, the prediction models of the situations assuming interaction start to predict a reduction in velocity of the other car in order to reduce the risk of collision. The measured trajectory does not fit well with those predicted trajectories and the assigned longitudinal prediction similarity of those two interaction-aware situations start to drop.

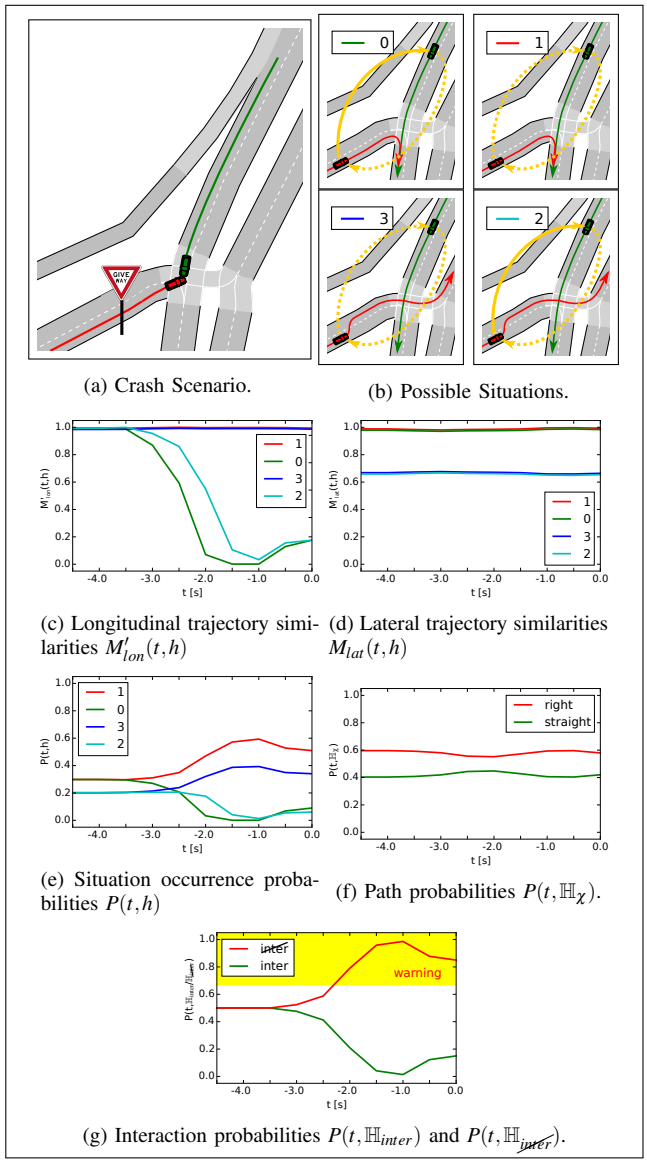
Looking at the assigned lateral prediction similarity in Fig. 7(d) it can be seen that all situations with a path on the left lane, have a lower similarity than situations with a path on the right lane, where the other car is currently driving. Here the lane assignment character of the lateral similarity measure can be seen.

Fig. 7(e) shows the occurrence probability of all 4 situations, which combines the impact of the longitudinal and lateral prediction similarity. If we combine the occurrence probabilities of all interaction-aware situations and of all non-interaction-aware situations in Fig. 7(g), we gain an estimation of the "lack of interaction" in this scenario. Similarly by combining situations with the same spatial paths we can perform standard lane assignment in Fig. 7(f).

B. Combined Evaluation of Multiple Scenarios

After presenting the general approach, we now apply it to further scenarios. For this purpose, we evaluated the lack

of interaction for 12 different intersection scenarios from GIDAS-PCM. The target is to show that our system is able to correctly detect and warn of dangerous situations, namely situations where a lack of necessary interaction was detected, e.g. the faulty behavior of another car by not giving way to the ego vehicle. Similar to section VI-A, further cases



(a) Crash Scenario.

(b) Possible Situations.

(c) Longitudinal trajectory similarities $M'_{lon}(t,h)$

(d) Lateral trajectory similarities $M_{lat}(t,h)$

(e) Situation occurrence probabilities $P(t,h)$

(f) Path probabilities $P(t,\mathbb{H}_\chi)$.

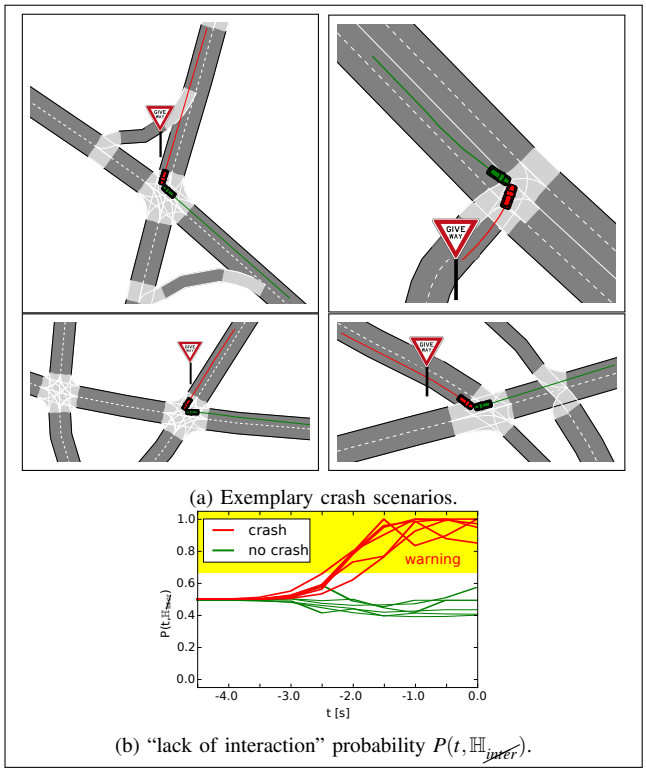
(g) Interaction probabilities $P(t,\mathbb{H}_{inter})$ and $P(t,\mathbb{H}_{\not inter})$.

