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Abstract: This work 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 about intentions and expectations 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 the specific case of road intersections. The proposed motion model takes into account the mutual influences between the maneuvers performed by vehicles at an intersection. It also incorporates information about the influence of the geometry and topology of the intersection on the behavior of a vehicle, and therefore can be applied to arbitrary intersection layouts. The approach was validated with field trials using passenger vehicles equipped with Vehicle-to-Vehicle wireless communication modems, and in simulation. The results demonstrate that the algorithm is able to detect dangerous situations early and complies with real-time constraints.

Key-words: Risk estimation, driver intention estimation, situational awareness, driver assistance systems, road intersection safety

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Méthode générale pour l'estimation du risque basée sur la comparaison d'intentions, et application aux intersections

Résumé : Ces travaux abordent le problème de l'estimation du risque sous un angle nouveau : nous proposons une structure de raisonnement pour analyser les scènes routières et le risque de collision à un niveau sémantique, contrairement aux approches classiques qui raisonnent au niveau des trajectoires. Le risque est calculé en estimant les intentions des conducteurs et en détectant les conflits, sans avoir à prédire les trajectoires futures des véhicules. Plus précisément, la détection des situations dangereuses est basée sur la comparaison entre ce que les conducteurs ont l'intention de faire et ce que les conducteurs devraient faire d'après les règles de la circulation. Ce raisonnement est réalisé de manière probabiliste afin de prendre en compte les incertitudes sur les mesures capteur et les ambigüités sur l'interprétation de la scène.

En théorie ce raisonnement peut être appliqué à tout type de scène routière ; dans ce document nous présentons son application aux intersections. Le modèle proposé prend en compte l'influence que la manœuvre d'un véhicule exerce sur la manœuvre des autres véhicules. Il incorpore aussi des informations sur l'influence de la géométrie et topologie de l'intersection sur le comportement d'un véhicule. L'approche proposée a été validée par des tests en environnement réel avec des véhicules communicants, ainsi qu'en simulation. Les résultats montrent que l'algorithme est capable de détecter les situations dangereuses et qu'il est compatible avec des applications sécuritaires temps-réel.

Mots-clés : Estimation du risque, estimation intention conducteur, compréhension de situation, systèmes d'aide à la conduite, sécurité aux intersections

1 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 current 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 work 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 novel 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.

The remainder of this report is organized as follows. Section 2 reviews related work. Section 3 describes the proposed approach for risk assessment for general traffic situations. Section 4 describes the application of this general framework to the specific case of road intersections. Section 5 presents results obtained in simulation for a two-way-stop cross intersection, and in field trials with passenger vehicles negotiating a T-shaped give-way intersection.

2 Related work

Risk estimation approaches can be classified in three main families.

2.1 Knowledge-Based Systems

An intuitive approach is to define a set of rules which detect danger based on the context and on the current observations of the state of the vehicles.

The rules can be simple heuristics on acceptable speeds in specific locations [3], or can include more advanced concepts such as the semantics of the location, weather conditions or the level of fatigue of the driver [4].

Because context is explicitly taken into account in KBS, they can be applied to a large number of scenarios. However an established limitation of these systems is their inability to account for uncertainties (both on the data and on the model), which results in instabilities in the output.

2.2 Data mining

An alternative is to use accident databases to learn typical collision patterns between two vehicles. This way potentially dangerous configurations can be identified when they occur again.

Neural Networks and Support Vector Machines have been used in the past to map the relationship between vehicles states (input) and collision risk (output) directly [5, 6].

However obtaining the data to learn from remains an issue, since real data is not available and simulations will not be representative of real accident situations. Another limitation is that these techniques learn collision patterns between pairs of vehicles without putting them in context with the other vehicles. Since the relationships between the different vehicles in the scene are not modeled, dangerous situations involving more than two vehicles will be detected very late (e.g. vehicle A preparing to overtake vehicle B, while vehicle C is driving on the same road but in the opposite direction).

