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Abstract: This work proposes a novel approach to risk assessment at road intersections. Unlike most approaches in the literature, it does not rely on trajectory prediction. Instead, dangerous situations are identified by comparing what drivers intend to do with what they are expected to do. What a driver intends to do is estimated from the motion of the vehicle, taking into account the layout of the intersection. What a driver is expected to do is derived from the current configuration of the vehicles and the traffic rules at the intersection. The proposed approach was validated in simulation and in field experiments using passenger vehicles and Vehicle-to-Vehicle communication. Different strategies are compared to actively avoid collisions if a dangerous situation is detected. The results show that the effectiveness of the strategies varies with the situation.

Key-words: Intelligent Transportation Systems (ITS), Advanced Driver Assistance System (ADAS), situation assessment, manoeuvre estimation, collision risk estimation

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Evaluation du risque aux intersections basée sur la détection d'intentions conflictuelles

Résumé : Ces travaux proposent une nouvelle approche pour l'évaluation du risque aux intersections. Contrairement aux approches traditionnelles, celle-ci ne se base pas sur de la prédiction de trajectoire. A la place, les situations dangereuses sont identifiées en comparant ce que les conducteurs ont l'intention de faire avec ce qu'ils devraient faire. L'intention d'un conducteur est estimée Ã partir du mouvement de son véhicule et de l'agencement de l'intersection. Pour déterminer ce qu'un conducteur devrait faire, la configuration actuelle des véhicules dans la scène est prise en compte, ainsi que les règles de la circulation. L'approche proposée a été validée en simulation et au cours de tests réels avec des véhicules de série équipés de modems de communication V2V. Différentes stratégies sont comparées pour l'évitement de collision lorsqu'une situation dangereuse est détectée. Les résultats montrent que l'efficacité des stratégies varie avec la situation.

Mots-clés : Systèmes de transport intelligents (ITS), aide à la conduite (ADAS), comprehension de situation, estimation de manœuvre, estimation du risque de collision

1 Introduction

Intersection safety remains a challenge both for Advanced Driver Assistance Systems (ADAS) and autonomous driving. Intersection-related accidents account for 40-60% of road crashes in most countries. Out of the seven collisions which occurred between autonomous vehicles during the DARPA Urban Challenge in 2008, five were located at intersections.

Within this perspective, driver intention estimation (and more generally situation assessment) has been identified as a key problem for intelligent vehicles, and one of the three main remaining challenges [1]. Indeed, traffic at intersections is highly dynamic and involves complex interactions between vehicles. Therefore, physical models of the evolution of vehicles are valid only for short-term and are insufficient for anticipatory risk evaluation. Instead, a high-level representation of the situation is needed.

Statistical studies of the causes of accidents at intersections have shown that 89% of them are due to driver error. The most common errors are perception failures (e.g. inattention), situation misunderstanding (e.g. misjudging the intentions of another driver), and wrong decision (e.g. incorrect maneuver) [2]. This work focuses on this majority of accidents which are caused by driver error and proposes a risk assessment method which does not involve predicting the future trajectories of the vehicles. Instead, dangerous situations are detected by comparing what drivers intend to do with what they are expected to do, in a probabilistic framework. What a driver intends to do is estimated from the motion of the vehicle, taking into account the layout of the intersection. What a driver is expected to do is derived from the current configuration of the vehicles and the traffic rules at the intersection. Subsequently risk is assessed based on these estimates, without the need to predict the future trajectories of the vehicles.

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 describes the proposed mathematical model of road intersection situations and the proposed solution for risk assessment. The algorithm was evaluated in simulation and in field trials using passenger vehicles equipped with V2V communication devices. The results are presented and analyzed in Section 4.

2 Related work

Collision risk estimation has been the focus of many works in the robotics domain, but most of them are concerned with unconstrained environments. The adaptation of these methods to the prediction of road traffic accidents is not straightforward and requires taking into account the fact that the road network is a highly constrained environment. This is important especially in intersection areas, where the complexity of the layouts and traffic rules makes the progression of vehicles particularly constrained, interactive, and dynamic.

