Intention-Aware Risk Estimation: Field Results

Stéphanie Lefèvre, Dizan Vasquez, Christian Laugier, Javier Ibañez-Guzmán

***Abstract*— This paper tackles the risk estimation problem from a new perspective: a framework is proposed for reasoning about traffic situations and collision risk at a semantic level, while classic approaches typically reason at a trajectory level. Risk is assessed by estimating the intentions of drivers and detecting conflicts between them, rather than by predicting the future trajectories of the vehicles and detecting collisions between them. More specifically, dangerous situations are identified by comparing what drivers intend to do with what they are expected to do according to the traffic rules. The reasoning is performed in a probabilistic manner, in order to take into account sensor uncertainties and interpretation ambiguities.**

This framework can in theory be applied to any type of traffic situation; here we present its application to road intersections. The approach was validated with field trials using passenger vehicles equipped with Vehicle-to-Vehicle wireless communication modems. The results demonstrate that the algorithm is able to detect dangerous situations early and complies with real-time constraints.

I. Introduction

Active safety systems are increasingly present in commercial vehicles, as part of a global effort to make roads safer. The purpose of such systems is to avoid or mitigate accidents through driver warnings or direct actions on the commands of the vehicles (braking, steering). At an algorithmic level, active safety functions rely on four processing steps: detect and track relevant entities in the environment (object assessment step), establish the relationship between these entities for a better understanding of the situation (situation assessment step), estimate the level of danger of the current situation (risk assessment step), and decide on the best course of action in order to promote safety (decision making step) [1].

The contribution of this paper concerns the second step. While classic approaches evaluate the risk of a traffic situation by predicting the future trajectories of vehicles and detecting collisions between them, we propose to reason on risk at a semantic level. In the proposed framework, risk is assessed by estimating the intentions of drivers and detecting conflicts between them. Traffic rules are explicitly represented in our model, which makes it possible to estimate both what drivers intend to do and what they are expected to do. Conflicts are then identified by comparing *intentions* and *expectations*. This formulation of risk reflects the fact that most road accidents are caused by driver error [2], and has the advantage that it does not require to predict the future trajectories of vehicles.

S. Lefèvre, D. Vasquez, and C. Laugier are with Inria Grenoble Rhône-Alpes, 655 av. de l'Europe - Montbonnot, 38334 Saint Ismier Cedex, France, {stephanie.lefevre, alejandro-dizan.vasquez-govea, christian.laugier}@inria.fr. J. Ibañez-Guzmán is with Renault S.A.S., 1 av. du Golf, 78288 Guyancourt, France, javier.ibanez-guzman@renault.com

The remainder of this paper is organized as follows. Section II reviews related work. Section III describes the proposed approach for risk assessment for general traffic situations. Section IV describes the application of this general framework to road intersections. Section V presents results obtained in field trials with passenger vehicles negotiating a T-shaped give-way intersection.

II. Related work

By far the most popular approaches to risk estimation are based on trajectory prediction [3]. The idea is to use a motion model to predict the possible future trajectories of each vehicle in the scene, and then to look for intersections between pairs of trajectories to detect future collisions.

Extensive research has been conducted on trajectory prediction. The most common solution is to rely on purely physical models (dynamic or kinematic) of the motion of a vehicle [4], [5], [6], [7], [8], [9], however those cannot reason at a high level about the situation and therefore are limited to short-term collision prediction. Long-term prediction can be improved by reasoning at a maneuver level instead of a purely physical level, and by taking into account the constraints imposed by the road network on the motion of vehicles. One strategy is to first identify the maneuver intention of each driver and to then generate trajectories corresponding to that maneuver intention on the current road layout. For this purpose, Aoude et. al. [10] used a combination of Support Vector Machines and Bayesian Filtering for maneuver intention estimation, and Rapidly-exploring Random Trees for trajectory generation. As an alternative, Laugier et. al. [11] proposed to combine Hidden Markov Models and Gaussian Processes. Another solution is to use Monte-Carlo simulation to explore the different possible realizations of a maneuver by sampling on the input variables [12]. Other works propose integrated frameworks based on Markov State Space Models (MSSM) which explicitly represent the maneuver intention of drivers and allow the prediction of future trajectories without the need of a separate "maneuver intention estimation" step [13], [14], [15].

The main limitation of approaches based on trajectory prediction is their high computational cost. For advanced motion models, which take into account the local shape of the road layout and the dependencies between the motion of different vehicles, the cost of computing all the possible future trajectories and the probability that they intersect is not compatible with real-time safety applications. The classic solution to reduce the complexity and the computation time is to assume independence between vehicles. However this

978-1-4673-8029-4/15/$31.00

leads to misinterpretations of traffic situations and to an overestimation of the risk [16].

III. Proposed approach for general traffic situations

To the best of our knowledge, only two motion models have been proposed in the literature which take into account the mutual dependencies between the vehicles [13], [14]. Both are based on MSSMs and suffer from the limitations mentioned in the previous section, i.e. the cost of predicting trajectories using such models is prohibitive for real-time safety applications. As an alternative we propose an approach to risk estimation which is also based on MSSMs but does not rely on trajectory prediction to estimate the risk of a situation.

A. Principle and examples

We propose to detect dangerous situations by comparing *what drivers intend to do* with *what drivers are expected to do according to the traffic rules*.

Example 1. Vehicle A is following vehicle B on the highway, then vehicle B starts braking. In this situation the driver of vehicle A is expected to either adapt its speed to the new speed of vehicle B, or to change lanes. If the intention of the driver does not match the expectation, e.g. if the driver intends to keep the same speed, the situation becomes dangerous.

