Risk Assessment at Road Intersections: Comparing Intention and Expectation

Stéphanie Lefèvre, Christian Laugier, Javier Ibañez-Guzmán

Risk Assessment at Road Intersections: Comparing Intention and Expectation

Stéphanie Lefèvre, Christian Laugier, Javier Ibañez-Guzmán

Abstract— **Intersections are the most complex and hazardous areas of the road network, and 89% of accidents at intersection are caused by driver error. We focus on these accidents and propose a novel approach to risk assessment: in this work dangerous situations are identified by detecting conflicts between *intention* and *expectation*, i.e. between what drivers intend to do and what is expected of them. Our approach is formulated as a Bayesian inference problem where *intention* and *expectation* are estimated jointly for the vehicles converging to the same intersection. This work exploits the sharing of information between vehicles using V2V wireless communication links. The proposed solution was validated by field experiments using passenger vehicles. Results show the importance of taking into account interactions between vehicles when modeling intersection situations.**

I. Introduction

Intersection-related accidents account for 40-50% of road crashes in most countries, hence the interest shown by numerous safety improvement programs in the past ten years [1], [2], [3]. Statistical studies of the causes of accidents at intersections have shown that 89% of them are due to driver error. The most common errors are perception failures, situation misunderstanding, and wrong decision [4].

The potential for Vehicle-to-Vehicle (V2V) technologies to address these situations is considerable. The sharing of information between vehicles over wireless links allows a vehicle to perceive its environment beyond the limits of the field of views of its on-board sensors (e.g. cameras or radars). This allows for an enlarged representation of the environment which can be used to assist the driver in perceiving and analyzing the situation. This paper focuses on the application of these technologies to the problem of situation and risk assessment at road intersections.

The problem can be formulated as follows. Each vehicle collects information over time about its own state and that of other vehicles, through proprioceptive sensors and V2V communication links. In order to assess the situation and the risk associated to it, algorithms are needed that can infer relevant information from this uncertain and incomplete information. One difficulty is that intersection scenes are highly dynamic and involve complex interactions between vehicles. Therefore physical models of the motion of vehicles are valid only for a short term and are insufficient for anticipatory risk evaluation. Instead, algorithms are needed that can reason at a higher level (e.g. maneuver intention).

In this paper we propose a probabilistic framework for reasoning about situations and risks at road intersections based on a semantic analysis of traffic situations. Vehicle motion at road intersections is modeled using a Dynamic Bayesian Network. Inference is performed on selected variables to estimate *intention* (i.e. what a driver intends to do) and *expectation* (i.e. what a driver is expected to do) jointly for all the drivers in the scene. Subsequently dangerous situations are detected by comparing the two estimates.

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 describes our mathematical modeling of road intersection situations and our solution for risk assessment. Results from field trials using passenger vehicles equipped with off-the-shelf V2V communication links are presented and analyzed in Section 4.

II. Related work

A simple and intuitive approach is to define a set of rules which detect danger based on the context and on the current observations [5]. Because context is explicitly taken into account, the characteristics of the environment can easily be incorporated. However an established limitation of rule-based systems is their inability to account for uncertainties or to reason on a high-level basis about a situation.

An alternative is to learn collision patterns from data so that dangerous configurations can be identified when they occur at a later time. Data mining techniques can be used to map the relationship between vehicles states (input) and collision risk (output) directly. A neural network was used in [6], while the authors of [7] applied the Expectation-Maximization algorithm to cluster data. Obtaining the data to learn from remains an issue, since real data is not available and simulations will not reflect real accident situations.

By far the most popular approach to collision risk estimation is the "trajectory prediction + collision detection" approach. In the first step, future trajectories are predicted for the objects in the scene using a motion model. The second step consists in checking these trajectories for intersection points. Numerous algorithms rely on a physical model of vehicles to do that [8], [9], [10], but they are not able to reason on a high-level basis about a situation and therefore are limited to short-term collision prediction. Other approaches estimate the maneuver intention of the drivers to better predict trajectories in the long term. The authors of [11], [12] used an evolution of the Rapidly-exploring Random Tree algorithm to generate possible future

S. Lefèvre and C. Laugier are with Inria Grenoble Rhône-Alpes, 655 av. de l'Europe - Montbonnot, 38334 Saint Ismier Cedex, France, {stephanie.lefevre, christian.laugier}@inria.fr

S. Lefèvre and J. Ibañez-Guzmán are with Renault S.A.S., 1 av. du Golf, 78288 Guyancourt, France, {stephanie.lefevre, javier.ibanez-guzman}@renault.com

trajectories, after identifying maneuver intentions using a Support Vector Machine in [11] and Gaussian Processes in [12]. In [13] the maneuver intention is estimated using a Hierarchical Hidden Markov Model, and potential trajectories are modeled by Gaussian Processes. The first limitation of these methods is the computational cost of calculating all the possible trajectories and the pairwise probabilities that they intersect. The second one is that, in order to reduce the complexity, it is generally assumed that vehicles on different roads move independently from each other. As will be shown in Section III-A.1 and in Section IV, this assumption is not valid at intersections and affects an algorithm's ability to understand a situation and assess the risk.

