Honda Research Institute EU
Honda Research Institute Europe GmbH
https://www.honda-ri.de/

Managing the Complexity of Inner-City Scenes: An Efficient Situation Hypotheses Selection Scheme

Stefan Klingelschmitt, Florian Damerow, Julian Eggert

2015

Preprint:

This is an accepted article published in Intelligent Vehicles Symposium (IV) 2015. The final authenticated version is available online at: https://doi.org/[DOI not available]

Managing the Complexity of Inner-City Scenes: An Efficient Situation Hypotheses Selection Scheme

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

***Abstract*— Due to the large number and the high variability of possible traffic situations, intersections are among the most accident-prone spots in inner-city traffic. To reliably assist the driving tasks elaborated risk assessment systems are needed. Current approaches are mainly based on the prediction of possible future trajectories of the involved traffic participants. However, considering the variability and combinatorics of intersection-related traffic situations, this becomes unfeasible for limited computational resources. Here, we present a general framework for an efficient situation hypotheses selection system. The selection process is based on reasoning about whether a particular situation results in a threat for the ego vehicle's behavior. Our approach combines the results of a probabilistic situation recognition and a fast risk assessment using state-of-the-art regression methods. We show that the proposed system is able to effectively reduce the number of unnecessarily considered situation hypotheses on average by over 80%.**

I. INTRODUCTION

Future Advanced Driver Assistance Systems (ADAS) aim to relief the stress on the driver in inner-city traffic scenarios. Especially in an urban environment, supporting the driving task is challenging due to issues arising from the large variability of: possibly involved participants, traffic rules and characteristic features of the road network. Particular intersections combine these factors which makes them a highly accident-prone spot. Therefore assistance systems supporting the task of safely passing an intersection will reduce the number of accidents occurring in urban environments [1].

Such assistance systems are typically based on elaborate criticality assessment techniques. They identify possible upcoming maneuvers of affecting, nearby traffic participants and infer their associated threat for the ego vehicle, like presented [2], [3] and [4]. If these threats exceed a certain threshold, an adaptation of the ego vehicle's behavior might be necessary. This can be done in various ways, e.g in the form of a warning system, a partially intervening assistant or a fully automated, planning vehicle.

Problems arise from the combinatorics and variability of intersection-related traffic scenes as follows. Partitioning the set of possible maneuver combinations into situations is a common approach in order to make more precise maneuver-dependent trajectory estimations. However, depending on the number of crossing road segments and involved traffic participants the set of possibly encountered prototypical situations expands rapidly. An example is illustrated in Fig. 1. If we consider the different route alternatives, a 4-way crossing involving only two traffic participants leads to 36 possible situations hypotheses, from the ego vehicle's point of view. In general, the situations arising from maneuver combinations scales exponentially with the number of present traffic participants. Considering all hypotheses might not be feasible, since the majority of criticality assessment techniques are based on simulating or sampling over a set of possible future trajectories in all their forms.

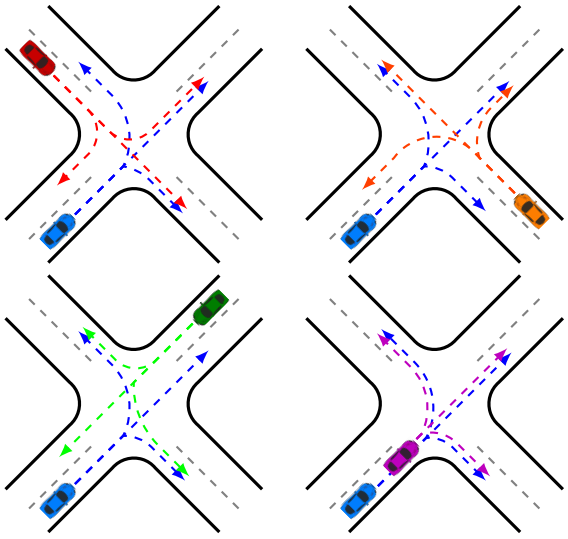

Fig. 1: Ego car (blue) approaches a crossing, respectively one affecting traffic participant approaches the crossing from different road segments.

Therefore, we propose a hypotheses selection scheme that reduces the number of analyzed situations and keeps computational resources at a reasonable level. Such a selection scheme should be able to efficiently reduce the number of closer inspected situation hypotheses by excluding unlikely and/or irrelevant situations for the ego vehicle's behavior. In this way, the computational load for subsequent detailed situation assessment techniques can be lowered.

An intuitive approach is to use a preceding situation classification to exclude unlikely situations. Nevertheless, maneuver detection solely based on detectable kinematic features is a demanding task. And yet, despite elaborate maneuver detection systems, like presented in [5] and [6], it is hard to determine upcoming maneuvers reliably, especially more than $30m$ away from an intersection.

[1]S. Klingelschmitt and F. Damerow are with Control Methods and Robotics Lab, Technical University of Darmstadt, D-64283 Darmstadt, Germany stefan.klingelschmitt@rmr.tu-darmstadt.de, fdamerow@rmr.tu-darmstadt.de

[2]J. Eggert is with Honda Research Institute Europe GmbH, D-63073 Offenbach am Main, Germany jeggert@honda-ri.de

Hence, the confidence needed for securely excluding a situation hypothesis is concomitantly high. This, on the other hand, leads to a high rate of superfluously inspected situations. For this reason, a selection solely based on the results of a situation recognition is not feasible, given the uncertainties of maneuver estimation systems. In this paper, we propose a system for the purpose of reducing situation hypotheses. The selection of hypotheses is achieved by combining a probabilistic situation recognition with a fast, probabilistic regression for assessing possible threats. This leads to a relevance based hypotheses selection.

This paper is organized as follows. In section II, we discuss related work. Section III gives a detailed description of our general framework for making efficient hypotheses selections. It includes a probabilistic situation recognition, a novel indicator and regressor for intersection-related criticality assessment. The system is evaluated in Section IV, using simulated and real-world data, showing that we can drastically reduce the number of superfluously inspected situations, on average, by over 80%. The results are summarized and an outlook is given in Section V.