Example 2. Vehicle A is approaching a give-way intersection, vehicle B is approaching the same intersection and has the right-of-way. In this situation the driver of vehicle A is expected to yield to vehicle B if the time gap before vehicle B reaches the intersection is too short for vehicle A to execute its maneuver. If the intention of the driver does not match the expectation, e.g. if the driver intends to proceed in the intersection while the time gap is too short, the situation becomes dangerous.

This approach to risk assessment reflects the fact that most road accidents are caused by driver error [2], and matches the intuitive notion that "dangerous" situations are situations where drivers act differently from what is expected of them.

B. Implementation

As explained above, the proposed approach relies on the estimation of:

1) The maneuver that a driver intends to perform
2) The maneuver that is expected of the driver

The former is already explicitly represented as a variable in the classic MSSM. The latter is implicitly encoded in the classic MSSM, in the multi-vehicle dependencies. In the proposed MSSM, what is expected of the driver is made explicit by defining an additional variable. The differences between the two models are illustrated graphically in Fig. 1 and Fig. 2, and explained in more detail below.

In the classic MSSM (Fig. 1), the motion of a vehicle is typically modeled based on three layers of abstraction:

- The highest level corresponds to the maneuver performed by the vehicle (e.g. overtake, turn right at the intersection). The variables at this level are discrete and hidden (not observable).
  We call I the conjunction of these variables. I_t^n therefore represents the maneuver being performed by vehicle n at time t. We call it I as "Intention", since the maneuver performed by a vehicle reflects the *intended maneuver* of the driver.
- This level corresponds to the physical state of the vehicle (e.g. position, speed). The variables at this level are hidden (not observable).
  We call Φ the conjunction of these variables. Φ_t^n therefore represents the *physical state* of vehicle n at time t.
- The lowest level corresponds to the measurements available (e.g. measurement of the vehicle's position). The variables at this level are observable. They often correspond to a noisy version of a subset of the physical variables.
  We call Z the conjunction of these variables. Z_t^n therefore represents the *measurements* of the state of vehicle n at time t.

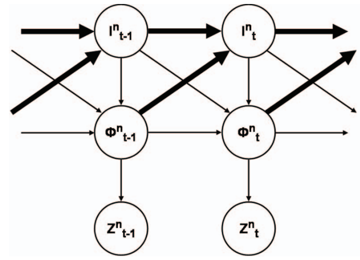

Fig. 1. Graphical representation of a classic MSSM. Bold arrows represent multi-vehicle dependencies, i.e. the influences of the other vehicles on vehicle n.

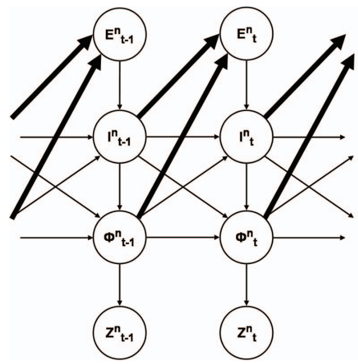

Fig. 2. Graphical representation of the proposed MSSM. Bold arrows represent multi-vehicle dependencies, i.e. the influences of the other vehicles on vehicle n.

In this model, what a driver is expected to do is implicitly encoded in the multi-vehicle dependencies: it is assumed that the current maneuver intention of the driver is dependent on the previous "situational context", i.e. on the maneuver intention and physical state of the other vehicles (see bold arrows in Fig. 1). For example, it is assumed that a vehicle driving on the highway will - with a high probability -

slow down or change lanes if the vehicle in front starts braking. Similarly, it is assumed that a driver approaching an intersection will - with a high probability - yield to vehicles with right-of-way.

In the proposed MSSM (Fig. 2), what a driver is expected to do is explicitly represented by the *expected maneuver* E_t^n. E_t^n is a conjunction of variables analogous to the intended maneuver I_t^n: every variable in the conjunction I_t^n has an equivalent in the conjunction E_t^n. As can be seen in the graph, the expected maneuver E_t^n is derived from the previous situational context and has an influence on the intended maneuver I_t^n.

In both the classic MSSM and the proposed MSSM, the dependencies between the vehicles are modeled by making the current intended maneuver I_t^n dependent on the previous "situational context". The difference is that the dependency is not direct in the proposed MSSM: the expected maneuver E_t^n is inserted as an intermediate. The previous "situational context" influences what the driver is expected to do, which in turn influences what the driver intends to do.

C. Applications

Modeling explicitly what is expected of a vehicle at time t, as proposed above, creates new possibilities for the estimation of the risk of a situation. Instead of using the MSSM to predict the future trajectories of the vehicles, we propose to use it to jointly infer what drivers currently intend to do (I_t) and what they are expected to do (E_t). The risk of a situation is computed based on the probability that *intention* and *expectation* do not match, given the measurements:

$$P([I_t^n \neq E_t^n]|Z_{0:t}) \tag{1}$$

Based on Eq. 1, a variety of safety-oriented applications can be derived.

1) Detection of hazardous vehicles: A "hazard probability" can be computed for every vehicle in the scene using Eq. 1. Subsequently, actions can be triggered depending on the value of the risk. An example ADAS application would be to warn all the drivers in the area when the risk is higher than a predefined threshold, i.e. if:

$$\exists n \in N : \; P([I_t^n \neq E_t^n]|Z_{0:t}) > \lambda \tag{2}$$

The warning message could be adapted to the level of danger, so that the driver is aware of the urgency of the situation. If autonomous braking is considered, the deceleration could be adapted to the risk value.