III. Proposed approach

The proposed approach focuses on intersection accidents caused by driver errors (89% of all intersection accidents). We propose to estimate jointly what each driver is expected to do in the current situation and each driver's actual intention. Risk is computed as the probability that *expectation* and *intention* do not match. The mutual influence between vehicle maneuvers is accounted for, as well as the uncertainty of the information. The following paragraphs describe the proposed model for the modeling of traffic situations at road intersections, as well as its applications to risk estimation.

A. Context-aware scene representation

1) On the importance of context: Vehicles operate on the road network and are therefore strongly constrained by its layout (geometry, topology). Besides, vehicles share the road and therefore their actions are strongly tied with other vehicles. Current approaches to situation and risk assessment for vehicles generally do not account for these facts, and assume that vehicles evolve independently from each other in a mostly unconstrained environment. Fig. 1 illustrates why this assumption, when applied to road intersection scenes, can lead to misinterpretations. The situation is the following: the dark vehicle slowed down when approaching the intersection, and is currently stopped at the entrance of the intersection. If independence between vehicles is assumed, this behavior will be (incorrectly) interpreted as an intention to make a turn. The correct interpretation is that the driver intends to yield to the white vehicle, which has priority. A more detailed study of the limitations of the independence assumption at road intersections can be found in [14].

One challenge for representing traffic situations at road intersections is that the model should be comprehensive enough to represent complex dynamic situations such as the one described above, but inference on the relevant variables should still be tractable. With this goal in mind, the variables below are defined for a scene featuring N vehicles.

Fig. 1: Illustration of the importance of taking context into account.

2) Physical variables (observed): In this work the available observations are the position, heading, and speed of the vehicles. For each vehicle $n \in N$ at time t, an observation variable is defined as:

$$O_t^n = (P_t^n S_t^n), \ with$$

- $P_t^n = (X_t^n Y_t^n \theta_t^n) \in \mathbb{R}^3$: the pose (i.e. position and orientation w.r.t. a local frame),
- $S_t^n \in \mathbb{R}$: the speed.

For the experimental validation (see Section IV), this information originates from the vehicles' proprioceptive sensors and is shared via Vehicle-to-Vehicle communication (V2V). However, the method can be applied independently of the type of sensors that are used to observe the scene.

3) Behavioral variables (hidden): The selection of the higher-level variables for representing the situation is a crucial step; a trade-off has to be found between representational power and complexity. We exploit the fact that the road network is a structured environment that constrains the motion of the vehicles, and automatically extract from the map the set of authorized maneuvers and the traffic rules (stop, give way, etc.). We use an "exemplar paths" representation, as illustrated by Fig. 2. An exemplar path is defined for each authorized maneuver as the typical path that is followed by a vehicle executing that particular maneuver in the intersection. In addition, we define a "stop point" for each exemplar path, which delimits the approaching and execution phases of a maneuver. The stop point is located at the entrance of the intersection when there is a stop or give way line, and inside the intersection for left turn across oncoming traffic maneuvers. The exemplar paths and associated stop points can be either automatically generated from the map, or learned by applying a path clustering technique to recorded data [15], [16]. For each vehicle $n \in N$ at time t, a behavior variable is defined as:

$$B_t^n = (M_t^n D_t^n I_t^n), \ with$$

- $M_t^n \in \{m_i\}_{i=1:N_M}$: the maneuver intention of the driver, with $\{m_i\}_{i=1:N_M}$ the set of authorized maneu-

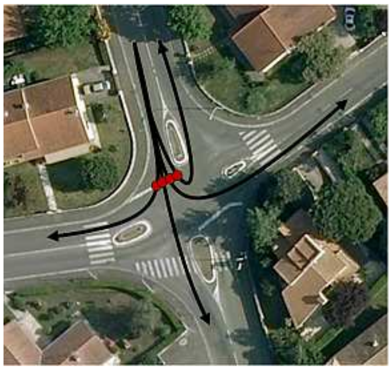

Fig. 2: Representation of a road intersection: the exemplar paths (black arrows) and associated stop points (red dots) originating from one road are displayed.

vers at the intersection of interest. For each maneuver, an exemplar path is defined (see Fig. 2).
- $D_t^n \in \mathbb{R}$: the distance traveled by the vehicle along the exemplar path of M_t^n, i.e. the curvilinear abscissa. D_t^n is negative when the vehicle has not yet reached the stop point, and positive after the vehicle passed the stop point.
- $I_t^n \in \{0,1\}$: the driver's intention to stop at the intersection (= *intention*).