Fig. 7: Multi-Lane Intersection Crash Scenario. The ego vehicle (green) and another car (red) approach an intersection, while the ego vehicle is on a priority road. Path alternatives for the other car are, staying on the right lane and turning right, or performing a lane change to the left lane and driving straight over the intersection. As behavior alternatives we consider that the other car does consider the ego car and interacts, or that it violates the "right of way" and does not interact. This results in the 4 situations shown in (b). The crash occurs at $t = 0s$. The longitudinal similarities $M'_{lon}(t,h)$ in (c) show a decline for the interaction-aware situations as the other car does not start braking. The lateral similarities $M_{lat}(t,h)$ in (d) show lower values for situations on the left lane, as the other car currently drives on the right lane. (e) shows the occurrence probabilities of each situation combing longitudinal and lateral similarity. According to (28) (f) shows the probability which spatial path the entity will most likely choose and finally (g) shows the probability according to (26) and (27) for the situations assuming the other car to interact or to not interact. The outcome of this real world GIDAS scenario analysis is an early crash prediction, because the other car did, indeed, violate the right-of-way.

where a violation of the right-of-way caused the accident (at $t = 0s$) are evaluated. Additionally, we simulate the same cases with an interaction-aware driver model, namely the Foresighted Driver Model (FDM) to achieve realistic trajectories with the same start constellation but which, due to considered interaction, avoid the crash. Here, we use a randomized parameter set for the driver models to include a higher variability in our tests. In those non-crash cases our system should correctly recognize the non-dangerous situations, which are not leading to any crash and should thus not giving a warning. A selection of the analyzed cases is shown in Fig. 8(a). It can be seen, that intersections of highly diverse road structures have been evaluated.

From Fig. 8(b), showing the "lack of interaction" probabilities for scenarios that actually did lead to a crash (red), it can be seen, that around 3 seconds before the occurring crash the probability for "lack of interaction" starts to rise and about 2 seconds before the crash our system determines the correct situation with high confidence and gives a warning.

It can also be seen, that the "lack of interaction" probabilities for the crash scenarios are in general more distinct compared to the probabilities in case of non-crash scenarios in Fig. 8(b,green). This can easily be explained. Our system evaluated the prediction similarity for different assumptions (here interaction and non-interaction). If we evaluate the interaction/non-interaction situation occurrence probabilities for the crash cases, we found that, as we get closer to the actual crash the prediction assuming interaction predicts a rise of interaction (e.g. deceleration), as this would be necessary to avoid the crash. Thus, the prediction similarity for the interaction-aware prediction heavily decreases compared to



(a) Exemplary crash scenarios.

(b) "lack of interaction" probability $P(t,\mathbb{H}_{\not inter})$.

Fig. 8: Multi Lane Intersection Crash Scenario.

the prediction assuming non-interaction and thus our system becomes very certain that there is a lack of interaction. In the non-crash cases, once the observed vehicle starts to interact, the situation becomes safer, which results in a reduced need of interaction. Thus, if we then evaluate the predictions with interaction and the predictions without interaction, the prediction similarity for "interaction" and "non-interaction" do not diverge as heavily as for the crash-cases.

Furthermore, in Fig. 8(b) of the non-crash cases (green), it can be seen that in one case our system first tends to favor "non-interaction" although interaction takes place. This can be understood as a direct result of our limited set of prediction models. In this case the prediction model assuming interaction estimates an acceleration of the other car to act in a safe manner (to pass in front of the ego vehicle). In fact the other car behaves more defensive than assumed by our prediction model and stops at the intersection. As we only evaluate "interaction" (here acceleration) and "non-interaction" (here constant velocity) the real behavior of braking fits better to the "non-interaction" prediction. At a certain point in time the prediction model adapts and starts to predict a deceleration and our system correctly favors "interaction".

The yellow area in Fig. 8(b) shows how to set up a warning system, which warns the ego driver in case the probability for "lack of interaction" crosses a threshold, $P(t, \mathbb{H}_{\not inter} \geq 0.65)$. In the evaluated cases our system was able to warn about 2 seconds before the crash actually occurred, which would in general be sufficient to avoid the upcoming collision.

VII. Discussion and Outlook

In this paper we presented a model-based approach for situation classification and interaction detection. We first introduced a general measure for the similarity of spatio-temporal trajectories based on the decomposition into lateral and longitudinal prediction similarity. We then evaluated the current traffic situation by performing situation-dependent predictions of prototypical trajectories for each involved entity and comparing those predictions to the actually sensed trajectories by using the measure of trajectory similarity. By defining situations as interacting and non-interacting and using an interaction-aware prediction model for the trajectory prediction, our system can be used to evaluate a "lack of interaction" in some other entity's behavior. Additionally our system is also able to estimate lane assignment. We could show in real world crash cases, as well as partly simulated cases that our system is able to warn the ego driver of upcoming risks due to "lack of interaction" about 1.5 seconds ahead. Systems for risk evaluation and behavior planning, such as [14], [17], [13], which rely on a situation assessment would strongly benefit from the presented approach, as it allows not only an estimation of a single other drivers intent, but also a situation analysis considering multiple interacting entities. Especially detecting dangerous near-crash situations is highly crucial to plan the future behavior and, due to the lack of training data, a challenging task for learning-based situation assessment approaches. For warning systems we expect a strong reduction of false-positive warnings, often caused by the neglection of interacting behavior.

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