2) Risk of a specific maneuver: The risk of a specific maneuver I_t^n can be computed for a vehicle n:

$$P(\bigcup_{m=1}^{N} [I_t^m \neq E_t^m]|I_t^n Z_{0:t}) \tag{3}$$

This is an important feature for autonomous driving, but also for ADAS. One application is to find the best escape maneuver in a dangerous situation. Another one is to assist the driver for tasks such as changing lanes on the highway or negotiating an intersection by computing the risk of each possible maneuver and informing the driver about how safe each maneuver is.

3) Other applications: The proposed model can be used to estimate the intended maneuver of a driver, or to predict future trajectories. These are useful features for numerous applications which need to reason about traffic situations [17].

IV. Application to road intersections

The model presented in the previous section could in theory be applied to any traffic situations, by defining the variables I_t^n, E_t^n, Z_t^n, and Φ_t^n accordingly. This section presents its application to unsignalized road intersections, i.e. intersections ruled by anything but traffic lights (stop, give-way, priority to the right). More specifically we address accidents caused by traffic sign violations. Driver error in the lateral direction (such as hazardous lane changes) is not addressed in this work.

The description of the algorithm follows the Bayesian Programming formalism [18]: first the variables are defined, then the proposed joint distribution, the parametric forms, and finally the calculation of risk. This algorithm has been described in our previous publications [16], [19]; here the formulation has been modified to match the more general risk estimation framework presented in the previous section.

A. Variable definition

This section proposes definitions for the intended maneuver I_t^n, the expected maneuver E_t^n, the physical state Φ_t^n, and the measurements Z_t^n, in the context of road intersections.

1) Intended maneuver : As was mentioned above, the focus of this work is on errors in the longitudinal execution of the maneuver. Since we want to be able to reason on the lateral motion and on the longitudinal motion separately, we make a distinction between the lateral and longitudinal components of a maneuver in our specification of the intended maneuver I_t^n.

Lateral component: For the lateral component we exploit the fact that intersections are highly structured areas where the lateral motion of vehicles is constrained by the geometry and the topology of the intersection. It is assumed that a digital map of the road network is available. From this digital map we extract a set of "courses", where a course is defined for each authorized maneuver at the intersection as the typical path that is followed by a vehicle when executing that particular maneuver. The concept of a course is illustrated in Fig. 3. The variable representing the lateral component of a maneuver is defined as:

- $Ic_t^n \in \{c_i\}_{i=1:N_C}$: the driver's *intended lateral motion*, which will also be called the driver's *intended course* in the context of road intersections. It corresponds to the course followed by vehicle n at time t. $\{c_i\}_{i=1:N_C}$ is the set of possible courses at the intersection, extracted from the digital map.

Longitudinal component: For the longitudinal component we exploit the fact that intersections are highly structured areas where the longitudinal motion of vehicles is constrained by

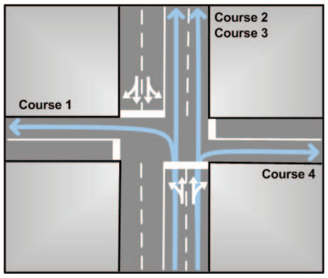

Fig. 3. Illustrative example for the "course" concept. The courses originating from one road are displayed as blue arrows.

the geometry and the topology of the intersection as well as by the traffic rules. For a vehicle n at time t we define two possible intentions with respect to the motion in the longitudinal direction: *go* and *stop*. The variable representing the longitudinal component of a maneuver is defined as:

- $Is_t^n \in \{go,\ stop\}$: the driver's *intended longitudinal motion*, which will also be called the driver's *intention to stop* in the context of road intersections. It corresponds to the driver's intention regarding the longitudinal execution of the maneuver.
  $Is_t^n = go$ means that the driver intends to adapt its speed to the layout of the intersection only. In other words, the driver intends to negotiate the intersection as if there were no constraints from the traffic rules (stop, give-way). This is typically the case for vehicles which have priority: drivers will adapt their speed to the topology and the geometry of the intersection (slowing down to make a turn) but will not slow down to stop or yield to another vehicle.
  $Is_t^n = stop$ means that the driver intends to adapt its speed to the layout of the intersection (similarly to $Is_t^n = go$), but will also adapt his speed so that he can stop at the intersection. Typically, this behavior will be adopted by vehicles approaching a stop intersection with the intention to respect the stop, and by vehicles which do not have the right-of-way and intend to yield to another vehicle.

2) Expected maneuver E_t^n: In the general framework presented in Section III, each variable in the conjunction I_t^n has an equivalent in the conjunction E_t^n. The purpose is twofold: to model the influences of the surrounding vehicles on the maneuver performed by a vehicle, and to compute the risk based on the probability that the expected maneuver and the intended maneuver do not match.

If this principle is applied to our problem, the expected maneuver E_t^n should contain two variables: the "expected lateral motion" (analogous to Ic_t^n) and the "expected longitudinal motion" (analogous to Is_t^n). However in our case it is not necessary to include an "expected lateral motion" variable, for two reasons. The first reason is that in the context of road intersections the dependencies between the vehicles mostly concern the longitudinal motion: whether a driver will stop or not at the intersection is influenced by the presence of other vehicles, but the course followed by a driver is not. Therefore it is reasonable to assume independence between the lateral motion of vehicles. The second reason is that, as mentioned earlier, this work addresses risks in the longitudinal direction only.