4) Expectation variable (hidden): For each vehicle $n \in N$, the relevant traffic rules at time t are incorporated into the variable:
- $E_t^n \in \{0,1\}$: whether or not the driver is expected to stop at the intersection (= *expectation*).

For more clarity in the equations, in the remaining of this paper factored states will be used to represent the states of all the vehicles in the scene, e.g. $M_t = (M_t^1 ... M_t^N)$ (and similarly for all the variables defined above). We argue that $(M_t D_t I_t E_t)$ is a relevant high-level representation of a road intersection traffic situation, since inference on these variables allow to estimate key features of the situation. The remaining of this section introduces the proposed model for linking behavioral, observation and expectation variables, and how it can be used for risk assessment.

B. Dynamic scene modeling

In the following paragraphs, a Dynamic Bayesian Network (DBN) is described that links together the variables defined above in order to model the evolution of a traffic situation at a road intersection. The use of the Bayesian formalism allows us to take into account uncertainties on the relationships between the variables.

1) Joint distribution: The graphical representation of the DBN is shown for one vehicle in Fig. 3. For all the vehicles, the following local joint distribution can be derived:

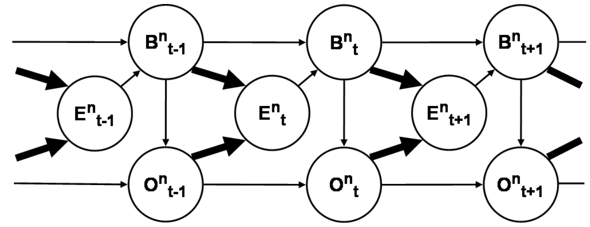

Fig. 3: Graphical representation of the DBN for one vehicle. Bold arcs correspond to multi-vehicle dependencies.

$$
\begin{aligned}
&P(E_{t-1}B_{t-1}O_{t-1}E_tB_tO_t)\\
&= P(E_{t-1}) \times P(B_{t-1}) \times P(O_{t-1})\\
&\times \prod_{n=0}^{N} P(E_t^n|B_{t-1}O_{t-1}) \times P(B_t^n|B_{t-1}^n E_t^n) \times P(O_t^n|O_{t-1}^n B_t^n)
\end{aligned}
$$

Further, we assume the following independencies:
- For the expectation variable:
  $P(E_t^n|B_{t-1}O_{t-1}) = P(E_t^n|M_{t-1}D_{t-1}S_{t-1})$
- For the behavioral variables:
  $P(B_t^n|B_{t-1}^n E_t^n) = P(M_t^n|M_{t-1}^n) \times P(I_t^n|I_{t-1}^n E_t^n) \times P(D_t^n|M_{t-1}^n D_{t-1}^n I_{t-1}^n)$
- For the physical variables:
  $P(O_t^n|O_{t-1}^n B_t^n) = P(P_t^n|M_t^n D_t^n) \times P(S_t^n|S_{t-1}^n M_t^n D_t^n I_t^n)$

By making I_t^n dependent of E_t^n, which itself depends on the other vehicles, we take into account the mutual influences between the maneuvers performed by the vehicles in the scene.
The parametric form of the conditional probability terms are described below, along with the hypotheses they build on.

2) Pose: The likelihood of a pose while executing maneuver m and being at distance d from the stop point is defined as a bivariate normal distribution with no correlation between the position and the orientation:

$$
P(P_t^n|[M_t^n = m][D_t^n = d]) = \frac{1}{2\pi\sigma_\delta\sigma_\alpha} \times e^{-\frac{1}{2}(\frac{\delta^2}{\sigma_\delta^2} + \frac{\alpha^2}{\sigma_\alpha^2})}
$$

where δ is the distance between the vehicle's position (x, y) and the point (x', y') with curvilinear abscissa d on the exemplar path of maneuver m, α is the angle between the vehicle's orientation θ and the orientation of the exemplar path at point (x', y'). σ_δ (resp. σ_α) is the standard deviation set for the distance (resp. the angle). They are set according to the precision of the pose sensor.