II. RELATED WORK

The related work can be split into three categories. The first category is concerned with situation recognition involving two or more interrelated traffic participants. The second category addresses inner-city risk assessment techniques. The third category combines situation recognition and risk assessment techniques in order to enhance either the situation or risk assessment.

Various approaches have been proposed focusing on situation recognition in an inner-city context, concerning more than one dynamic entity. The work presented in [7] concentrates on identifying how two entities are related, given the current scene. Using Bayesian Networks, a probabilistic assessment of the driving situation is performed. The authors of [8] recognize maneuvers of approaching non-ego vehicles using case-based reasoning. The interactions between the two traffic participants are implicitly incorporated by the selected features. Approaches presented in [9] and [10] formulate an ontology for inner-city traffic situation analysis.

The majority of work presented in combination with risk assessment in an urban environment is based on detecting possible conflicts of future trajectories. A more complete overview can be found in [11]. Several approaches have been proposed treating the problem of detecting imminent collisions in a probabilistic manner, such as [2] and [3]. A general definition for a probabilistic and continuous risk indicator, as well as its possible application to inner-city traffic scenarios is discussed in [12]. This formal definition is the basis of the risk indicator formulated in our approach.

Approaches combining a beforehand situation recognition with risk assessment, addressing a variety of problems, have been recently proposed. The system presented in [13] combines a probabilistic maneuver estimation with a subsequent criticality assessment. The criticality assessment is based on a generalization of the common TTC indicator. The authors of [14] present a similar approach to calculate a collision probability. This information is used to enhance the situation recognition considering collision prone situations as less likely candidates of normal driving behavior.
However, none of these approaches addresses explicitly the scalability of their approaches in conjunction with increasing complexity of possible occurring situations.

In [15] an approach is presented to overcome this problem by reasoning about a situation on a more abstract level. The risk of a current scene is assessed by comparing the estimated intention with the expected behavior of traffic participants, using a Dynamic Bayesian Network. If the intention and expectation differ from each other, the situation is automatically rated as risky. Likewise, efficiently assessing risk in combination with a situation recognition is addressed in [16]. The authors propose a two-staged system consisting of an intention predictor and a subsequent threat assessor. The threat assessor is based on a rapidly-exploring random-tree (RRT) extension, for detecting possible conflicting trajectories. RRTs are well known for their ability for fast trajectory generation.
Though, the risk assessment of both approaches are currently limited to detecting unexpected or errant behaviors. It remains unclear how these approaches could be used to assess the scene when maneuvers cannot be categorized as expected or unexpected. E.g. turning right or left maneuvers, could both be valid maneuver alternatives.
A real-time capable approach for a right of way warning system is introduced in [17]. It is based on weighting the output of a handcrafted fuzzy logic based risk assessment for each particular identified conflict with the corresponding occurrence probability. The weighted risk is presented to the driver. As part of the KoPER project, a similar approach for an intersection warning system is presented in [18]. Several Time-To-X metrics are computed and occupancy times for overlapping path areas are calculated.

To our knowledge there is no previous work that explicitly addresses the problems arising from the large number of possibly encountered inner-city traffic situations, in terms of making a preceding hypotheses selection, for any kind of ADAS application.

III. SYSTEM OVERVIEW

We propose a situation hypotheses selection in order to overcome the addressed scaling problems, arising from a large number of prototypical situations, covering the variability of inner-city traffic scenarios. The set of all prototypical situations is defined as

$$\mathcal{S} = \{s_1, s_2, ..., s_n\}, \tag{1}$$

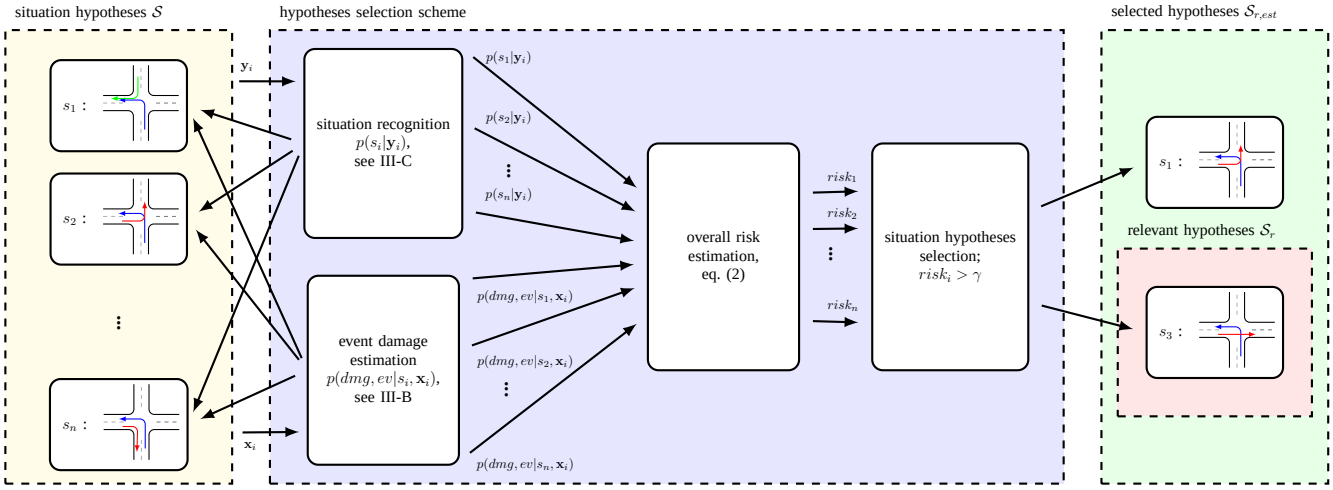

Fig. 2: System overview. Starting from a large set of prototypical situations $\mathcal{S}$ the belief $p(s_i|\mathbf{y}_i)$ and the event damage probability $p(dmg, ev|s_i, \mathbf{x}_i)$ are determined. Both values are combined according to (2). A subsequent threshold based hypothesis selection is performed, leading to a reduced situation hypotheses set $\mathcal{S}_{r,est}$.

