Detection of Unusual Behaviours for Estimation of Context Awareness at Road Intersections

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Abstract— In general, Advanced Driving Assistance Systems (ADAS) warn drivers once a high risk situation has been inferred. This is made under the assumption that all drivers react in the same manner. However, it is not the case as drivers react as a function of their own driving style. This paper proposes a framework which allows the estimation of the degree of awareness with regard to the focus object of the context that is governing the vehicle behaviour (e.g. the arrival to an intersection). The framework learns the manner in which individual drivers behave for a given context, and then detects whether or not the driver is behaving differently under similar conditions. In this paper the principles of the framework are applied to a fundamental use-case, the arrival to a stop intersection. Results from experiments under controlled conditions are included. They show that the formulation allows for a coherent estimation of the driver awareness while approaching to such intersections.

I. INTRODUCTION

Statistics have shown that most road accidents are due to human errors, inferred by factors such as distraction, tiredness, over speeds, etc [16]. These result in bad situation understanding which often leads to abnormal and dangerous situations.

Road intersections represent complex environments where over 40% of collisions and 20% of fatalities occur [12]. Further, most of those involved in such collisions are young inexperienced drivers and the elderly. Given the complexity that exists at road intersections, namely the convergence of various entities to the same area, intersections represent a major challenge for ADAS.

An underlying framework for the estimation of unusual behaviours with regard to the road context and the driver individualities is presented. The tenet is that the vehicle evolves within a context which is built of contextual elements. These impose constraints to the subject vehicle, and usually one object has more influence than the rest. The framework takes into consideration this contextual object, and also the usual vehicle response (driver pattern) as it interacts with this object. This is then compared with the actual behaviour. If the driver actual behaviour differs much from the expected one, it is considered as unusual, which could be synonym of context misunderstanding and thus a source of risk. This concept is exploited in a simple scenario,

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road intersections. The aim of the framework is not to warn the driver when the situation becomes dangerous, but to make sure that the driver has all necessary information for coherent decision making.

The remainder of the paper is organized as follows. Section II includes results of the state of the art review for risk estimation at road intersections, followed by the problem formulation. In Section III, the proposed model of the framework is described, and Section IV presents preliminary results from experiments applied to road intersections. Section V concludes the paper.

II. RELATED WORK AND PROBLEM STATEMENT

A. Related Work

Road intersection safety is of much concern. Some risk reduction has been achieved with the introduction of roundabouts instead of classic intersections. Another long term solution is to use communication technologies [6]. Currently, increasing driver awareness before arriving to the intersection remains a challenge.

One of the most intuitive approaches consists in using rules associated to the context. The set of rules, function of contextual inputs (e.g. the vehicle state, the maximum velocity, etc.) define the situations which can be considered as risk situations. In [6], rules are set to define when the velocity is not safe when a vehicle is reaching an intersection. The main problem of these approaches is the difficulty to take uncertainties into account. In addition, when such systems become complex, rules become interleaved and hence difficult to trace.

Several of the algorithms available in the literature are mainly based on the estimation of the so called Time To Collision (TTC) [9], [7]. This indication estimates the time remaining before a collision between two objects. Alerts are usually given as soon as the TTC becomes lower than a threshold. However no conclusion can be drawn before the situation gets critical.

Other approaches include the driver as part of the system to infer driver manoeuvres. Given a context, by observing the differences between the driver intention and the expected behaviour, risky situations can be detected. In [8], this risk is inferred within a Dynamic Bayesian Network (DBN) implemented in cooperative vehicles. In [3], it is proposed to decompose manoeuvres into a series of consecutive actions which are then represented as Hidden Markov Models (HMM). A framework based on Support Vector

Machines (SVM) coupled with HMM to determine the driver's behaviour is presented in [1]. The system proposed in [13] also decomposes the manoeuvres into a sequence of elementary states, and a multilayer perceptron is used to learn the mapping between the current situation and the future vehicle states. All these systems generate warning only when the situation becomes dangerous. In addition, except driver actuations, no information about the driver is used to improve performances in term of reactivity.