A simple and intuitive approach is to define a set of rules that detect danger based on the context and on the current observations of the state of the vehicles. The rules can be simple heuristics defining acceptable speeds when approaching an intersection [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 rule-based systems, the characteristics of the environment can easily be incorporated. However an established limitation of these algorithms is their inability to account for uncertainties (both on the data and on the model) and to reason on a high-level basis about a situation (e.g. driver intention).

An alternative is to learn typical collision patterns from data so that potentially dangerous configurations can be identified later on. A neural network was used in [5], while the authors of [6] applied the Expectation-Maximization algorithm to data and stored collision patterns in a knowledge base. Obtaining the data to learn from remains an issue, since real data is not available and simulations will not reflect real accident situations.

By far the most popular approach to collision risk estimation is the "trajectory prediction + collision check" approach. In the first step, future trajectories are predicted for the objects in the scene. The second step consists in checking these trajectories for intersection points. There has been extensive research focusing on this approach. Numerous algorithms are variations of the Time-To-Collision calculus [7, 8], which relies on a physical model of vehicles to detect future collisions. As was mentioned in the introduction, physical models are valid only for a very short term at intersections and therefore these approaches are limited to the prediction of imminent collisions. The authors of [9] propose the use of stochastic reachable states to compute the probability of a collision for a specific trajectory of an autonomous car. A Support Vector Machine is used to classify errant and harmless vehicles in [10], and combined with an evolution of the Rapidly-exploring Random Tree algorithm to predict future trajectories. Subsequently risk is computed as a function of the earliest time of collision over all the possible trajectories. In [11] the maneuver intention is estimated using Hierarchical Hidden Markov Models, and Gaussian Processes are used to represent the uncertainty on the realization of the maneuver. The authors point out that the definition of risk can take different forms depending on how the risk output is going to be used. The main limitation of all the trajectory prediction-based approaches is the computational cost of calculating all the possible trajectories and the pairwise probabilities that they will intersect.

We argue that an important challenge for future algorithms is to be able to integrate contextual information about the road network and account for the uncertainties, while keeping the complexity manageable.

3 Proposed approach

The proposed approach focuses on intersection accidents caused by driver error (89% of all intersection accidents). We propose to estimate jointly what each driver is expected to do in the current situation and each driver's actual intention. Risk is computed as the probability that *expectation* and *intention* do not match.

3.1 Context-aware scene representation

One challenge for representing traffic sits at road intersections is that the model should be comprehensive enough to represent complex and highly dynamic situations, but inference on the relevant variables should still be tractable. With this goal in mind, the following variables are defined for a scene featuring N vehicles:

3.1.1 Physical variables (observed)

In this work the available observations are the position, heading, speed, turn signal of the vehicles. For each vehicle $n \in N$ at time t, an observation variable is defined as:

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

- $P_t^n = (X_t^n Y_t^n \theta_t^n) \in \mathbb{R}^3$: the local pose,
- $T_t^n \in \{left, right, none\}$: the turn signal state,

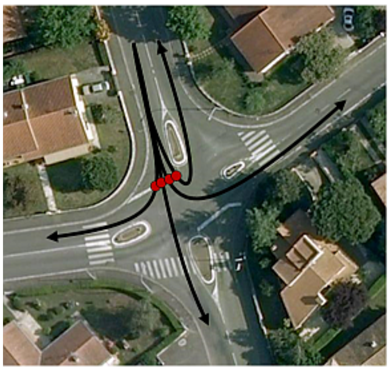

Figure 1: Representation of a road intersection: the exemplar paths (black arrows) and associated stop points (red points) originating from one road are displayed.

- $S_t^n \in \mathbb{R}$: the speed.