containing n prototypical situation hypotheses s_i.
The objective is to identify the set of relevant situation hypotheses $\mathcal{S}_r \subset \mathcal{S}$. We define a relevant situation as a situation that can actually be detected and exceeds a user-defined criticality threshold. This definition results in the possibility of $\mathcal{S}_r = \emptyset$, in the case of no actual occurring situation exceeding this criticality threshold. Our system is able to identify a set $\mathcal{S}_{r,est}$ of estimated relevant situation hypotheses at a specified distance or time before the actual situation. It approximates $\mathcal{S}_r$, such that $\mathcal{S}_r \subseteq \mathcal{S}_{r,est}$. Due to the predictive character of situation recognition and risk assessment techniques, it is unlikely to predict $\mathcal{S}_r = \mathcal{S}_{r,est}$. Given the objective definition of a relevant situation, analyzing superfluous situation hypotheses will be inevitable, when facing long term behavior prediction of several traffic participants. However, a human driver also makes uncertain predictions of possibly dangerous future situations and eventually categorizes them as behavior relevant. Thus, superfluously selected situations hypotheses might not be superfluous from a subjective human point of view, even if these situation hypotheses do not occur. Nevertheless, such assessments are highly subjective. Therefore, we use the given objective definition of a relevant situation, for benchmarking our proposed hypotheses selection scheme.

The decision whether to assign a situation hypothesis s_i to $\mathcal{S}_{r,est}$ is based on an overall, situation specific calculated risk $risk_i$, according to [12]. The hypotheses selection step is based on comparing the indicator $risk_i$ with a threshold γ. Appropriate values for γ can be chosen dependent on the prediction horizon and associated reliability. The situation specific risk is formally given by

$$risk_i = c(dmg, ev)\, p(dmg, ev|s_i, \mathbf{x}_i)\, p(s_i|\mathbf{y}_i) p(s_i). \tag{2}$$

Quantifying the cost $c(dmg, ev)$ of a damage (dmg) caused by a critical event (ev) happening is beyond the scope of this work and is set to 1. The joint probability $p(dmg, ev|s_i, \mathbf{x}_i)$ of a critical event (*ev*) with an involved damage (*dmg*) happening is conditioned on a particular situation hypothesis s_i and the event specific scene information $\mathbf{x}_i$ (e.g. relative entity distances, velocities and/or orientations). It is the criticality measure used for the proposed framework. An example for a possible collision event and its associated damage are further discussed in III-A.

The belief for a particular situation hypothesis, is given by the conditional probability $p(s_i|\mathbf{y}_i)$, where $\mathbf{y}_i$ represents the particular situation information used for inferring $p(s_i|\mathbf{y}_i)$ (e. g. current velocity, position to the intersection, etc.) It is the result of a probabilistic situation recognition. An intersection-related system for detecting maneuver combinations is introduced in III-C. In order to not bias the selection towards frequently occurring situations, while discarding rarely occurring but critical situations, we set the prior probability $p(s_i)$ to $\frac{1}{n}$. However, it could be used to incorporate a priori knowledge.
An illustration of the complete selection process can be seen in Fig. 2.

A. Damage Event Probability, $p(dmg, ev|s_i, \mathbf{x}_i)$

The criticality of intersection-related traffic situations is understood as combination of a critical *event* happening and the associated event *damage* occurring. We define the term *event* as a point in time where a critical configuration of scene entities is present. In the most extreme case this might be the physical collision of two scene entities or it can correspond to the violation of a minimal defined distance d_{min}, between two scene entities. For the collision example, the event *damage* would be a measure for rating the severity of the collision.

As the assessment of traffic scenes is usually affected by uncertainties, the created models must be able to cope with these. Therefore, we treat the problem in a probabilistic manner, by calculating the joint probability $p(dmg, ev|s_i, \mathbf{x}_i)$, indicating a specific event and damage occuring simultane-

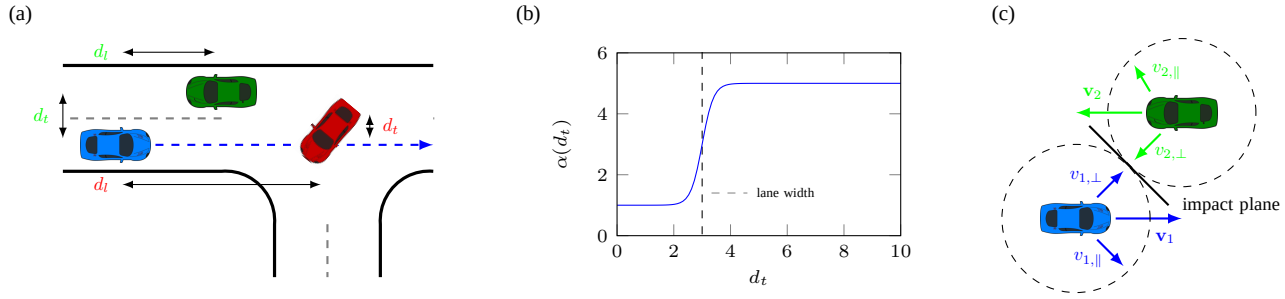

Fig. 3: (a) Separation of d into a transversal and longitudinal part, with respect to the ego vehicle's intended path; (b) a sigmoidal function $\alpha(d_t)$ for the scaling of d_t; (c) partially inelastic impact example.

ously. It can be further divided according to

$$p(dmg, ev|s_i, \mathbf{x}_i) = p(dmg|ev, \mathbf{x}_i)p(ev|s_i, \mathbf{x}_i). \quad (3)$$

The first term, $p(dmg|ev, \mathbf{x}_i)$, models the damage probability conditioned on a specific event and the current scene information $\mathbf{x}_i$. In addition, $p(ev|s_i, \mathbf{x}_i)$ models the probability of an event actually happening, dependent on specific assumptions on a situation s_i and the current scene information $\mathbf{x}_i$.