2.3 Trajectory prediction

By far the most popular approaches to risk estimation are based on trajectory prediction. 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 [7, 8, 9, 10, 11, 12], 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. [13, 14] 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. [15] 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 [16]. 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 [17, 18, 19].

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 leads to misinterpretations of traffic situations and to an overestimation of the risk [20].

3 Proposed approach for general traffic situations

To our knowledge, only two motion models have been proposed in the literature which take into account the mutual dependencies between the vehicles [17, 18]. 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 risk estimation and incompatible with real-time safety applications. As an alternative we propose a novel approach to risk estimation which is also based on MSSMs but does not rely on trajectory prediction to estimate the risk of a situation.

3.1 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.*

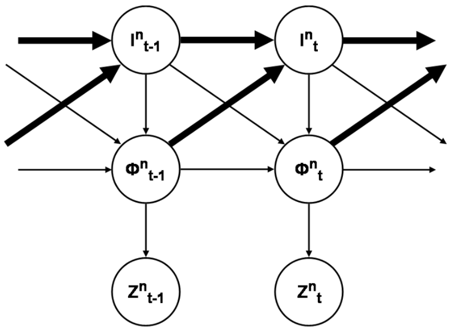


Figure 1: Graphical representation of a classic MSSM. Bold arrows represent multi-vehicle dependencies, i.e. the influences of the other vehicles on vehicle n.

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 novel 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 are acting differently from what is expected of them.

3.2 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.

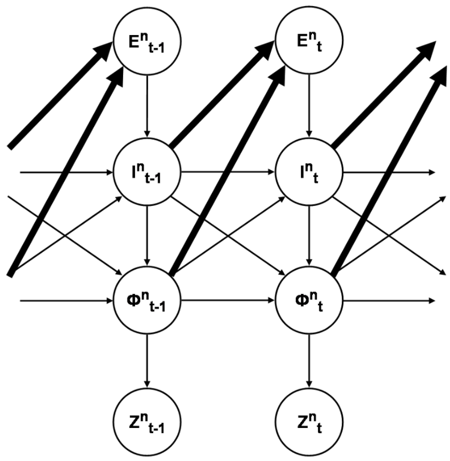


Figure 2: Graphical representation of the proposed MSSM. Bold arrows represent multi-vehicle dependencies, i.e. the influences of the other vehicles on vehicle n.

- 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.

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.

3.3 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.

3.3.1 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.

3.3.2 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.

3.3.3 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 [21].

4 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

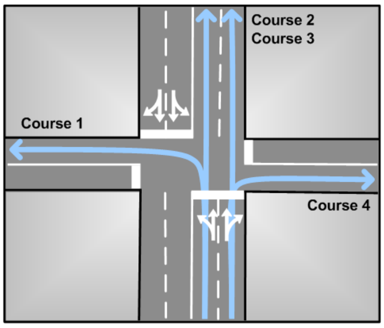


Figure 3: Illustrative example for the "course" concept. The courses originating from one road are displayed as blue arrows.

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 [22]: first the variables are defined, then the proposed joint distribution, the parametric forms, and finally the calculation of risk.

4.1 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.

4.1.1 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 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.

4.1.2 Expected maneuver E_t^n

In the general framework presented in Sec. 3, 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.

4.1.3 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 Sec. 5.3), 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.

4.1.4 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.

4.1.5 Summary and notations

The variables of our MSSM were defined by adapting the general model proposed in Sec. 3 to the context of road intersections. The following variables were defined for a vehicle $n \in N$ at time t:

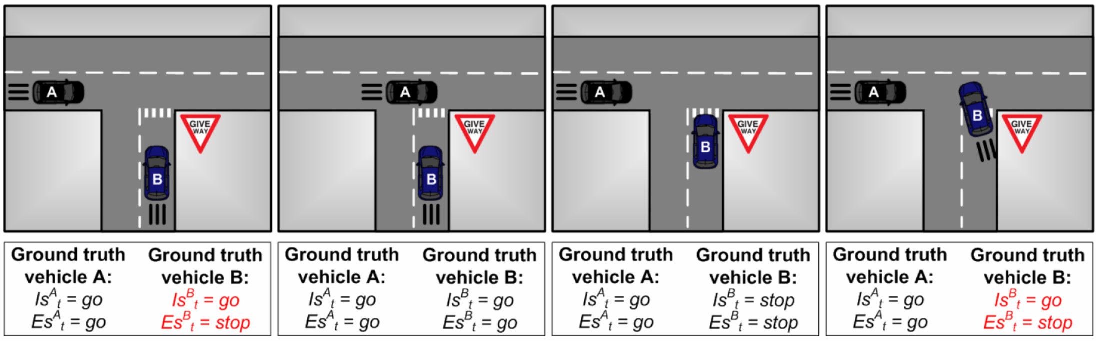
- For the intended maneuver: $I_t^n = (Ic_t^n Is_t^n)$
- For the expected maneuver: $E_t^n = Es_t^n$
- For the measurements: $Z_t^n = (Pm_t^n Sm_t^n)$
- For the physical state: $\Phi_t^n = (P_t^n S_t^n)$

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*, as illustrated in Fig. 4 with some example scenarios.

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 remainder of this report 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.



(a) Dangerous case: B should stop to yield to A, but does not intend to stop

(b) Non-dangerous case: B does not need to stop, and does not intend to stop

(c) Non-dangerous case: B should stop to yield to A, and is stopped

(d) Dangerous case: B should have stopped to yield to A, but proceeded instead

Figure 4: Detection of dangerous situations by comparing *intention* I_t^n and *expectation* E_t^n: example scenarios.

4.2 Joint distribution

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

$$\begin{aligned} &P(\mathbf{E_{0:T}I_{0:T}\Phi_{0:T}Z_{0:T}}) = P(\mathbf{E_0I_0\Phi_0Z_0}) \\ &\times \prod_{t=1}^{T} \times \prod_{n=1}^{N} \left[P(E_t^n|\mathbf{I_{t-1}\Phi_{t-1}}) \times P(I_t^n|\Phi_{t-1}^n I_{t-1}^n E_t^n) \right. \\ &\left. \times P(\Phi_t^n|\Phi_{t-1}^n I_{t-1}^n I_t^n) \times P(Z_t^n|\Phi_t^n) \right] \end{aligned} \tag{5}$$

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:

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

4.3 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.

4.3.1 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" [23]. 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 [24, 25]:

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

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 ([24] for merging cases, [25] 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 (as illustrated earlier in Fig. 4).

4.3.2 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.

4.3.3 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.

4.3.4 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.

4.3.5 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 $\mu_s(s^n_{t-1}, p^n_{t-1}, c^n_t, is^n_t)$ is a function which computes the mean speed and $\sigma_s(s^n_{t-1}, p^n_{t-1}, c^n_t, is^n_t)$ 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 [26]. 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^n_{t-1}. The predicted speed profile will therefore adapt to "sporty" drivers as well as to more "relaxed" drivers.

4.3.6 Measured pose Pm^n_t

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:

$$P(Pm^n_t|[P^n_t = p^n_t]) = \mathcal{N}(p^n_t,\ \sigma_{xy\theta}) \tag{20}$$

4.3.7 Measured speed Sm^n_t

A classic sensor model is assumed, with a normal distribution centered on the true state:

$$P(Sm^n_t|[S^n_t = s^n_t]) = \mathcal{N}(s^n_t,\ \sigma_s) \tag{21}$$

4.3.8 Summary

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

$$\begin{aligned}
&P(\mathbf{E_{0:T} I_{0:T} \Phi_{0:T} Z_{0:T}}) = P(\mathbf{E_0 I_0 \Phi_0 Z_0}) \\
&\times \prod_{t=1}^{T} \times \prod_{n=1}^{N} [P(Es^n_t|\mathbf{Ic_{t-1} P_{t-1} S_{t-1}}) \\
&\times P(Ic^n_t|Ic^n_{t-1}) \times P(Is^n_t|Is^n_{t-1} Es^n_t) \\
&\times P(P^n_t|P^n_{t-1} S^n_{t-1} Ic^n_t) \times P(S^n_t|S^n_{t-1} P^n_{t-1} Ic^n_t Is^n_t) \\
&\times P(Pm^n_t|P^n_t) \times P(Sm^n_t|S^n_t)]
\end{aligned} \tag{22}$$