For the experimental validation (see Section 4.2), this information originates from the vehicles' proprioceptive sensors and is shared via Vehicle-to-Vehicle communication (V2V). However, the method can be applied independently of the type of sensors that are used to observe the scene.

3.1.2 Behavioral variables (hidden)

The selection of the higher-level variables for representing the scene is a crucial step; a trade-off has to be found between representational power and complexity. We exploit the fact that the road network is a structured environment that constrains the motion of the vehicles, and automatically extract from the map the set of authorized maneuvers and the traffic rules (stop, give way, etc.). We use an "exemplar paths" representation, as illustrated by Figure 1. An exemplar path is defined for each authorized maneuver as the typical path that is followed by a vehicle executing that particular maneuver in the intersection. In addition, we define a "stop point" for each exemplar path, which delimits the approaching and execution phases of a maneuver. The stop point is located at the entrance of the intersection when there is a stop or give way line, and inside the intersection for left turn across oncoming traffic maneuvers. The exemplar paths and associated stop points can be either automatically generated from the map, or learned by applying path clustering techniques to recorded data [12, 13]. For each vehicle $n \in N$ at time t, a behavior variable is defined as:

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

- $M_t^n \in \{m_i\}_1^{N_M}$: the maneuver intention of the driver, with N_M the number of possible maneuvers. For each possible maneuver, an exemplar path is defined.
- $D_t^n \in \mathbb{R}$: the distance traveled by the vehicle along the exemplar path of M_t^n (i.e. the curvilinear abscissa). D_t^n is negative when the vehicle has not yet reached the stop point, and positive after the vehicle passed the stop point.
- $I_t^n \in \{0, 1\}$: the driver's intention to stop at the intersection (= *intention*).

3.1.3 Expectation variable (hidden)

For each vehicle $n \in N$, the relevant traffic rules at time t are incorporated into the variable:

- $E_t^n \in \{0, 1\}$: whether or not the driver is expected to stop at the intersection (= *expectation*).

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

The remaining of this section introduces the proposed vehicle motion model (linking behavioral and observation variables), the proposed vehicle expectation model (linking the state of the vehicles with the necessity to stop), and how they can be used for risk assessment.

3.2 Vehicle motion model

The relations between the behavioral variables and the physical variables of a vehicle are modeled using a Dynamic Bayesian Network (DBN), assuming independence between the vehicles. The DBN is of the form of a Hidden Markov Chain with a relaxation of the independence assumptions, since the model assumes that the current observations depend on the current and past state as well as on the previous observations [14]. The graphical representation of the DBN is given in Fig. 2, and its decomposition in Eq. 1.

$$\begin{aligned}
&P(B_{0:t}^n, O_{0:t}^n) \\
&= P(B_t^n | B_{t-1}^n) \times P(O_t^n | B_t^n O_{t-1}^n) \times P(B_{0:t-1}^n, O_{0:t-1}^n) \\
&= P(M_t^n | M_{t-1}^n) \times P(D_t^n | M_{t-1}^n D_{t-1}^n I_{t-1}^n) \times P(I_t^n | I_{t-1}^n) \\
&\quad \times P(P_t^n | M_t^n D_t^n) \times P(T_t^n | M_{t-1:t}^n) \times P(S_t^n | M_t^n D_{t-1:t}^n I_t^n S_{t-1}^n) \\
&\quad \times P(B_{0:t-1}^n, O_{0:t-1}^n)
\end{aligned} \tag{1}$$

The conditional probability terms of the decomposition are defined below.

3.2.1 Maneuver intention

Continuity in the maneuver intention is assumed.

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

3.2.2 Distance to stop point

The distribution on D_t^n is normal and defined as:

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

where μ_D and σ_D are extracted from the speed profiles described in 3.2.6.