1) Event Probability Model, $p(ev|s_i, \mathbf{x}_i)$: An event is a critical configuration of one or more scene entities. In this paper we focus on collision events. These are modeled based on the distance between two scene entities, compared to a minimum desired distance d_{min}. According to [12] we model the instantaneous event rate, which we interpret as the probability of the critical event actually happening, using an exponential function

$$p(ev|s_i, \mathbf{x}_i) = \min(e^{-\beta_d(d-d_{min})}, 1), \quad (4)$$

where d represents the current distance between two scene entities. β_d models the steepness of the event probability with decreasing distance, which can be used to incorporate sensor measurement uncertainties.

However, a purely spatial distance based criticality assessment is not sufficient to model the subjectively experienced criticality of human drivers. For example, a human driver is able to confidently pass forthcoming traffic, positioned on different lanes, with a relatively small spatial distance. This circumstance is mainly caused by two reasons. The transversal positioning along an intended path can be determined with relatively high confidence. To the contrary, the absolute longitudinal position, on that path, is relatively hard to determine, considering the high velocity in longitudinal direction. Additionally, the capability of a vehicle to suddenly change its transversal position is limited due to non-holonomic constraints.

In order to incorporate these assumptions into our event probability model, the introduced distance measure is divided into a longitudinal and transversal part

$$d = \sqrt{d_t^2 + d_l^2}, \quad (5)$$

with respect to the ego vehicle intended path. The longitudinal part d_l corresponds to the distance between ego and other traffic participant along the ego vehicle's intended path. The transversal distance d_t corresponds to the shortest, orthogonally projected distance from the traffic participants position to the ego vehicle's intended path. An explanation of these two distances can be found in Fig. 3(a).

To take the addressed limitations into account we artificially overweight d_t, if the affecting vehicle is transversally not located within the lane of the ego vehicle's intended path. By doing so, we imply that the actually encountered distance, calculated according to (5), is larger than the physically measurable transversal distance between the two scene entities. The scaled transversal distance is calculated with

$$d_t' = \alpha(d_t)d_t, \quad (6)$$

where $\alpha(d_t)$ is a monotonous scaling function. Here, we chose a sigmoidal function, as shown in Fig 3(b). The scaled overall distance is given by $\sqrt{d_t'^2 + d_l^2}$. The proposed scaling of d_t leads to a larger event probability $p(ev|s_i, \mathbf{x}_i)$ for the blue ego-car in combination with the red car compared to the combination with the green car, as seen in Fig. 3(a).

2) Damage Probability Model, $p(dmg|ev, \mathbf{x}_i)$: The damage probability, for the modeled collision event, is modeled as the probability for the ego vehicle's difference in pre- and post-collision velocities exceeding a critical value. This velocity difference is an essential factor for the severity of possible human injuries [19]. The velocity of a scene entity after colliding with another scene entity can be estimated using a partially elastic impact model. For this purpose, the velocity vectors $\mathbf{v}$, usually given in the spatial x, y-coordinate system, have to be separated into components orthogonal $v_\perp$ and parallel $v_\parallel$ to the impact plane. This is illustrated in Fig. 3(c). As the velocity component $v_\parallel$ remains unaffected, we focus on calculating $v_\perp'$ after a possible collision. It is determined by

$$v_{1,\perp}' = \frac{m_1 v_{1,\perp} + m_2 v_{2,\perp} - m_2(v_{1,\perp} - v_{2,\perp})C_R}{m_1 + m_2}. \quad (7)$$

The indices $_1$ and $_2$ address the respective traffic participants' velocities and masses m. The coefficient of restitution $C_R \in [0, 1]$ indicates the elasticity of a collision. For an inelastic collision C_R is equal to 1, whereas $C_R = 0$ describes a completely elastic collision.

After obtaining the post-collision velocity, we can calculate the velocity difference

$$\Delta v_{col} = |v_{1,\perp} - v'_{1,\perp}|, \tag{8}$$

The instantaneous damage rate, which we interpret as the damage probability, is quantified using an exponential function resulting in

$$p(dmg|ev, \mathbf{x}_i) = \min(e^{-\beta_v(\Delta v_{max} - \Delta v_{col})}, 1), \tag{9}$$

where Δv_{max} specifies a critical velocity difference. β_v can be used to control the steepness of damage probability increase. [1]

B. Estimation of $p(dmg, ev|s_i, \mathbf{x}_i)$

For the purpose of assessing the joint event damage probability of future events starting from time t_0, it is necessary to extensively simulate or to sample over possible future states $\mathbf{x}_{i,t}, t \in [t_0, t_{end}]$. This is in contrast to our objective of an efficient hypotheses selection scheme. Therefore, we propose to learn a situation-specific regression model M_i that is able to predict the maximum

$$\max_{t \in [t_0, t_{end}]} p(dmg, ev|s_i, \mathbf{x}_{i,t}) = M_i(\mathbf{x}'_i), \tag{10}$$

of the complete future temporal course of a situation, where $\mathbf{x}'_i$ specifies the input features for the regression model.

The data needed to learn a regression model for each prototypical situation could be obtained from several sources:

1) recorded real-world data of accidents and dangerous situations ([20]),
2) using a realistic, simulated traffic situation environment and intentionally provoking dangerous situations,
3) taking ordinary recorded driving data and manipulate it in order to take a different course ([14]).