4.4 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:

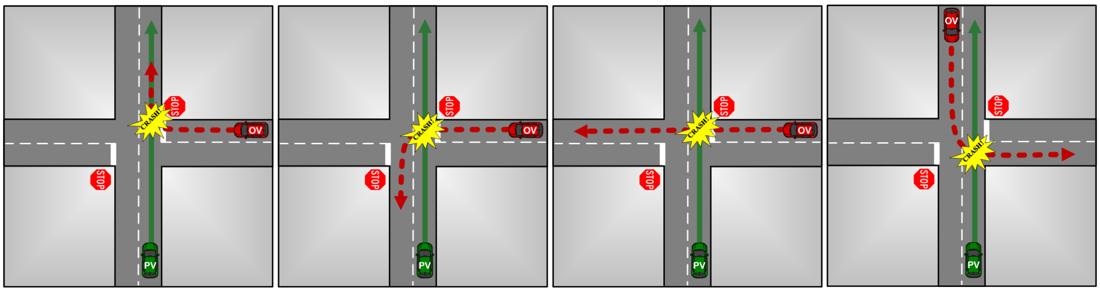


Figure 5: Simulated collision scenarios. For each scenario the maneuver of the Other Vehicle (OV) is shown in dotted red and the maneuver of the Priority Vehicle (PV) is shown in plain green. Collisions occur where the maneuvers intersect.

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

Exact inference on such a non-linear non-Gaussian model is not tractable. Here, approximate inference is performed using the classic bootstrap filter [27]. For two vehicles, we found that a good compromise between computation time and quality of the estimation was achieved for a number of particles $N_{particles} = 400$.

5 Results

5.1 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 before a collision the algorithm is able to classify the situation as *dangerous*. The collision prediction horizon $T_{prediction}$ is defined as:

$$T_{prediction} = t_{collision} - t_{detection} \tag{24}$$

with $t_{collision}$ the time at which the collision happens and $t_{detection}$ the earliest time when the situation is classified as *dangerous* by the algorithm.

Throughout this section, *dangerous* and *non-dangerous* situations are classified using the "hazard probability" criterion introduced in Sec. 3.3.1. 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* 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:

$$\exists n \in N : \ P([Is_t^n = go][Es_t^n = stop]|\mathbf{Pm_{0:t}Sm_{0:t}}) > \lambda \tag{25}$$

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.

Tests were run both in simulation and with real vehicles, and the results are reported in the next two sections.

5.2 Simulations

5.2.1 Scenarios

The approach was evaluated in simulation at a two-way stop intersection for seven collision scenarios. The scenarios are illustrated in Fig. 5. All of them involve a Priority Vehicle (PV) driving on the main road and an Other Vehicle (OV) performing a dangerous maneuver. These scenarios were selected because they cover 70% of all accident scenarios at road intersections in Europe [2]. Four maneuvers are considered for the OV: merging right, merging left, crossing, and left turn across path. For each of these maneuvers except for the last one, there is a priority violation scenario and a stop violation scenario. A priority violation scenario is a situation where the OV stops at the stop line but then proceeds into the intersection when it should have yielded to the PV, causing an accident[1]. A stop violation scenario is a situation where the OV does not stop at the stop sign, causing an accident[2]. There is no stop violation scenario for the left turn across path maneuver since the regulation does not require the OV to stop when executing this maneuver. A total of 240 instances of these scenarios were simulated, by varying the speed profiles of the OV and the synchronization between the trajectories of the two vehicles..