3) Speed: It is assumed that drivers adapt their speed to their intentions and to the geometry of the road. The distribution on S_t^n is normal and defined as:

$$
P(S_t^n|[S_{t-1}^n = s][M_t^n = m][D_t^n = d][I_t^n = i]) = \mathcal{N}(\mu_S, \sigma_S)
$$

with the calculation of μ_S detailed below.
A number of statistical analyses of the behavior of drivers approaching an intersection can be found in the literature, e.g. [17]. From these it is possible to derive generic speed

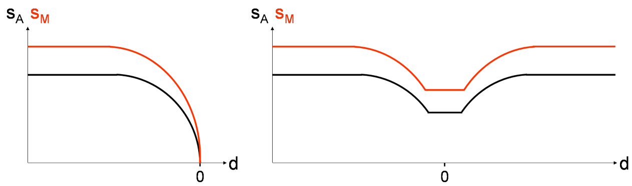

Fig. 4: Example average (s_A) and maximum (s_M) speed profiles generated for a pair ($M_t^n = m$, $I_t^n = 1$) (left) and for a pair ($M_t^n = m$, $I_t^n = 0$) (right). When $I_t^n = 0$, the lowest speed in the profile is a function of the curvature of the path associated with the maneuver m.

profiles for vehicles negotiating an intersection. We define $s_A = f(d)$ the average speed profile at the intersection and $s_M = f(d)$ the maximum speed profile (i.e. the highest speed at which it is possible to negotiate the intersection). Additionally we take into account the geometry of the road: for each possible pair (M_t^n, I_t^n), the generic speed profiles are adapted to match the constraints imposed by the curvature of the exemplar path. In Fig. 4 the general aspect of the speed profiles is shown. They serve as a basis for predicting the evolution of the speed of a vehicle given the driver's intention, following the equation:

$$\mu_S = s_A(d) - \frac{s_A(d) - s_M(d)}{s_A(d') - s_M(d')} \times (s_A(d') - s)$$

with d' the distance at the previous timestep calculated as $d' = d - s \times \Delta t$.

4) Distance to stop point: The distribution on D_t^n is normal and defined as:

$$P(D_t^n | M_{t-1}^n D_{t-1}^n I_{t-1}^n) = \mathcal{N}(\mu_D, \sigma_D)$$

where μ_D and σ_D are extracted from the speed profiles described in III-B.3.

5) Maneuver intention: Continuity in the maneuver intention is assumed.

$$P(M_t^n | M_{t-1}^n) = \begin{cases} 0.9 & if\ M_t^n = M_{t-1}^n \\ \frac{0.1}{N^M - 1} & otherwise \end{cases}$$

The value 0.9 was set manually and matches the authors' interpretation of "continuity in the maneuver intention", but should ideally be learned from data.

6) Expectation to stop: It is assumed that the necessity for a driver to stop at an intersection is a consequence of the context at time $t-1$ (priority rules, presence of other vehicles). The necessity for a vehicle to stop given the context is derived using probabilistic gap acceptance models found in [18], [19]. If we take as an example a vehicle v^n heading towards a give way intersection, the calculation is:

i. Project forward the position of v^n until the time t^n when it reaches the stop point of the maneuver. A constant speed model is used, with a combination of the vehicle's current speed and the average speed profile s_A of the maneuver.
ii. For each vehicle v^m whose maneuver is prioritary w.r.t. the maneuver of v^n, project forward the position of v^m until the time t^m when it reaches the stop point of the maneuver (following the same procedure as for v^n).
iii. Select the smallest positive time gap available for v^n to execute its maneuver:
$t_{min} = min_m(t^m - t^n),\ for\ t^m - t^n \geq 0$
iv. The necessity for v^n to stop at the intersection is calculated as the probability p_{stop} that the gap t_{min} is not sufficient, using a probabilistic gap acceptance model (from [18] for merging cases, from [19] for left turn across oncoming traffic cases):

$$\begin{cases} P([E_t^n = 0] | M_{t-1} D_{t-1} S_{t-1}) & = 1 - p_{stop} \\ P([E_t^n = 1] | M_{t-1} D_{t-1} S_{t-1}) & = p_{stop} \end{cases}$$

This context-aware reasoning about the necessity for a vehicle to stop at the intersection will allow us to detect vehicles running stop signs, or vehicles entering an intersection when they should have waited for another vehicle to pass. A similar calculation can be done for intersections ruled by traffic lights, but this is not the focus of this work.