The maximum event damage probability of each available example of prototypical situation i, as well as the features $\mathbf{x}'_i$, obtained from the scene information $\mathbf{x}_i$, leading up to the maximum, form the training data set $\mathcal{D}_i = \{(f_{j,i}, \mathbf{x}'_{j,i})_{j=1,2,...,p}\}$, containing p training examples. For the discussed example of detecting hazardous events, involving maneuver combinations of two traffic participants in an intersection-related context, we found that the **T**ime-**T**o-**I**ntersection (*TTI*) is a very expressive feature. It predicts the remaining time until a traffic participant will enter the intersection. Using the remaining distance to the intersection entry d_{int}, the current velocity v and acceleration a; it can be calculated by

$$TTI = \begin{cases} \frac{-v + \sqrt{v^2 + 2d_{int}a}}{a} & a \neq 0 \text{ or } a > -\frac{v^2}{2d_{int}} \\ \frac{d_{int}}{v} & \text{else.} \end{cases} \tag{11}$$

The feature vector $\mathbf{x}'_i$ is composed of

$$\mathbf{x}'_i = (TTI_1, TTI_2), \tag{12}$$

i. e. the *TTI* features of the ego vehicle $_1$ and the affecting traffic participant $_2$. The information the *TTI* features provide, combined with the implicit motion model adapted by the situation specific regression model, are used to estimate $p(dmg, ev|s_i, \mathbf{x}_i)$.

After specifying the data sets $\mathcal{D}_i$ the regression model can be learned. We choose a state-of-the art random forest regressor. Since random forests are fast and non-parametric, they are well suited for our problem, keeping the scalability of our approach in mind.

C. Situation Recognition, $p(s_i|\mathbf{y}_i)$

In order to calculate the $risk_i$ according to (2), the belief $p(s_i|\mathbf{y}_i)$ for each situation hypothesis is needed. This task corresponds to a straightforward situation recognition where the probability for situation hypothesis s_i to actually hold true is estimated based on available scene information $\mathbf{y}_i$, respectively feature vector. The modeled situations arising for intersection-related traffic scenarios are determined by the combination of possible maneuvers. Thus, the situation recognition is strongly related to estimating the upcoming maneuver $\mathcal{M}$ of each traffic participant. The ego vehicle has $\mathcal{M}_{1,k}$ with $k \in \{1, ..., l\}$ and the affecting vehicle has $\mathcal{M}_{2,q}$ with $q \in \{1, ..., m\}$ possible maneuvers. The probability of a situation s_i occurring is given by the joint probability of the particular maneuver combination $\{\mathcal{M}_{1,k}, \mathcal{M}_{2,q}\}$ as

$$p(s_i|\mathbf{y}_i) = \frac{p(\mathcal{M}_{1,k}, \mathcal{M}_{2,q}|\mathbf{y}_i)}{\sum_{k=1}^{l} \sum_{q=1}^{m} p(\mathcal{M}_{1,k}, \mathcal{M}_{2,q}|\mathbf{y}_i)}. \tag{13}$$

At this point we would like to express that no interactions between the ego vehicle and the affecting traffic participant are modeled. While it is a valid assumption that usually a driver tries to avoid risky situations, it should be kept in mind that our system is designed to determine the relevant situations for the ego vehicle's point of view. Assuming that the ego vehicle is already aware of possibly risky situations would make such a system unnecessary. However, incorporating this knowledge for the other traffic participant might be useful; to a certain degree.

Therefore, based on this independence assumption, the situation belief can be calculated using

$$p(s_i|\mathbf{y}_i) = \frac{p(\mathcal{M}_{1,k}|\mathbf{y}_{1,i}) p(\mathcal{M}_{2,q}|\mathbf{y}_{2,i})}{\sum_{k=1}^{l} \sum_{q=1}^{m} p(\mathcal{M}_{1,k}|\mathbf{y}_{1,i}) p(\mathcal{M}_{2,q}|\mathbf{y}_{2,i})}, \tag{14}$$

where $p(\mathcal{M}_{1,k}|\mathbf{y}_{1,i})$ corresponds to the probability of the ego vehicle performing maneuver k, given $\mathbf{y}_{1,i}$. Likewise $p(\mathcal{M}_{2,q}|\mathbf{y}_{2,i})$ corresponds to the probability of the affecting vehicle performing maneuver q, given $\mathbf{y}_{2,i}$, leading to

$$\mathbf{y}_i = (\mathbf{y}_{1,i}, \mathbf{y}_{2,i}). \tag{15}$$

In [5], an approach combining situation and kinematic behavior information to reliably distinguish several intentions is introduced. The kinematic behavior recognition is based on a logistic regression using the remaining distance to the

[1] For our tests, we chose the parameters to $\Delta v_{max} = 5\frac{m}{s}$, $\beta_v = 1$, $C_R = 0.15$, $d_{min} = 5m$ and $\beta_d = 0.2$. A situation is defined as relevant if $p(dmg, ev|s_i, \mathbf{x}_i) > 0.5$.

intersection d_{int} and the **A**nticipated **V**elocity at **S**top line (*AVS*), as input features.
We use the proposed behavior recognition using a logistic regression to calculate the individual maneuver probabilities. For each vehicle one model is trained containing the competing maneuver alternatives. The input features are modeled such that

$$\mathbf{y}_{1,i} = (d_{1,int}, AVS_1), \tag{16}$$

$$\mathbf{y}_{2,i} = (d_{2,int}, AVS_2). \tag{17}$$

Including situation-specific context information is omitted in this work, but could easily be added by e.g. including more advanced features like turning light information or gaze directions.

The belief calculation of (14) allows to incorporate prior knowledge of the ego vehicle's intended maneuver, if present, by simply adjusting the corresponding prior probabilities $p(s_i)$. This might be particular helpful in order to simplify the situation recognition in context of navigating systems or automated vehicles.