The same number of instances was simulated for equivalent *non-dangerous* scenarios. Trajectories were generated for the same configurations as in Fig. 5, this time without violating the traffic rules and with a safety distance of 3 seconds: the vehicles were always at least 3 seconds apart when passing the point where their paths intersected.

5.2.2 Results

There were no false alarms and no missed detections.

Collision prediction horizon: Fig. 6 shows the percentage of detected collisions as a function of the time remaining before the collision, for the 240 *dangerous* tests. The graph show that every collision in the dataset was predicted at least 0.6 s before it occurred, and that a majority of collisions were predicted between 2 s and 3 s ahead of time. In 80% of the cases the algorithm was able to predict collisions at least 2 s before they occurred. This opens possibilities for accident avoidance and mitigation, by triggering relevant actions on a vehicle after a danger has been detected [28].

[1]Such accidents are typically caused by the driver of the OV failing to notice the PV, or misjudging the speed and distance of the PV [2].

[2]Such accidents are typically caused by the driver of the OV failing to notice the presence of the stop sign, or choosing to ignore it [2].

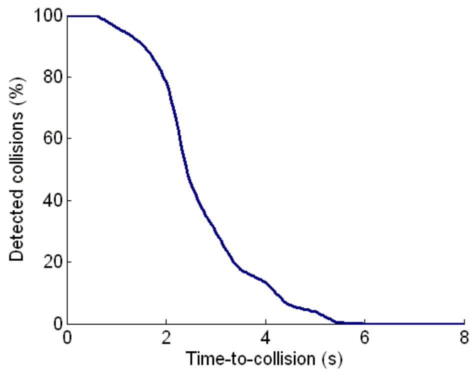


Figure 6: Percentage of detected collisions (over 240 collision instances) as a function of the time remaining before the collision.

Impact of the type of violation: In order to analyze the influence of the type of violation on the performance of our algorithm, results for priority violation scenarios are compared with results for stop violation scenarios in Fig. 7. On average, collisions which are caused by a stop violation are detected 1 s earlier than the ones caused by a priority violation. All of them are detected more than 1.5 s before the crash, against 0.6 s for priority violations. This is explained by the fact the OV's intention to violate the stop is given away by the evolution of the vehicle's speed while it is approaching the intersection, while priority violations can be detected only as the OV accelerates to enter the intersection.

Impact of the type of maneuver: In order to analyze the influence of the type of maneuver executed by the OV on the performance of our algorithm, results for the four maneuvers present in our dataset are compared in Fig. 8: merging right, merging left, crossing, and left turn across path. The graph shows that 100% of the collisions are predicted at least 1.5 s before they occur for crossing and merging maneuvers. This means that all the collisions which were detected less than 1.5 s in advance in the previous graphs (Fig. 6 and Fig. 7) correspond to left turn across path maneuvers. These results highlight the fact that collisions caused by a priority violation during a left turn across path maneuver are more difficult to predict than other collisions. Indeed, contrary to crossing and merging maneuvers there is no marking on the road to indicate where a vehicle making a left turn across path should stop to yield to a vehicle with right-of-way. As a result there is a lot of variation in the way vehicles execute a left turn across path maneuver, and this makes it more challenging to estimate the intentions of drivers. The high variation in driver behavior during left turn across path maneuvers has been pointed out in the past by other works [25].

5.3 Field trials

5.3.1 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

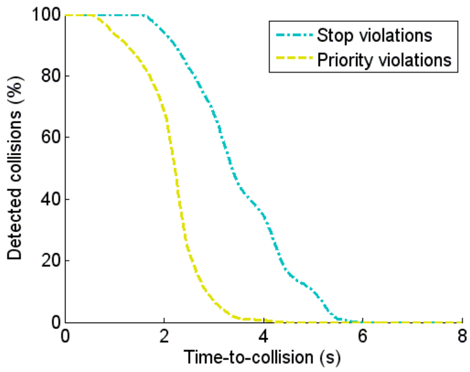


Figure 7: Comparison of the performance for priority violations scenarios and stop violations scenarios.