7) Intention to stop: The evolution model for the driver's intention to stop is based on the comparison between I_{t-1}^n and E_t^n. If the driver's intention at time $t-1$ coincides with what is currently expected of him, it is assumed that chances are high that the driver will comply. Otherwise a uniform prior (0.5) is assumed.

$$P([I_t^n = 1] | I_{t-1}^n E_t^n) = \begin{cases} 0.9 & if\ I_{t-1}^n = E_t^n = 1 \\ 0.1 & if\ I_{t-1}^n = E_t^n = 0 \\ 0.5 & if\ I_{t-1}^n \neq E_t^n \end{cases}$$

The values 0.9 and 0.1 were set manually and match the authors' interpretation of "chances are high that the driver will comply", but should ideally be learned from data.
Results (see Section IV) show that this simple modeling of the interactions between vehicles leads to a better situation and risk estimation, compared with a constant uniform prior on I_t^n.

C. Bayesian risk assessment

Using the DBN described above, from the successive observations (pose and speed) it is possible to infer the intentions of the drivers as well as what they are expected to do. As an alternative to the conventional "trajectory prediction + collision check" approach to risk estimation, we propose to base the computation of the risk on the probability that *expectation* and *intention* do not match, i.e.:

$$P([I_t^n = 0][E_t^n = 1] | P_{0:t} S_{0:t}) \quad (1)$$

In this work inference was performed using a particle filter. The results presented in Section IV were obtained with 400 particles.

One advantage of this approach resides in its flexibility in terms of applications. An example of a safety-oriented application is the detection of hazardous vehicles: the system can compute a "hazard probability" for every vehicle in the scene using Eq. 1 and warn all the drivers in the intersection area when the probability is higher than a predefined threshold. Alternatively the model can be used to compute the risk of a specific maneuver for a vehicle, which is an important feature for autonomous driving. Another interesting aspect of the model is that it is predictive, therefore the future states of the vehicles can be estimated. The applications targeted by this paper do not exploit this feature, but it is relevant to numerous applications.

IV. Experimental evaluation

The objective is to evaluate the ability of the algorithm to assess the risk of a situation. The choice of an evaluation method is not trivial, since there exists no ground truth for the quantity "risk of a situation". A solution is to perform a comparative study between two algorithms, comparing the issuance time of warnings in dangerous situations and the frequency of false alarms in non-dangerous situations. Another relevant comparison is their ability to assess situations correctly, e.g. the maneuver intention of the drivers in the scene, for which the ground truth M_{GT} is available. We selected two versions of our algorithm to be compared :

- Proposed model: corresponds to the model described in Section III. Interactions between vehicles are accounted for in $P(I_t^n | I_{t-1}^n E_t^n)$.
- Reference model: corresponds to a modified version the model described in Section III. Independence is assumed between the vehicles in the scene by replacing $P(I_t^n | I_{t-1}^n E_t^n)$ by a uniform prior $P(I_t^n)$.

Comparing these two models will allow us to evaluate the benefits of taking into account vehicle interactions when performing situation and risk assessment at road intersections.

A. Experimental setup

Two passenger vehicles were equipped with off-the-shelf V2V communication modems (802.11p) and shared their pose and speed information at a rate of 10 Hz. In each vehicle the pose information was obtained via a GPS + IMU unit with a precision of $\sigma = 2m$ for the position. The CAN provided the speed information. In its current non-optimized state the algorithm runs at 10 Hz on a dedicated dual core 2.26 GHz processor PC.

Experiments were conducted at a give-way intersection. Five scenarios were defined, involving a Subject Vehicle (SV) driving on the main road and an Other Vehicle (OV) performing various maneuvers. They are illustrated in Fig. 5.

- Scenario 1: OV approaches on the secondary road and makes a right turn without stopping.
- Scenario 2: OV approaches on the secondary road, and proceeds to make a left turn when SV is about to reach the intersection.
- Scenario 3: OV approaches on the secondary road, stops at the give way line, waits until SV has passed and makes a left turn.
- Scenario 4: OV approaches on the main road from the opposite direction, stops in the intersection, and proceeds to make a left turn when SV is about to reach the intersection.
- Scenario 5: OV approaches on the main road from the opposite direction, stops in the intersection, waits until SV has passed and makes a left turn.

In the rest of this section we consider an application whose goal is to issue a warning whenever it detects that a situation is dangerous. A warning is triggered iff:

$$\exists n \in N : \ P([I_t^n = 0][E_t^n = 1] | P_{0:t} S_{0:t}) > \lambda$$

Scenarios 2 and 4 are *dangerous* scenarios where emergency braking is the only way to avoid an accident, therefore we expect the application to issue a warning as early as possible. Scenarios 1, 3 and 5 are *non-dangerous* scenarios where a warning would be considered a false alarm.

In total ninety trials were carried out, with five different drivers for OV. In order to generate some variations in the scenarios, the drivers of OV were not given clear instructions about the execution of the various maneuvers and were only told to create what they felt were *dangerous* and *non-dangerous* situations.