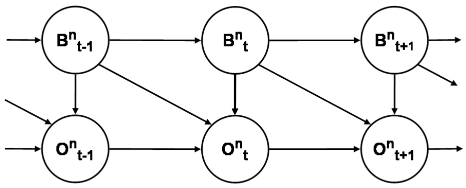

Figure 2: Graphical representation of the vehicle motion model.

3.2.3 Intention to stop

Continuity in the intention to stop is assumed.

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

3.2.4 Pose

The likelihood of a pose while executing maneuver m_i and being at distance d from the stop point is defined as a bivariate normal distribution with no correlation between the position (x, y) and the orientation θ_t^n:

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

where δ_i is the distance between the vehicle's position (x, y) and the point (x', y') with curvilinear abscissa d on the exemplar path of maneuver m_i, θ_i is the angle between the vehicle's orientation θ and the orientation of the exemplar path at point (x', y'). σ_δ (resp. σ_θ) is the standard deviation set for the distance (resp. the angle), and is set according to the accuracy and precision of the pose sensor.

3.2.5 Turn signal

Turn signals are used by drivers to indicate their maneuver intentions. We determine

$$P(T_t^n|[M_{t-1}^n = m_i][M_t^n = m_j])$$

as described in [15], using a rule-based algorithm which uses the geometrical and topological characteristics of the intersection to determine the chances that a driver will put a specific turn signal on. The model takes into account that turn signals can also indicate an intention to change lanes.

3.2.6 Speed

Drivers adapt their speed to their intentions and to the geometry of the road, therefore the evolution of the speed of a vehicle is an indication of the driver's intention to stop. We model the

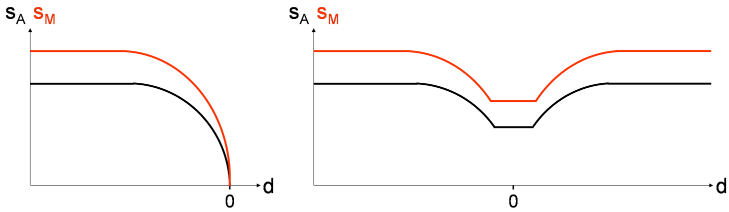

Figure 3: Example average (s_A) and maximum (s_M) speed profiles generated a pair ($M_t^n = m_i$, $I_t^n = 1$) (left) and ($M_t^n = m_i$, $I_t^n = 0$) (right). When $I_t^n = 0$, the lowest speed in the profile is a function of the curvature of the path associated with the maneuver m_i.

causal relations between S, I, M, D by assuming the distribution on S_t^n is normal and defined as:

$$\begin{aligned} & P(S_t^n|[M_t^n = m][D_{t-1}^n = d_1][D_t^n = d_2][I_t^n = i][S_{t-1}^n = s_1]) \\ & = \mathcal{N}(s_{mean}, \sigma_S) \end{aligned} \tag{2}$$

with the calculation of s_{mean} detailed below.
A number of statistical analyses of the behavior of drivers approaching an intersection can be found in the literature, e.g. [16]. From these it is possible to derive generic speed profiles for vehicles negotiating an intersection. We define $s_A = f(d)$ the average speed profile at the intersection, and $s_M = f(d)$ the maximum speed profile, i.e. the highest speed possible for negotiating the intersection. Additionally we take into account the geometry of the road: for each possible pair (M_t^n, I_t^n), the generic speed profiles are adapted to match the curvature of the exemplar path. In Fig. 3 the general aspect of the speed profiles is shown. They serve as a basis for predicting the evolution of the speed of a vehicle given the driver's intention, following the equation:

$$s_{mean} = s_A(d_2) - \frac{s_A(d_2) - s_M(d_2)}{s_A(d_1) - s_M(d_1)} \times (s_A(d_1) - s_1)$$

3.3 Vehicle expectation model

It is assumed that the necessity for a driver to stop at an intersection is a consequence of the context (priority rules, presence of other vehicles):

$$P(E_t^n|M_{0:t}D_{0:t}S_{0:t}) = P(E_t^n|M_tD_tS_t)$$

Modeling the causal dependencies between the vehicles as a function of the current situational context instead of pairwise interactions greatly reduces the computational complexity [17].
The necessity for a vehicle to stop given the context is derived using probabilistic gap acceptance models found in [18, 19]. If we take as an example a vehicle v^k heading towards a give way intersection, the calculation is:

1. Project forward the position of v^k until the time t^k when it reaches the stop point of the maneuver. A constant speed model is used, with a combination of the vehicle's current speed and the average speed profile s_A of the maneuver.