IV. EVALUATION

We evaluate our proposed hypotheses selection scheme using the prototypical situations arising from the ego vehicle approaching a 4-way intersection, while one other car is approaching the same intersection. Each vehicle has three maneuver options: turn right, turn left and go straight, like shown in Fig. 1. This results in 36 possible situation hypotheses, where each hypothesis corresponds to one maneuver combination. For the sake of simplicity, it is assumed that it can be securely determined from which side the affecting vehicle is approaching. This leads to a beforehand exclusion of not regarded situation hypotheses, resulting in nine remaining competing situation hypotheses in S. However, it could have been modeled probabilistically and incorporated in form of the prior $p(s_i)$, in (2).

In order to learn the parameters of the situation recognition and regression models a dataset is needed. Since no real-world dataset including recordings of accidents and especially dangerous situations is to our disposal, we simulate such situations.

In order to model these simulations as realistic as possible we adapted the driver model presented in [6] and used available map data (OpenStreetMap/OSM) of a real intersection. We enriched the OSM data with estimated curvatures, for obtaining possible paths for each maneuver. The driver model takes the curvature of the intended path into account in order to adapt a car's velocity such that a maximum lateral acceleration is not exceeded. Through additional parameter variation, we obtain highly varying, realistic intersection approaches, for each individual car. The respective intersection entry points ($d_{1,int}, d_{2,int} = 0$) as well as the obtained velocity profiles can be seen in Fig. 4.

About 100 situations of each prototypical situation are simulated, randomly varying the start point of the ego vehicle and affecting vehicle, resulting in the dataset used for training the situation recognition and regression models.

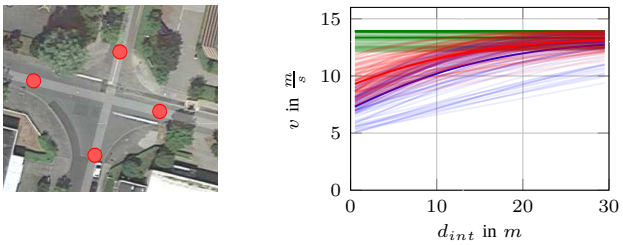

Fig. 4: Exemplary simulated velocity profiles for turn right, turn left and straight maneuvers, based on the shown intersection (Google, Aerowest) with respective intersection entry points.

A. Quantitative Evaluation

For the purpose of demonstrating the effectiveness of our approach, we perform a quantitative evaluation showing that our hypotheses selection scheme is able to efficiently select a set of relevant situation hypotheses $S_{r,est.}$. The created dataset is split situation-specific into training and test data, using a 10-fold cross validation. As we are striving for a system that recognizes the relevant situation early enough for an appropriate reaction, the hypotheses selection is performed $d_{1,int} = 40m$ before the ego vehicle enters the intersection, while the affecting vehicles are regarded within a range of $d_{2,int} \in [0, 40]m$.

We evaluate our approach comparing the ROC curves of the proposed hypotheses selection, combining situation belief and expected criticality with a purely situation belief based hypotheses selection. This selection is solely based on the determined situation probabilities $p(s_i|\mathbf{y}_i)$. However, to make a fairer comparison we exclude hypotheses from $\mathcal{S}$, (only) for the belief based hypotheses selection. Hypotheses are excluded that never lead to a critical situation, for this particular example intersection. E.g. for scenes where the affecting vehicle approaches from an opposite road segment, hypotheses for (straight, straight), (right, straight), (straight, right) and (right, right) are excluded; the first maneuver indicates the ego behavior.

The ROC curves are created by varying, on one hand the risk threshold γ for the risk ($risk_i > \gamma$); on the other hand the belief threshold γ_b from which a situation hypothesis is categorized as relevant ($p(s_i|\mathbf{y}_i) > \gamma_b$). We define a *true positive*, as each actual situation hypothesis s such that

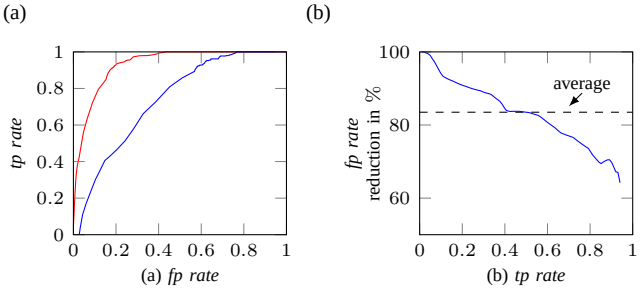

Fig. 5: ROC curve for the proposed hypotheses selection scheme (red), belief based selection (blue); Relative *fp rate* reduction in relation to belief based selection.

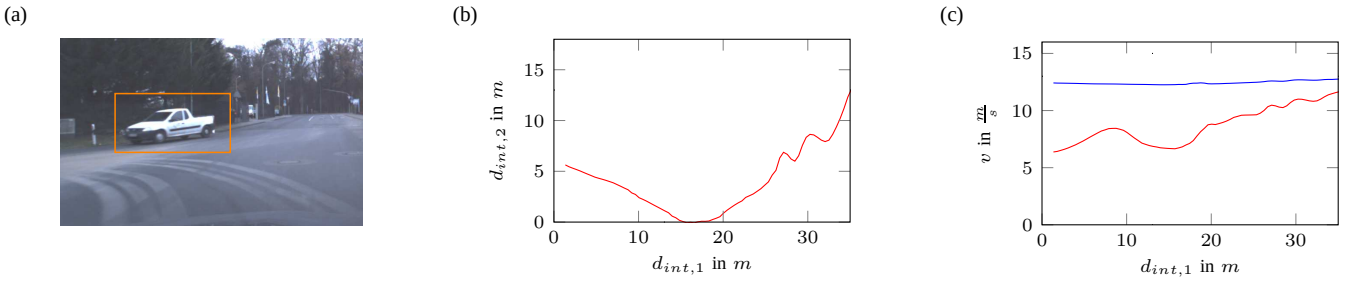

Fig. 6: (a) Affecting vehicle performing the right turn; (b) affecting vehicle's distance to intersection $d_{int,2}$ and velocity v_2 (red) and the ego vehicle's velocity v_1 (blue) (c).