B. Qualitative results

In order to appreciate and understand the performance differences between the two models, it is useful to analyze the results on sample instances. To this end we display in Fig. 6 the estimation results for the maneuver intention of the drivers and for the probability that OV is dangerous in example instances of Scenarios 1, 2 and 3.

1) Scenario 1: In this scenario OV can execute his maneuver without considering SV since the vehicles always stay on different lanes.

$t_1 - t_2$: the model which assumes independence between the vehicles has no way to tell whether the intention of OV's driver is to turn right or left when he enters the intersection. Since executing a left turn maneuver at this time is clearly a violation of the priority rules, the probability of danger peaks at 0.5 for a short period before resuming to a lower value. The approach which models the influences between vehicle maneuvers favors the right turn as the most likely intention of the driver of OV, and as a result the probability of danger always remains lower than 0.2.

This difference has a direct consequence on the implementation of the application. The threshold λ has to be set with the double objective to issue a warning as early as possible in dangerous situations and to keep the rate of false alarms low. In the case of the Reference model, λ has to be set to a value higher than 0.5 in order to avoid systematic false alarms in

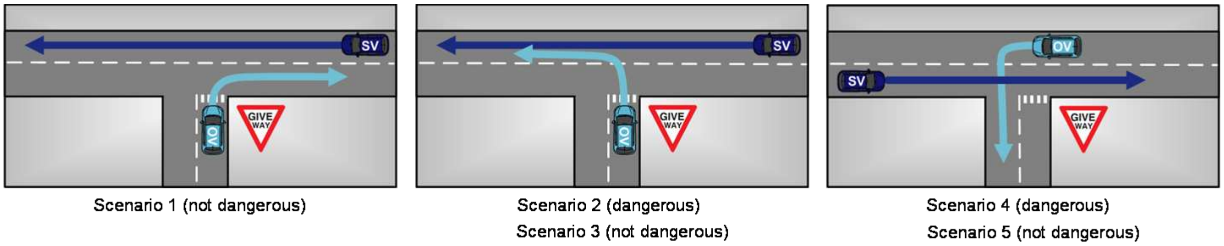

Fig. 5: Test scenarios.

situations like Scenario 1. In the case of the Proposed model, λ can be set to a much lower value. A statistical analysis of our results lead us to set $\lambda = 0.65$ for the Reference model and $\lambda = 0.3$ for the Proposed model.
This means that the sensitivity of the risk estimation [20] is significantly higher with the Proposed approach, since in dangerous situations the value of the risk varies in the range $[0.3\ 1.0]$, against $[0.65\ 1.0]$ with the Reference approach.

2) Scenario 2: In this scenario OV violates the priority, and without an emergency braking the situation would have resulted in a crash.
Using the values of λ defined in the previous paragraph, we can see that there is no difference between the two models on the time of issuance of the warning (t_3 on the graph).

3) Scenario 3: In this scenario both vehicles behave as expected given the priority rules and there is no danger.
Neither of the models produces a false alarm, however there is a noticeable difference in their ability to assess the situation correctly. Indeed, in the interval $t_4 - t_5$ the Proposed approach is able to interpret the behavior of OV (waiting at the entrance of the intersection while SV proceeds) as an indication that the driver's intention is to turn left. The Reference approach does not have this ability, since it assumes independence between the vehicles.

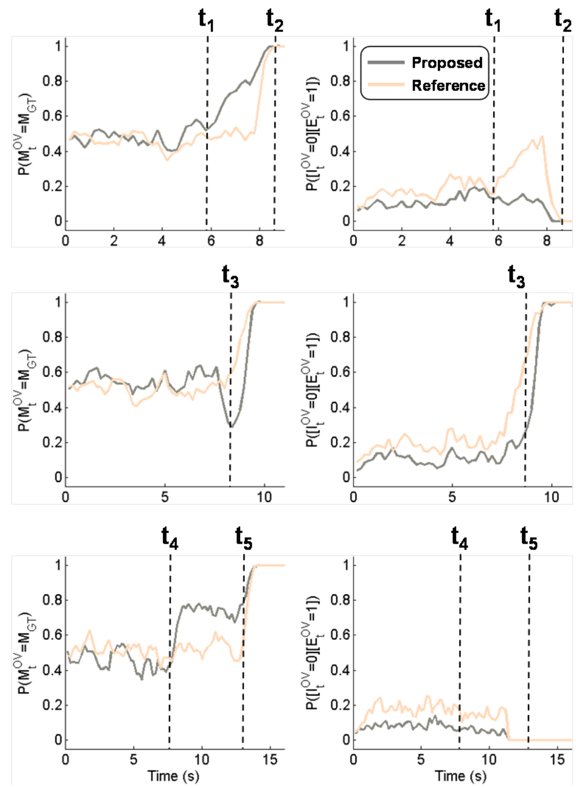

Fig. 6: Estimated maneuver intention of OV (left) and danger introduced by OV (right) in a sample instance of Scenario 1 (top), 2 (middle) and 3 (bottom).