2. For each vehicle v^n whose maneuver is prioritary w.r.t. the maneuver of v^k, project forward the position of v^n until the time t^n when it reaches the stop point of the maneuver (following the same procedure as in 1.).

3. Select the smallest positive time gap available for v^k to execute its maneuver:

$$t^{nk} = min_n(t^n - t^k),\ for\, t^n - t^k \geq 0$$

4. The necessity for v^n to stop at the intersection is calculated as the probability p^{nk} that the gap is not sufficient, using a probabilistic gap acceptance model:

$$P(E_t^n | M_t D_t S_t) = \begin{cases} 1 - p^{nk} & if\, E_t^n = 0 \\ p^{nk} & if\, E_t^n = 1 \end{cases}$$

   The model presented in [18] is used for merging cases, the model presented in [19] is used for left turn across oncoming traffic cases.

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

3.4 Risk assessment

From the vehicle motion model and expectation model it is possible to infer a driver's intention as well as what he is expected to do from the successive pose, turn signal and speed of the vehicles in the scene. As an alternative to the conventional "trajectory prediction + collision check" approach to risk estimation, we propose to base the computation of risk on the probability that *expectation* and *intention* do not match, i.e.:

$$P([I_t^n = 0][E_t^n = 1] | P_{0:t} T_{0:t} S_{0:t}) \tag{3}$$

In this work inference was performed using a particle filter.

The advantages of this approach reside in its computational efficiency (no need to perform trajectory prediction) and in the flexibility it provides in terms of applications. An example of a safety-oriented application is the detection of hazard vehicles: the system can compute a "hazard probability" for every vehicle in the scene using Eq. 3 and warn all the drivers in the intersection area when the probability is higher than a predefined threshold. Alternatively the model can be used to compute the risk of a specific maneuver for a vehicle, which is an important feature for autonomous driving [9].

4 Evaluation

The goal is to evaluate the ability of the proposed approach to estimate the collision risk of traffic situations at road intersections. To this end we consider an application which classifies a situation as dangerous iff:

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

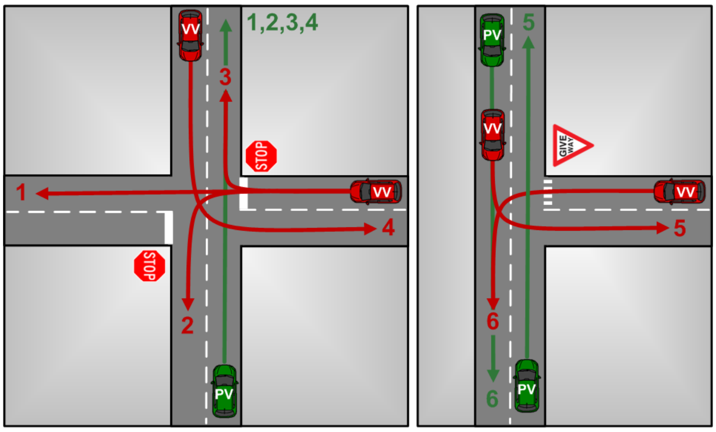

Figure 4: Simulated collision scenarios (1-4) and field trials scenarios (5-6). For each scenario the maneuver of the Priority Vehicle (PV) is shown in green and the maneuver of the Violator Vehicle (VV) is shown in red. Collisions occur where the maneuvers intersect.