For a vehicle n at time t we define the following variable:

- $Es_t^n \in \{go,\ stop\}$: the *expected longitudinal motion*, which will also be called the *expectation to stop* in the context of road intersections. It corresponds to the expected longitudinal motion of the vehicle according to the traffic rules.
  The definitions of $Es_t^n = go$ and $Es_t^n = stop$ are analogous to the definitions provided for $Is_t^n = go$ and $Is_t^n = stop$ in the previous section; the only difference is that is corresponds to what the driver should do (according to the traffic rules) instead of what he intends to do:
  $Es_t^n = go$ means that the driver should adapt his speed to the layout of the intersection only.
  $Es_t^n = stop$ means that the driver should adapt his speed to the layout of the intersection, and should also adapt his speed so that he can stop at the intersection.

3) Measurements Z_t^n: In this work, the following measurements of the state of a vehicle $n \in N$ at time t are available:

- $Pm_t^n = (Xm_t^n Ym_t^n \theta m_t^n) \in \mathbb{R}^3$: the *measured pose*, i.e. the position and orientation of the vehicle in the Universal Transverse Mercator (UTM) coordinate system.
- $Sm_t^n \in \mathbb{R}$: the *measured speed* of the vehicle.

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

4) Physical state Φ_t^n: Based on the available measurements (see previous section), the following variables are selected to represent the physical state of a vehicle $n \in N$ at time t:

- $P_t^n = (X_t^n Y_t^n \theta_t^n) \in \mathbb{R}^3$: the *true pose* of the vehicle.
- $S_t^n \in \mathbb{R}$: the *true speed* of the vehicle.

5) Summary and notations: The variables of our MSSM were defined by adapting the general model proposed in Section III to the context of road intersections. The following variables were defined for a vehicle $n \in N$ at time t:

- For the intended maneuver: $I_t^n = (Ic_t^n Is_t^n)$
- For the expected maneuver: $E_t^n = Es_t^n$
- For the measurements: $Z_t^n = (Pm_t^n Sm_t^n)$
- For the physical state: $\Phi_t^n = (P_t^n S_t^n)$

The variables Z_t^n and Φ_t^n were defined according to the measurements available, and the variables I_t^n and E_t^n were defined with the objective to detect dangerous situations at a road intersection by comparing driver *intention* and driver *expectation*.

In the next sections we carry on with the specification of the model, still following the Bayesian Programming formalism. For more clarity in the equations, in the remaining of this article a bold symbol will be used to represent the conjunction of variables for all the vehicles in the scene. For example, for a variable $\mathbf{X}$:

$$\mathbf{X} \triangleq (X^1 ... X^N) \tag{4}$$

with X^n the variable associated with vehicle n.

B. Joint distribution

For the general model proposed in Fig. 2, the joint distribution over all the vehicles is as follows:

$$\begin{aligned} &P(\mathbf{E_{0:T} I_{0:T} \Phi_{0:T} Z_{0:T}}) = P(\mathbf{E_0 I_0 \Phi_0 Z_0}) \\ &\times \prod_{t=1}^{T} \times \prod_{n=1}^{N} [P(E_t^n | \mathbf{I_{t-1} \Phi_{t-1}}) \times P(I_t^n | \Phi_{t-1}^n I_{t-1}^n E_t^n) \\ &\times P(\Phi_t^n | \Phi_{t-1}^n I_{t-1}^n I_t^n) \times P(Z_t^n | \Phi_t^n)] \end{aligned} \tag{5}$$

In this section we adapt this general model to road intersection situations, with the variables defined in the previous section. We start by making the following classic independence assumptions:

For the intended maneuver: The current intended lateral motion and intended longitudinal motion are conditionally independent given $(\Phi_{t-1}^n I_{t-1}^n E_t^n)$. Therefore the following simplification is obtained:

$$P(I_t^n | \Phi_{t-1}^n I_{t-1}^n E_t^n) = P(Ic_t^n | \Phi_{t-1}^n I_{t-1}^n E_t^n) \times P(Is_t^n | \Phi_{t-1}^n I_{t-1}^n E_t^n) \tag{6}$$

For the physical state: The current pose and current speed are conditionally independent given $(\Phi_{t-1}^n I_{t-1}^n I_t^n)$. Therefore the following simplification is obtained:

$$P(\Phi_t^n | \Phi_{t-1}^n I_{t-1}^n I_t^n) = P(P_t^n | \Phi_{t-1}^n I_{t-1}^n I_t^n) \times P(S_t^n | \Phi_{t-1}^n I_{t-1}^n I_t^n) \tag{7}$$

For the measurements: A classic sensor model is used, i.e. the measurements are conditionally independent given the physical quantities they are associated with. Therefore the following simplification is obtained:

$$P(Z_t^n | \Phi_t^n) = P(Pm_t^n | P_t^n) \times P(Sm_t^n | S_t^n) \tag{8}$$

After applying these independence assumptions, and taking into account that $E_t^n = Es_t^n$, the joint distribution (Eq. 5) becomes:

$$\begin{aligned} &P(\mathbf{E_{0:T} I_{0:T} \Phi_{0:T} Z_{0:T}}) = P(\mathbf{E_0 I_0 \Phi_0 Z_0}) \\ &\times \prod_{t=1}^{T} \times \prod_{n=1}^{N} [P(Es_t^n | \mathbf{I_{t-1} \Phi_{t-1}}) \\ &\times P(Ic_t^n | \Phi_{t-1}^n I_{t-1}^n Es_t^n) \times P(Is_t^n | \Phi_{t-1}^n I_{t-1}^n Es_t^n) \\ &\times P(P_t^n | \Phi_{t-1}^n I_{t-1}^n I_t^n) \times P(S_t^n | \Phi_{t-1}^n I_{t-1}^n I_t^n) \\ &\times P(Pm_t^n | P_t^n) \times P(Sm_t^n | S_t^n)] \end{aligned} \tag{9}$$

C. Parametric forms

In this section the parametric forms of the conditional probability terms in Eq. 9 are described, along with the hypotheses they build on.