C. Statistical results

We compute statistical results over the ninety test instances in order to verify if the differences observed on specific instances (see previous paragraph) can be generalized. The performances of the two models are measured by looking at their ability to:

- Correctly estimate the maneuver intention of the drivers: this is measured by $P(M_t = M_{GT})$.
- Correctly assess the situation in general: this will be reflected by N_{eff}, the effective sample size of the particle filter (divided by the number of particles so that a relative value is obtained).
- Correctly assess the risk. In the case of a dangerous situation, this means issuing a warning at time t_{warn} as early as possible. In the case of a non-dangerous situation the risk should not be overestimated: this feature can be evaluated by monitoring $\Delta P([I_t = 0][E_t = 1])$.

The performance differences $\Delta P(M_t = M_{GT})$, $\Delta Neff$, Δt_{warn} and $\Delta P([I_t = 0][E_t = 1])$ are calculated by subtracting the results obtained by the Reference model to the results obtained by the Proposed model. They are displayed for *dangerous* and *non-dangerous* situations in Fig. 7 and commented below.

1) Maneuver intention estimation: For dangerous situations, the two approaches perform similarly on average. When there is no danger, the two approaches are able to estimate the maneuver intention equally well 55% of the time. However the Proposed approach leads to a better estimation on average and performs better 40% of the time.

2) Neff: Accounting for the interactions between the vehicles has a positive and significant impact on N_{eff} both when the situation is dangerous and when it is not. In both cases the performance is increased 60% of the time and mostly equivalent the rest of the time. These results validate our modeling of vehicle interactions since the value of N_{eff}

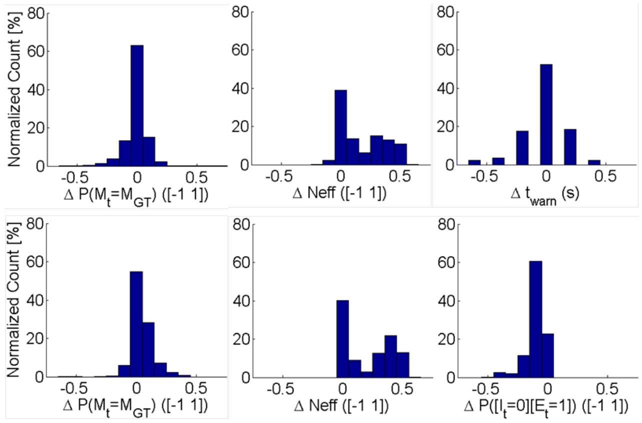

Fig. 7: Comparative results for *dangerous* (top) and *non-dangerous* (bottom) situations.

reflects the quality of the tracking, which itself is dependent on how well the model matches the reality.

3) Risk estimation: For every instance of a dangerous situation during the field trials, both approaches were able to issue a warning early enough that the collision was avoided by braking. In 55% of the cases the warning was issued at the exact the same time by the two approaches. When the situation was not dangerous, neither models produced any false alarm during the experiments. However, the plot of $\Delta P([I_t = 0][E_t = 1])$ shows that the risk is systematically higher when estimated using the Reference model.

V. Conclusions and future work

This paper presented a novel framework for reasoning about situations and risk at road intersections. The risk of a situation is assessed based on the comparison between what drivers intend to do and what they are expected to do. This intuitive formulation of risk provides a lot of flexibility for safety applications and is relevant to both ADAS and autonomous driving.

The approach was validated by field experiments in the context of communicating vehicles, using passenger cars and off-the-shelf V2V communication links. The results demonstrated the ability of the algorithm to issue a warning in dangerous situations, and the benefits of taking into account interactions between the vehicles when reasoning about situations and risk at road intersections.

In its current form the method may be applied to any intersection layout and any number of vehicles, but this was not demonstrated in this paper and will be evaluated in future work. The performance of the algorithm should also be compared with that of state-of-the-art works. Further, the estimation of drivers' intentions could be improved by taking into account information about drivers' actions such as steering angle and pedal pressure.

Acknowledgement

The authors would like to thank D. Vasquez and E. Mazer for useful discussions about the model.