The threshold λ is set to the lowest value that does not trigger false alarms on the test dataset. The approach is evaluated both in simulation and with field trials, on collision scenarios between a Violator Vehicle (VV) and a Priority Vehicle (PV). The performance of the algorithm is measured by how early it is able to classify the scenarios as dangerous.

4.1 Results in simulation

Simulation allows to generate a large number of collision scenarios from which statistical results can be obtained. We chose to perform simulation at a two-way stop intersection on the 4 scenarios illustrated in Fig. 4. These scenarios were selected because they cover 70% of all accident scenarios at road intersections in Europe [20]. A total of 320 instances of these scenarios were simulated, by varying the speed profiles of the VV and alternating between instances where the collision is caused by the VV violating the stop and instances where the collision is caused by the VV violating the priority rule, i.e. the driver stopped but then entered the intersection when he should have waited for the PV to pass.

4.1.1 Detection time

Fig. 5 shows the percentage of detected collisions as a function of the time remaining before the collision. In all instances the collision was predicted at least 0.5 s before the collision, but there is a significant difference between the performance on stop violation instances and priority violation instances. On average, collisions that are caused by a stop violation are detected 1 s earlier than the ones caused by a priority violation. This is an intuitive result since the VV's intention to violate the stop is given away by the evolution of the vehicle's speed in the approaching phase, while priority violations can be detected only as the VV accelerates to enter the intersection.

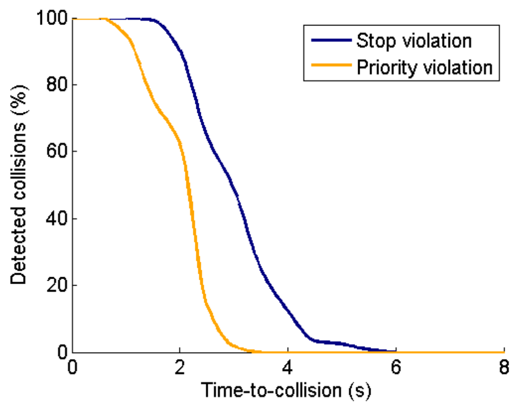

Figure 5: Percentage of detected collisions (over 320 collision instances) as a function of the time-to-collision.

4.1.2 Avoided collisions

In this paragraph, the results on detection time are analyzed in order to evaluate the potential impact of different strategies to avoid a collision if a dangerous situation is detected. Four strategies are compared: autonomous emergency braking on the PV, autonomous emergency braking on the VV, warning the driver of the PV, and warning the driver of the VV. The time needed by a vehicle driving at speed s_t to reach a full stop is calculated using the model described in [20], assuming a dry road and average response times:

$$TTS = \begin{cases} \frac{s_t}{\delta} + T_{machine} + T_{driver} & (emergency\ braking) \\ \frac{s_t}{\delta} + T_{machine} & (driver\ warning) \end{cases}$$

with $\delta = 7\ m/s^2$ the deceleration (assumed to be constant), $T_{machine} = 0.4\ s$ the braking system $+$ warning system response time and $T_{driver} = 1.4\ s$ the driver brake response time. If a collision is detected earlier than TTS, it is considered to be avoidable. The results are displayed in Table 1 and commented below.

- The most efficient strategy is always to trigger an autonomous emergency braking on the VV. The reason is that the speed of the VV is generally lower than the speed of the PV. Indeed the speed of the VV is limited by the curvature of the road during turning maneuvers (Scenarios 2, 3 and 4), leading to a smaller TTS.

- Actions on the PV are more efficient in stop violation instances than in priority violation instances, while it is the opposite for the VV. Once again this can be explained by the speed difference.

  The PV drives at the same speed in stop violation instances and priority violation instances, therefore the TTS is constant. The difference is that stop violations are detected earlier (see Fig. 5), which leaves more time for the PV to stop compared with priority violation instances.