$s \in S_r \wedge s \in S_{r,est.}$ A *false positive* is each identified situation hypothesis s such that $s \notin S_r \wedge s \in S_{r,est.}$. Based on this definition the *true positive (tp) rate* and *false positive (fp) rate* can be calculated according to [21].
Fig. 5(a) shows the comparison of the two obtained ROC curves. As it can be seen, using our proposed selection schemes the *fp rate* can be kept at a significantly lower level. These results are emphasized in 5(b), where the relative reduction of the proposed selection scheme's *fp rate*, compared to the belief based selection's *fp rate*, is shown. Additionally, it is indicated that the *fp rate* can on average be reduced by 83%.

One estimation of $S_{r,est}$, which includes estimating $risk_i$ and making a subsequent threshold detection for each available situation hypothesis s_i, takes less than $2ms$ in our unoptimized python implementation on one core of an Intel Core $i5$ with a maximum clock speed of $3.1Ghz$.

B. Real-World Evaluation Example

In order to test our approach on real-world data a not staged traffic scene is evaluated. The recordings were performed using a test car equipped with a forward facing laser-scanner and a consumer grade GPS. The vehicle state information is gathered from the CAN-Bus. Based on the relative distance and velocity, obtained from the laser-scanner, as well as the current ego vehicle's state, the absolute position and velocity of the affecting vehicle is determined. Fig 6 shows the velocity profiles (c) and the affecting vehicle's distance (b) to its intersection entrance point. In the analyzed example the ego vehicle crosses the intersection straight. The affecting vehicle approaches from the opposite road segment and performs a right turn. A picture of the scene, for $d_{1,int} \sim 0m$, can be seen in 6(a). The affecting vehicle can first be detected at $d_{1,int} \sim 35m$ and enters the intersection at $d_{1,int} \sim 18m$.

In Fig. 7 the detailed courses for the belief, criticality and overall estimated risk of each particular possible situation is shown. It can be seen that our proposed hypotheses selection scheme clearly identifies one possible situation hypothesis (s_2 (left, right)) as most risky situation. Taking a closer look at the velocity profiles this seems reasonable. Taking into account that the ego vehicle is performing a going straight maneuver, the velocity is comparatively slow, as seen in Fig. 6(c). Hence, it could easily be confused with a fast turn left maneuver. The affecting vehicle most likely performs a right turning maneuver. Assuming that the ego vehicle would in fact perform a fast turn left maneuver, the two cars would get very close to each other in the course of the scene. This circumstances are clearly represented in the curves of $p(s_2|\mathbf{y}_2)$ and $p(dmg, ev|s_2, \mathbf{x}_2)$. Therefore, identifying s_2 as the most relevant hypothesis is a reasonable choice.
It should be noted that these reasonable assessments are obtained using the selection scheme trained with our simulated dataset. This emphasizes the realistic conditions of our simulations.

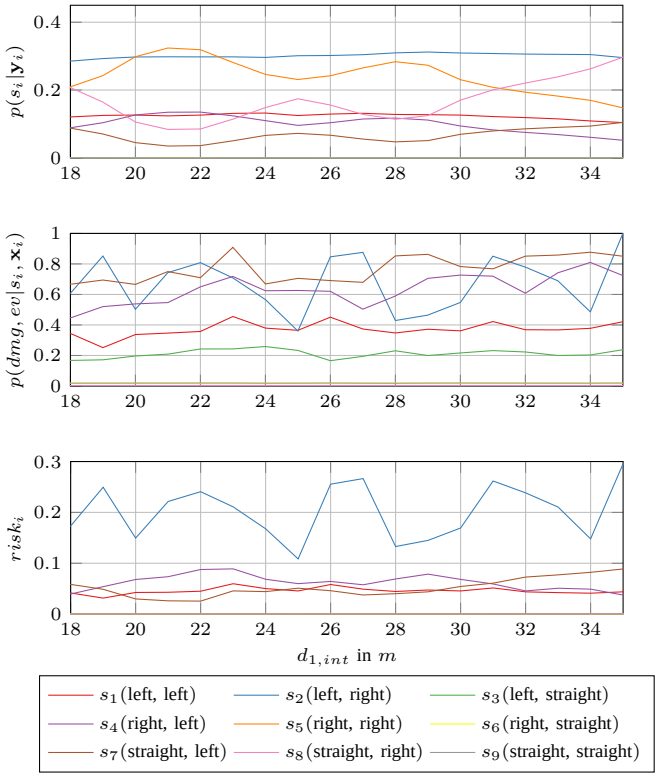

Fig. 7: Detailed courses for the belief $p(s_i|\mathbf{y}_i)$, the estimated criticality $p(dmg, ev|s_i, \mathbf{x}_i)$ and overall $risk_i$. (Curves corresponding to situations not seen in the plots are close to the x-axes)

Performing a full hypotheses selection for a prediction

horizon of $d_{1,int} = 30m$, leads to the hypotheses selected shown in Table I. We choose the detection thresholds γ and

	$risk_i > \gamma$	$p(s_i\|\mathbf{y}_i) > \gamma_b$
$S_{r,est}$	s_2 (left, right)	s_1 (left, left) s_2 (left, right) s_4 (right, left) s_7 (straight, left)
$\|S_{r,est}\|$	1	4

TABLE I: The selected situation hypotheses for a prediction horizon of $d_{1,int} = 30m$ ($t_{1,int} \approx 2.5s$) are shown.

γ_b, based on the evaluation performed in Section IV-A. They are set to values providing at least a *true positive rate* of 95% on the evaluated test set, for a hypotheses selection at $d_{1,int} = 40m$. Comparing the selected hypotheses, the number of superfluously selected hypotheses can be reduced by 75%.