References

[1] K. Fuerstenberg and B. Roessler, "Advanced intersection safety - the EC project INTERSAFE," in *Proc. IEEE Intelligent Vehicles Symposium*, 2006, pp. 89–93.

[2] M. Maile, F. Ahmed-Zaid, S. Bai, L. Caminiti, P. Mudalige, M. Peredo, and Z. Popovic, "Objective testing of a cooperative intersection collision avoidance system for traffic signal and stop sign violation," in *Proc. IEEE Intelligent Vehicles Symposium*, 2011, pp. 130–137.

[3] M. Sugimoto, K. Aoyama, D. Shimizu, and Y. Maekawa, "Realization of head-on collision warning system at intersections-DSSS: driving safety support systems," in *Proc. IEEE Intelligent Vehicles Symposium*, 2000, pp. 731–735.

[4] TRACE project, "Deliverable D2.2, Accident causation and pre-accidental driving situations - In-depth accident causation analysis," 2008.

[5] S. Worrall, D. Orchansky, F. Masson, and E. Nebot, "Improving vehicle safety using context based detection of risk," in *Proc. IEEE Intelligent Transportation Systems Conference*, 2010, pp. 379–385.

[6] A. Chinea and M. Parent, "Risk assessment algorithms based on recursive neural networks," in *Proc. International Joint Conference on Neural Networks*, 2007, pp. 1434–1440.

[7] F. D. Salim, S. W. Loke, A. Rakotonirainy, B. Srinivasan, and S. Krishnaswamy, "Collision pattern modeling and real-time collision detection at road intersections," in *Proc. IEEE Intelligent Transportation Systems Conference*, 2007, pp. 161–166.

[8] H.-S. Tan and J. Huang, "DGPS-based vehicle-to-vehicle cooperative collision warning: engineering feasibility viewpoints," *IEEE Transactions on Intelligent Transportation Systems*, vol. 7, no. 4, pp. 415–428, 2006.

[9] A. Eidehall and L. Petersson, "Statistical threat assessment for general road scenes using Monte Carlo sampling," *IEEE Transactions on Intelligent Transportation Systems*, vol. 9, no. 1, pp. 137–147, 2008.

[10] M. Brännström, E. Coelingh, and J. Sjöberg, "Model-based threat assessment for avoiding arbitrary vehicle collisions," *IEEE Transactions on Intelligent Transportation Systems*, vol. 11, no. 3, pp. 658–669, 2010.

[11] G. S. Aoude, B. D. Luders, K. K. H. Lee, D. S. Levine, and J. P. How, "Threat assessment design for driver assistance system at intersections," in *Proc. IEEE Intelligent Transportation Systems Conference*, 2010, pp. 25–30.

[12] G. Aoude, J. Joseph, N. Roy, and J. How, "Mobile agent trajectory prediction using bayesian nonparametric reachability trees," in *Proc. of AIAA Infotech@Aerospace*, 2011.

[13] C. Laugier, I. Paromtchik, M. Perrollaz, M. Yong, J. Yoder, C. Tay, K. Mekhnacha, and A. Negre, "Probabilistic analysis of dynamic scenes and collision risks assessment to improve driving safety," *IEEE Intelligent Transportation Systems Magazine*, vol. 3, no. 4, pp. 4–19, 2011.

[14] S. Lefèvre, C. Laugier, J. Ibañez-Guzmán, and P. Bessière, "Modelling dynamic scenes at unsignalised road intersections," INRIA Research Report 7604, April 2011.

[15] B. Morris and M. Trivedi, "Learning trajectory patterns by clustering: experimental studies and comparative evaluation," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, 2009, pp. 312–319.

[16] C. Hermes, C. Wohler, K. Schenk, and F. Kummert, "Long-term vehicle motion prediction," in *Proc. IEEE Intelligent Vehicles Symposium*, 2009, pp. 652–657.

[17] H. Berndt, S. Wender, and K. Dietmayer, "Driver braking behavior during intersection approaches and implications for warning strategies for driver assistant systems," in *Proc. IEEE Intelligent Vehicles Symposium*, 2007, pp. 245–251.

[18] M. A. Pollatschek, A. Polus, and M. Livneh, "A decision model for gap acceptance and capacity at intersections," *Transportation Research Part B: Methodological*, vol. 36, no. 7, pp. 649–663, 2002.

[19] C.-Y. Chan, "Characterization of driving behaviors based on field observation of intersection left-turn across-path scenarios," *IEEE Transactions on Intelligent Transportation Systems*, vol. 7, no. 3, pp. 322–331, 2006.

[20] A. Saltelli, "Sensitivity analysis for importance assessment," *Risk Analysis*, vol. 22, no. 3, pp. 579–590, 2002.