  The VV drives at a higher speed in stop violations instances, compared with priority violation instances. Therefore, even if stop violations are detected earlier (see Fig. 5) the resulting collisions are harder to avoid.

Table 1: Percentage of avoided collisions depending on the type of violation and on the action taken when a danger is detected

	Action on VV		**Action on PV**	
	Braking	**Warning**	**Braking**	**Warning**
Stop violations	88.4%	53.2%	75.2%	20.7%
Priority violations	98.2%	54.3%	30.3%	3.0%

- The outermost numbers are obtained for priority violation instances: while 98.2% of the collisions in the dataset could be avoided by applying emergency braking on the VV, only 3% could be avoided by warning the driver of the PV.

4.2 Experimental validation

Experiments were conducted at a T-shaped give-way road intersection for the scenarios illustrated in Fig. 4. Two passenger vehicles are equipped with off-the-shelf Vehicle-to-Vehicle (V2V) modems and share their pose, turn signal and speed information at a rate of 10 Hz. In each vehicle the pose information is obtained via a GPS + IMU unit with a precision of $\sigma = 1\ m$ for the position. The CAN provides the turn signal and speed information. In its current non-optimized state the algorithm runs at 10 Hz on a dedicated dual core 2.26 GHz processor PC. The vehicles are not equipped with autonomous emergency braking functions. Instead, the driver is warned by a visual and auditory alert when the situation is classified as dangerous. The system architecture is illustrated in Fig. 6.

In total 90 trials were carried out, with 6 different drivers for the VV. In order to generate some variations in the scenario instances, the drivers of the VV were not given clear instructions about the execution of the maneuvers and were only told to create what they felt were dangerous situations. Two warning strategies were tested: 60 trials were performed with the warning system running on the PV, and 30 trials with the warning system running on the VV.

For every of the 90 test runs, the system was able to issue a warning early enough that the driver avoided the collision by braking. It may seem like this contradicts the results obtained in simulation, where only 3% of the collisions following a priority violation could be avoided by warning the driver of the PV. In reality this difference can be explained by the presence of strong safety rules for the field trials. Drivers of the PV were told to not drive faster than 40 km/h during the field trials, while the simulated scenarios contain instances where the PV drives above the speed limitation. Another difference is that the simulation assumes an average driver reaction time, while drivers who took part in the experiments were ready to hit the brakes as soon as the warning was triggered.

Since we did not go so far as to create real collisions, the statistical analysis 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 V2V communication link.

5 Conclusions and future work

A novel framework for reasoning about situations and risk at road intersections was presented in this paper. The risk of a situation is assessed based on the comparison between what drivers intend to do and what they are expected to do, in a probabilistic framework. This intuitive

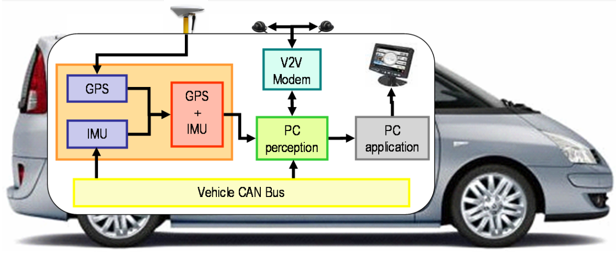

Figure 6: System architecture in the test vehicles.

formulation of risk takes takes into account the fact that the road network is a structured environment governed by traffic rules, and does not require predicting the future trajectories of the vehicles.

The approach was evaluated in simulation and in field experiments using passenger cars and Vehicle-to-Vehicle communication links. The results demonstrated the ability of the algorithm to issue a warning in dangerous situations, and compared different strategies to avoid a collision if a dangerous situation is detected.

In its current form the method may be applied to any intersection layout and any number of vehicles, but this was not demonstrated in this paper and will be evaluated in future work. Another objective will be to extend the analysis of the results to investigate collision mitigation capabilities.

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