1) Expected longitudinal motion Es_t^n: The expected longitudinal motion of a vehicle is derived from the previous intended course, pose and speed of all the vehicles in the scene:

$$P(Es_t^n | \mathbf{I_{t-1} \Phi_{t-1}}) = P(Es_t^n | \mathbf{Ic_{t-1} P_{t-1} S_{t-1}}) \tag{10}$$

What is expected of vehicles on the road is regulated by traffic rules, but a lot is left to the judgment of drivers. If we take as an example give-way intersections in France, the rules specify that the driver which does not have the right-of-way must "yield to vehicles driving on the other road(s) and make sure there is no danger before entering the intersection" [20]. There exists no formula to calculate whether it is legal or not for a driver to enter an intersection at time t in a specific context. Instead, our expectation model is based on typical driver behavior, i.e. on a statistical analysis of what drivers consider to be acceptable. The necessity for a vehicle to stop given the context is derived using probabilistic gap acceptance models [21], [22]:

$$\begin{aligned} &P([Es_t^n = stop] | [\mathbf{Ic_{t-1}} = \mathbf{c_{t-1}}][\mathbf{P_{t-1}} = \mathbf{p_{t-1}}][\mathbf{S_{t-1}} = \mathbf{s_{t-1}}]) \\ &= f(\mathbf{c_{t-1}},\ \mathbf{p_{t-1}},\ \mathbf{s_{t-1}}) \end{aligned} \tag{11}$$

with $\mathbf{c_{t-1}}$ the conjunction of courses for the N vehicles in the scene, $\mathbf{p_{t-1}}$ the conjunction of positions for the N vehicles in the scene, $\mathbf{s_{t-1}}$ the conjunction of speeds for the N vehicles in the scene, and f a function which computes the probability that the gap available for vehicle n to execute its maneuver is sufficient given the previous situational context $(\mathbf{c_{t-1}},\ \mathbf{p_{t-1}},\ \mathbf{s_{t-1}})$. For a vehicle n heading towards a give-way intersection, the calculation is detailed below:

i. Project forward (or backward) the position of vehicle n until the time t^n when it reaches the intersection, using the vehicle's previous state $(c_{t-1}^n,\ p_{t-1}^n,\ s_{t-1}^n)$ and a constant speed model.
ii. Let V_{ROW} be the set of vehicles whose maneuvers have the right-of-way w.r.t. the maneuver of vehicle n. For each vehicle $m \in V_{ROW}$ project forward (or backward) the position of vehicle m until the time t^m when it reaches the intersection, using the vehicle's previous state $(c_{t-1}^m,\ p_{t-1}^m,\ s_{t-1}^m)$ and a constant speed model.
iii. Find the vehicle $k \in V_{ROW}$ which is the most likely to cause vehicle n to stop, by finding the smallest positive time gap available for vehicle n to execute its maneuver:

$$\begin{cases} k & = \underset{m \in V_{ROW}}{\arg\min}\,(t^m - t^n),\ for\, t^m - t^n \geq 0 \\ g_{min} & = t^k - t^n \end{cases} \tag{12}$$

iv. The necessity for vehicle n to stop at the intersection is calculated as the probability that the gap g_{min} is not sufficient, using a probabilistic gap acceptance model ([21] for merging cases, [22] for left turn across path cases).

For a vehicle approaching a stop intersection the calculation is similar, except the probability that the vehicle is expected to stop is set to 1 until it reaches the intersection (i.e. $P([Es_t^n = stop]|\mathbf{Ic_{t-1}P_{t-1}S_{t-1}}) = 1$), and after that point the last two steps of the calculation above are used (i.e. steps 3 and 4).

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.

2) Intended longitudinal motion Is_t^n: A number of different strategies could be applied for the intended longitudinal motion model, to model drivers' habits in terms of compliance with traffic rules. In this work, the evolution model is based on the comparison between the previous intention Is_{t-1}^n and the current expectation Es_t^n:

$$P(Is_t^n|\Phi_{t-1}^n I_{t-1}^n Es_t^n) = P(Is_t^n|Is_{t-1}^n Es_t^n) \tag{13}$$

If the driver's intention at time $t-1$ coincides with what is currently expected of him, it is assumed that the driver will comply with a probability P_{comply}. Otherwise a uniform prior (0.5) is assumed:

Is_{t-1}^n	Es_t^n	$P([Is_t^n = go]\|Is_{t-1}^n Es_t^n)$
go	*go*	P_{comply}
go	*stop*	0.5
stop	*go*	0.5
stop	*stop*	$1.0 - P_{comply}$

The probability P_{comply} is set to $P_{comply} = 0.9$ to reflect our assumption that chances are high that the driver will comply, but ideally it should be learned from data.