V. CONCLUSION & FUTURE WORK

Given the combinatorics and variability of inner-city traffic scenarios an efficient hypotheses selection scheme, prior to elaborate risk assessment or path planning techniques, will be from great benefit. In this paper, we presented a general framework for dealing with this large number of possible occurring prototypical situations. We argue that is not sufficient to base the situation hypotheses selection solely on situation recognition, but it is important to take the behavioral relevance for the ego vehicle into account.

For the discussed intersection example, additionally to a probabilistic situation recognition, we introduce a new intersection related probabilistic criticality measure. In order to cope with the addressed scaling problems a regression method for efficiently predicting the possibly encountered maximum criticality, for each situation hypothesis, is presented. It should be noted that the models developed for the discussed example can be substituted by other probabilistic criticality measures and situation recognition systems, addressing different scenarios.

We showed that our hypotheses selection helps to efficiently reduces the number of superfluously regarded situation hypotheses, while keeping computational resources at a reasonable level. The *false positive rate* could be reduced, on average, by over 80%.

As a next step we are preparing more tests involving real-world data. Furthermore, we plan to incorporate methods for explicitly dealing with the uncertain prediction of the event damage probability, for the purpose of making a more robust decision. In order to demonstrate the effectiveness of our selection scheme we will increase the number of prototypical situations, including interactions emanating form other traffic participants.

REFERENCES

[1] K. C. Fuerstenberg and U. Lages, "New european approach for intersection safety - the ec-project intersafe," in *Intelligent Vehicle Symposium, 2005, Proceedings, IEEE*, June 2005, pp. 177–180.

[2] M. Althoff, O. Stursberg, and M. Buss, "Model-based probabilistic collision detection in autonomous driving," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 10, no. 2, pp. 299–310, June 2009.

[3] A. Houénou, P. Bonnifait, and V. Cherfaoui, "Risk assessment for collision avoidance systems," in *Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on*, Oct 2014, pp. 386–391.

[4] F. Damerow and J. Eggert, "Predictive risk maps," in *Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on*, Oct 2014, pp. 703–710.

[5] S. Klingelschmitt, M. Platho, H.-M. Gross, V. Willert, and J. Eggert, "Combining behavior and situation information for reliably estimating multiple intentions," in *Intelligent Vehicles Symposium Proceedings, 2014 IEEE*, June 2014, pp. 388–393.

[6] M. Liebner, F. Klanner, M. Baumann, C. Ruhhammer, and C. Stiller, "Velocity-based driver intent inference at urban intersections in the presence of preceding vehicles," *Intelligent Transportation Systems Magazine, IEEE*, vol. 5, no. 2, pp. 10–21, Summer 2013.

[7] M. Platho, H. Gross, and J. Eggert, "Traffic situation assessment by recognizing interrelated road users," in *Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on*, Sept 2012, pp. 1339–1344.

[8] R. Graf, H. Deusch, F. Seeliger, M. Fritzsche, and K. Dietmayer, "A learning concept for behavior prediction at intersections," in *Intelligent Vehicles Symposium Proceedings, 2014 IEEE*, June 2014, pp. 939–945.

[9] A. Armand, D. Filliat, and J. Ibañez-Guzmán, "Ontology-based context awareness for driving assistance systems," in *Intelligent Vehicles Symposium Proceedings, 2014 IEEE*, June 2014, pp. 227–233.

[10] R. Kohlhaas, T. Bittner, T. Schamm, and J. Zollner, "Semantic state space for high-level maneuver planning in structured traffic scenes," in *Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on*, Oct 2014, pp. 1060–1065.

[11] S. Lefèvre, D. Vasquez, and C. Laugier, "A survey on motion prediction and risk assessment for intelligent vehicles," *ROBOMECH Journal*, vol. 1, no. 1, 2014. [Online]. Available: http://dx.doi.org/10.1186/s40648-014-0001-z

[12] J. Eggert, "Predictive risk estimation for intelligent adas functions," in *Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on*, Oct 2014, pp. 711–718.

[13] M. Schreier, V. Willert, and J. Adamy, "Bayesian, maneuver-based, long-term trajectory prediction and criticality assessment for driver assistance systems," in *Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on*, Oct 2014, pp. 334–341.

[14] E. Käfer, C. Hermes, C. Wöhler, H. Ritter, and F. Kummert, "Recognition of situation classes at road intersections," in *Robotics and Automation (ICRA), 2010 IEEE International Conference on*, May 2010, pp. 3960–3965.

[15] S. Lefèvre, C. Laugier, and J. Ibañez-Guzmán, "Risk assessment at road intersections: Comparing intention and expectation," in *Intelligent Vehicles Symposium (IV), 2012 IEEE*, June 2012, pp. 165–171.

[16] G. Aoude, B. Luders, K. Lee, D. Levine, and J. How, "Threat assessment design for driver assistance system at intersections," in *Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on*, Sept 2010, pp. 1855–1862.

[17] J. Zhang and B. Roessler, "Situation analysis and adaptive risk assessment for intersection safety systems in advanced assisted driving," in *Autonome Mobile Systeme 2009*, ser. Informatik aktuell, R. Dillmann, J. Beyerer, C. Stiller, J. Zöllner, and T. Gindele, Eds. Springer Berlin Heidelberg, 2009, pp. 249–258.

[18] F. Seeliger, G. Weidl, D. Petrich, F. Naujoks, G. Breuel, A. Neukum, and K. Dietmayer, "Advisory warnings based on cooperative perception," in *Intelligent Vehicles Symposium Proceedings, 2014 IEEE*, June 2014, pp. 246–252.

[19] D. Richards, R. Cuerden, and G. Britain, *The relationship between speed and car driver injury severity*. Department for Transportation, 2009.

[20] G. Aoude, V. Desaraju, L. Stephens, and J. How, "Behavior classification algorithms at intersections and validation using naturalistic data," in *Intelligent Vehicles Symposium (IV), 2011 IEEE*, June 2011, pp. 601–606.

[21] T. Fawcett, "An introduction to roc analysis," *Pattern Recogn. Lett.*, vol. 27, no. 8, pp. 861–874, 2006.