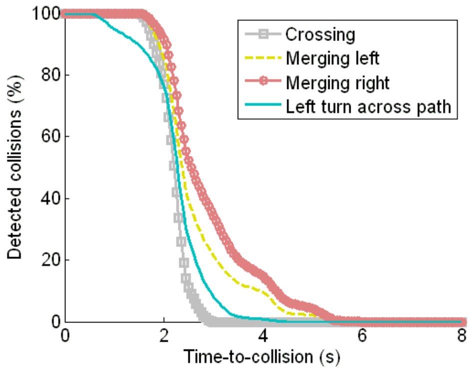


Figure 8: Comparison of the performance for the different types of maneuver executed by the OV.

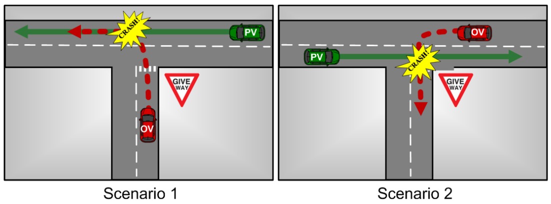


Figure 9: Test scenarios for the field trials. For each scenario the maneuver of the Other Vehicle (OV) is shown in dotted red and the maneuver of the Priority Vehicle (PV) is shown in plain green.

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.

5.3.2 Scenarios

Experiments were conducted at a T-shaped give-way intersection for two collision scenarios. The scenarios are illustrated in Fig. 9. 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, using the same configurations as in Fig. 9 but this time without violating the traffic rules.

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 with the warning system running on the OV.

5.3.3 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. 10 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, the statistical analysis about the collision prediction horizon that was performed on the simulated data cannot be performed on the real data. However, the field trials proved that our approach can operate with success in real-life situations where passenger vehicles share data via a Vehicle-to-Vehicle wireless link.

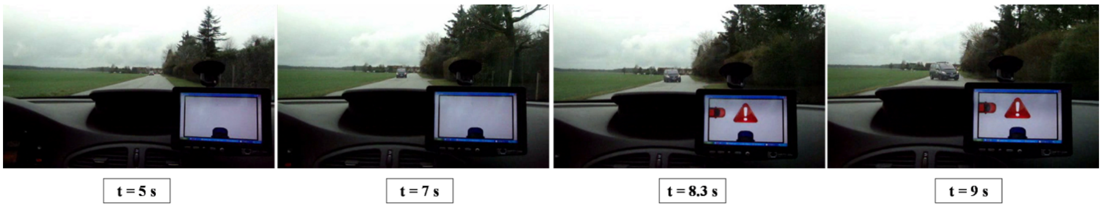


Figure 10: *Dangerous* situation detected during the field trials (view from inside the Priority Vehicle).

6 Conclusions

In this work 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 state art approaches relying on trajectory prediction the proposed approach reasons on risk at a semantic level. As a result it can run in real-time without having to assume independence between vehicles.

This general framework was implemented and tested in the context of unsignalized road intersections. The necessity for a driver to stop at an intersection is represented in the model, as well as the driver's intention to comply. In order to compute the risk, inference on these two variables is performed given measurements of the pose and speed of all the vehicles in the scene. The model takes into account the mutual influences between the maneuvers performed by the vehicles, and can be used with an arbitrary number of vehicles. It models the influence of the topology and the geometry of the intersection on the behavior of a vehicle (position, speed), and therefore can automatically adapt to any intersection layout.

Tests were conducted in simulation for collision scenarios at a two-way stop intersection, and 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 and different driving styles.

In order to show the applicability of the "comparing intentions and expectations" risk estimation algorithm, future work will include the implementation of that approach in the context of highway driving. Another line of research will be the addition of learning components so that the model adapts to different drivers.

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