3) Intended lateral motion Ic_t^n: In the general case of a vehicle driving from point A to point B on the road network, the lateral motion will change with time as one maneuver is performed after another. In this work the focus is on road intersections, and the possible lateral motions were defined as a set of possible courses. Courses cover the entire maneuver at the intersection (approaching phase + execution inside the intersection + exit phase), and there is no reason to believe that a driver will change his mind about the course he wants to follow. For this reason, it is assumed that the probability of a course at time t is dependent on the previous intended course only (Eq. 14) and that drivers keep the same intention between two timesteps with probability P_{same}, all the other courses being equally probable (Eq. 15).

$$P(Is_t^n|\Phi_{t-1}^n I_{t-1}^n Es_t^n) = P(Ic_t^n|Ic_{t-1}^n) \tag{14}$$

$$P([Ic_t^n = c_t^n]|[Ic_{t-1}^n = c_{t-1}^n]) = \begin{cases} P_{same} & if\ c_t^n = c_{t-1}^n \\ \frac{1.0 - P_{same}}{N_C - 1} & otherwise \end{cases} \tag{15}$$

The value of P_{same} was set manually to $P_{same} = 0.9$ to indicate that drivers rarely change their intended course, but should ideally be learned from data.

4) Pose P_t^n: It is assumed that a vehicle performing a maneuver will follow the course corresponding to that maneuver. The evolution of the pose of a vehicle is computed from its previous pose, previous speed, and current intended course:

$$P(P_t^n|\Phi_{t-1}^n I_t^n) = P(P_t^n|P_{t-1}^n S_{t-1}^n Ic_t^n) \tag{16}$$

The likelihood of a pose is defined as a trivariate normal distribution with no correlation between x, y and θ:

$$\begin{aligned} &P(P_t^n|[P_{t-1}^n = p_{t-1}^n][S_{t-1}^n = s_{t-1}^n][Ic_t^n = c_{t-1}^n]) \\ &= \mathcal{N}(\mu_{xy\theta}(p_{t-1}^n,\, s_{t-1}^n,\, c_{t-1}^n),\, \sigma_{xy\theta}) \end{aligned} \tag{17}$$

where $\mu_{xy\theta}(p_{t-1}^n, s_{t-1}^n, c_{t-1}^n)$ is a function which computes the mean pose $(\mu_x, \mu_y, \mu_\theta)$, and $\sigma_{xy\theta} = (\sigma_x, \sigma_y, \sigma_\theta)$ is the standard deviation.

The mean pose of the vehicle is computed from the previous pose, the previous speed, and the current maneuver intention as the average between two poses: the first one is obtained through a constant velocity model, the second one is obtained by projecting the first one orthogonally on the exemplar path. This average provides a compromise between the current pose of the vehicle and the "ideal" pose that the vehicle would have if following the exemplar path.

5) Speed S_t^n: It is assumed that drivers adapt their speed to their intentions and to the geometry of the road. The evolution of the speed of a vehicle is computed from its previous speed, previous pose, and current intended maneuver:

$$P(S_t^n|\Phi_{t-1}^n I_t^n) = P(S_t^n|S_{t-1}^n P_{t-1}^n Ic_t^n Is_t^n) \tag{18}$$

The distribution on S_t^n is assumed normal and defined as:

$$\begin{aligned} &P(S_t^n|[S_{t-1}^n = s_{t-1}^n][P_{t-1}^n = p_{t-1}^n][Ic_t^n = c_t^n][Is_t^n = is_t^n]) \\ &= \mathcal{N}(\mu_s(s_{t-1}^n,\, p_{t-1}^n,\, c_t^n,\, is_t^n),\, \sigma_s(s_{t-1}^n,\, p_{t-1}^n,\, c_t^n,\, is_t^n)) \end{aligned} \tag{19}$$

where $\mu_s(s_{t-1}^n, p_{t-1}^n, c_t^n, is_t^n)$ is a function which computes the mean speed and $\sigma_s(s_{t-1}^n, p_{t-1}^n, c_t^n, is_t^n)$ is a function which computes the standard deviation.

The mean speed is computed as a function of the previous speed, the previous pose, the current course intention, and the current intention to stop, using a set of typical speed profiles. These speed profiles are created based on generic speed profiles of vehicles negotiating intersections found in the literature [23]. These generic speed profiles are automatically modified in our algorithm to match the speed limit and the geometry of the intersection of interest (e.g. the speed is made dependent on the curvature of the course). Moreover the calculation of the mean speed accounts for some variations in the driving styles, by taking into account the previous speed of the vehicle s_{t-1}^n. The predicted speed profile will therefore adapt to "sporty" drivers as well as to more "relaxed" drivers.

6) Measured pose Pm_t^n: A classic sensor model is assumed, with a trivariate normal distribution centered on the true state and with no correlation between x, y and θ:

$$P(Pm_t^n|[P_t^n = p_t^n]) = \mathcal{N}(p_t^n,\, \sigma_{xy\theta}) \tag{20}$$

7) Measured speed Sm_t^n: A classic sensor model is assumed, with a normal distribution centered on the true state:

$$P(Sm_t^n|[S_t^n = s_t^n]) = \mathcal{N}(s_t^n, \sigma_s) \tag{21}$$

8) Summary: Throughout this section a number of independence assumptions were made. As a result the joint distribution in Eq. 9 becomes:

$$\begin{aligned}
&P(\mathbf{E_{0:T}I_{0:T}\Phi_{0:T}Z_{0:T}}) = P(\mathbf{E_0I_0\Phi_0Z_0}) \\
&\times \prod_{t=1}^{T} \times \prod_{n=1}^{N} [P(Es_t^n|\mathbf{Ic_{t-1}P_{t-1}S_{t-1}}) \\
&\times P(Ic_t^n|Ic_{t-1}^n) \times P(Is_t^n|Is_{t-1}^n Es_t^n) \\
&\times P(P_t^n|P_{t-1}^n S_{t-1}^n Ic_t^n) \times P(S_t^n|S_{t-1}^n P_{t-1}^n Ic_t^n Is_t^n) \\
&\times P(Pm_t^n|P_t^n) \times P(Sm_t^n|S_t^n)]
\end{aligned} \tag{22}$$

D. Bayesian risk estimation

The equation for risk estimation is given in Eq. 1 for general traffic situations. When applied to our problem, the principle of comparing *intention* and *expectation* leads to computing the risk based on the probability that a driver does not intend to stop at the intersection while he is expected to:

$$P([Is_t^n = go][Es_t^n = stop]|\mathbf{Pm_{0:t}Sm_{0:t}}) \tag{23}$$

Exact inference on such a non-linear non-Gaussian model is not tractable. Here, approximate inference is performed using the classic bootstrap filter [24]. For two vehicles, we found that a good compromise between computation time and quality of the estimation was achieved for a number of particles $N_{particles} = 400$.

V. Field Trials

A. Evaluation strategy

Evaluating the performance of risk assessment algorithms is not straightforward: the ground truth of the risk of a situation is not available, therefore the evaluation cannot be conducted on the output of the algorithm directly. Instead it is generally conducted at the "application" level by applying a threshold on the risk value to separate *dangerous* and *non-dangerous* situations. The algorithm is then evaluated based on:

1. The rate of false alarms, i.e. *non-dangerous* situations classified as *dangerous* by the algorithm
2. The rate of missed detections, i.e. *dangerous* situations classified as *non-dangerous* by the algorithm
3. The collision prediction horizon, i.e. how early the algorithm classifies the situation as *dangerous*

Throughout this section, *dangerous* and *non-dangerous* situations are classified using the "hazard probability" criterion introduced in Section III-C.1. The idea is to compute a "hazard probability" for every vehicle in the scene by comparing the driver's *intention* Is_t^n with the *expectation*

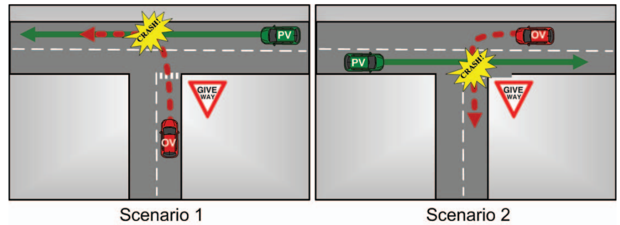

Fig. 4. Test scenarios for the field trials. For each scenario the maneuver of the Other Vehicle (OV) is shown in dotted red and the maneuver of the Priority Vehicle (PV) is shown in plain green.

Es_t^n. Subsequently a situation is classified as *dangerous* if the hazard probability is higher than a threshold for at least one vehicle, i.e. iff:

$$\exists n \in N : P([Is_t^n = go][Es_t^n = stop]|\mathbf{Pm_{0:t}Sm_{0:t}}) > \lambda \tag{24}$$

The threshold λ is set with the double objective to detect *dangerous* situations as early as possible and to avoid false alarms in *non-dangerous* situations. After a recall and precision analysis, $\lambda = 0.3$ was found to be the optimal value and was used in all the experiments.

B. Experimental setup

Two passenger vehicles were equipped with off-the-shelf Vehicle-to-Vehicle communication modems (802.11p) and shared their pose and speed information at a rate of 10 Hz. In each vehicle the pose and speed information was obtained via a GPS + IMU unit with a precision of $\sigma = 2m$ for the position. In its current non-optimized state the risk estimation algorithm runs at 10 Hz on a dedicated dual core 2.26 GHz processor PC. The test vehicles were not equipped with autonomous emergency braking functions. Instead, an auditory and a visual warning were triggered whenever the algorithm detected a *dangerous* situation.

C. Scenarios

Experiments were conducted at a T-shaped give-way intersection for two collision scenarios. The scenarios are illustrated in Fig. 4. All of them involve a Priority Vehicle (PV) driving on the main road and an Other Vehicle (OV) performing a *dangerous* maneuver. In these scenarios, emergency braking is the only way to avoid an accident, therefore we expect the application to issue a warning as early as possible.

Non-dangerous tests were also run, with the same configurations as in Fig. 4 but this time following the traffic laws.

In total 90 *dangerous* and 20 *non-dangerous* tests were run. We alternated between 6 different drivers both for the PV and the OV. In order to generate some diversity in the scenario instances, the drivers of the OV were not given precise instructions about the execution of the maneuvers; they were told to execute the maneuver in a manner that they felt was *dangerous* or *non-dangerous*. Out of the 90 *dangerous* trials, 60 were performed with the warning system running on the PV, and 30 running on the OV.

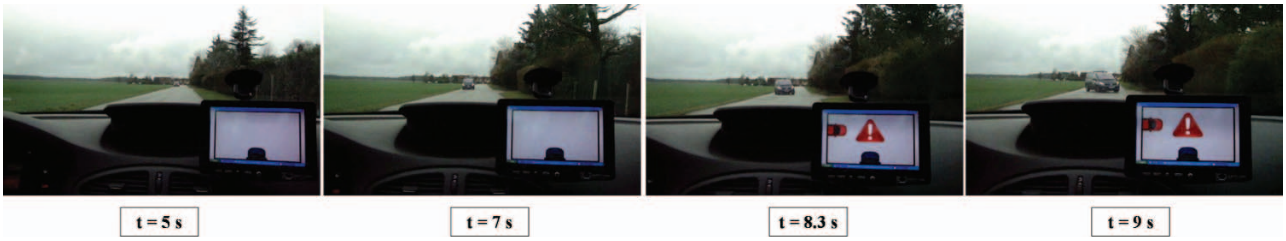

Fig. 5. *Dangerous* situation detected during the field trials (view from inside the Priority Vehicle).

D. Results

In the 20 *non-dangerous* tests there was no false alarm, i.e. no warning was ever triggered by the system.

For every of the 90 *dangerous* tests, the system was able to issue a warning early enough that the driver avoided the collision by braking. Fig. 5 shows a sample *dangerous* left turn across path scenario during which we recorded the view from inside the PV. The danger is detected as soon as the OV starts to execute the left turn. The driver of the PV receives a warning indicating that a *dangerous* situation was detected and that the danger comes from a vehicle on the left side.

Since we did not create real collisions, we could not perform a statistical analysis about the collision prediction horizon like was done in [16], [19]. However, the field trials demonstrated that our approach can operate with success in real-life situations where passenger vehicles share data via a Vehicle-to-Vehicle wireless link.

VI. Conclusions

In this paper a probabilistic framework was proposed to reason about the motion of vehicles and the associated risk in general traffic situations. The intentions of drivers are explicitly modeled, as well as what the traffic rules expect of drivers in the current situation. Risk is then computed as the probability that *intentions* and *expectations* do not match, given the available observations. As opposed to classic approaches relying on trajectory prediction, the proposed approach reasons about risk at a semantic level. As a result it can run in real-time without having to assume independence between vehicles. Tests were conducted with passenger vehicles equipped with off-the-shelf Vehicle-to-Vehicle communication modems at a T-shaped give-way intersection. The results show that the algorithm is able to detect dangerous situations in real-time for different types of collision scenarios.

References

[1] D. Hall and J. Llinas, "An introduction to multisensor data fusion," *Proceedings of the IEEE*, vol. 85, no. 1, pp. 6–23, 1997.

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

[3] S. Lefèvre *et al.*, "A survey on motion prediction and risk assessment for intelligent vehicles," *Robomech Journal*, vol. 1, no. 1, 2014.

[4] S. Ammoun and F. Nashashibi, "Real time trajectory prediction for collision risk estimation between vehicles," in *Proc. IEEE Intelligent Computer Communication and Processing*, 2009, pp. 417–422.

[5] M. Brännström *et al.*, "Model-based threat assessment for avoiding arbitrary vehicle collisions," *IEEE Transactions on Intelligent Transportation Systems*, vol. 11, no. 3, pp. 658–669, 2010.

[6] T. Batz *et al.*, "Recognition of dangerous situations within a cooperative group of vehicles," in *Proc. IEEE Intelligent Vehicles Symposium*, 2009, pp. 907–912.

[7] 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.

[8] J. Hillenbrand *et al.*, "A multilevel collision mitigation approach: situation assessment, decision making, and performance tradeoffs," *IEEE Transactions on Intelligent Transportation Systems*, vol. 7, no. 4, pp. 528–540, 2006.

[9] A. Polychronopoulos *et al.*, "Sensor fusion for predicting vehicles' path for collision avoidance systems," *IEEE Transactions on Intelligent Transportation Systems*, vol. 8, no. 3, pp. 549–562, 2007.

[10] G. S. Aoude *et al.*, "Threat assessment design for driver assistance system at intersections," in *Proc. IEEE Intelligent Transportation Systems Conference*, 2010, pp. 25–30.

[11] C. Laugier *et al.*, "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.

[12] M. Althoff and A. Mergel, "Comparison of Markov chain abstraction and Monte Carlo simulation for the safety assessment of autonomous cars," *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 4, pp. 1237–1247, 2011.

[13] G. Agamennoni *et al.*, "Estimation of multivehicle dynamics by considering contextual information," *IEEE Transactions on Robotics*, vol. 28, no. 4, pp. 855–870, 2012.

[14] T. Gindele *et al.*, "A probabilistic model for estimating driver behaviors and vehicle trajectories in traffic environments," in *Proc. IEEE Intelligent Transportation Systems Conference*, 2010, pp. 1625–1631.

[15] N. Oliver and A. P. Pentland, "Graphical models for driver behavior recognition in a SmartCar," in *Proc. IEEE Intelligent Vehicles Symposium*, 2000, pp. 7–12.

[16] S. Lefèvre *et al.*, "Risk assessment at road intersections: comparing intention and expectation," in *Proc. IEEE Intelligent Vehicles Symposium*, 2012, pp. 165–171.

[17] L. Fletcher *et al.*, "The MIT-Cornell collision and why it happened," *Journal of Field Robotics*, vol. 25, pp. 775–807, 2008.

[18] O. Lebeltel *et al.*, "Bayesian robot programming," *Autonomous Robots*, vol. 16, no. 1, pp. 49–79, 2004.

[19] S. Lefèvre *et al.*, "Evaluating risk at road intersections by detecting conflicting intentions," in *Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2012, pp. 4841–4846.

[20] "Code de la route français - Article R415-7," available at http://www.legifrance.gouv.fr.

[21] A. Spek *et al.*, "Intersection approach speed and accident probability," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 9, no. 2, pp. 155–171, 2006.

[22] D. R. Ragland *et al.*, "Gap acceptance for vehicles turning left across on-coming traffic: implications for intersection decision support design," in *Proc. Transportation Research Board Annual Meeting*, 2006.

[23] H. Berndt *et al.*, "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.

[24] M. S. Arulampalam *et al.*, "A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking," *IEEE Transactions on Signal Processing*, vol. 50, no. 2, pp. 174–188, 2002.