In addition, several driver centric systems have been studied. Most of them are using either physiological sensors [5] or vision technologies [17] to look at the driver and get some vigilance information. Whilst progress has been achieved, reliability remains a problem. Moreover, using this kind of technologies requires more sensors in the vehicle which is not compatible with vehicle OEM constraints.

B. Problem Statement

The literature has shown that most of risk assessment systems estimate the risk only when the situation becomes dangerous and thus when an accident is imminent. These systems can be called curative systems. Some studies have highlighted the negative effects that ADAS can sometimes have on drivers, for instance in term of emotions, and time to react [11], [10]. Surrounding vehicles may also be directly impacted by the consequence of an alert lately or not well interpreted by the driver. In addition, these studies have shown that early warnings improve the efficiency of the alerts. Thus, the main challenge of risk assessment systems remains the responsiveness of the system and the integrity of generated information, so that such systems can become preventive instead of remedial.

In addition, to our knowledge, there is no related work that takes advantage of drivers' individualities. Though, some highlight the differences of behaviour between different drivers in similar contexts [4], [2]. For example, it is unlikely that a driver used to decelerate smoothly decides intentionally to decelerate much harder than usual.

In this paper, it is proposed to take advantage of driver patterns with regard to road contexts, to detect unusual behaviours which might be signs of incomplete situation awareness. Multiple sources of data are used within the framework, with respect to the subject vehicle, the road context and the driver. An underlying architecture of the system is presented, followed by a concrete exploitation in a road intersection context. It is shown that the use of driver individualities may help detect unusual behaviours (i.e. indicators of situation unawareness) to provide early advices instead of late warnings.

III. PROPOSED APPROACH

A. Concept

The aim of the framework is not to generate alerts when the situation is getting dangerous, but rather to provide advices as a human copilot would do. For instance, a fellow
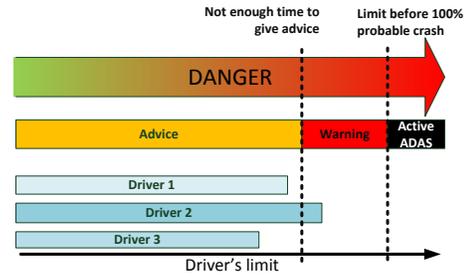

Fig. 1. Solutions to avoid accident: advice, warning and active ADAS. Drivers react more or less rapidly to the context, depending on their habits. For some of them, early advices can be given instead of warnings.

traveller who feels that the driver did not understand or perceive something would say "Have you seen ... ?" instead of waiting the last minute to say "Brake !". A copilot usually knows the driver's practices, and can estimate the need to advice the driver in case of unusual behaviour.

Figure 1 illustrates the nuance between warnings and advices, such as:

- Active ADAS: the situation is critical, and the TTC is too small to let the driver react and brake. The vehicle takes the control.
- Warning: the situation is dangerous, however the driver has time to react and to avoid accidents. The system warns the driver.
- Advice: the situation is not yet dangerous, however it seems that the driver is not aware of a contextual object. The system gives a pertinent advice to make sure that the driver has all the required information for a coherent decision making.

Depending on the manner a driver is used to drive and to behave in particular contexts, advices can become relevant, or not. For instance, a sporty driver usually starts braking late at stop intersections. The situation becomes abnormal for him very late, and the situation can become dangerous very quickly. It is more relevant to warn the driver than giving him an advice. On the contrary, a relaxed driver who does not brake as early as usual can become suspect, and even if the situation is not yet dangerous an advice can be relevant for him.

B. Framework

The framework uses inputs from different information sources, as illustrated in Figure 2:

- Environment & Context. The environment can be known through digital maps which store informations about the road network and infrastructure. On the other hand, dynamic objects which cannot be included in maps (vehicles, pedestrians, etc.) have to be perceived in real time by using sensors such as cameras or radars.
- Vehicle State. The position, speed and other parameters related to the subject vehicle are provided by localization devices (GNSS, etc.) and the vehicle CAN bus.
- Driver. Actuations of the driver can be directly provided by messages in the vehicle CAN bus. Driver patterns
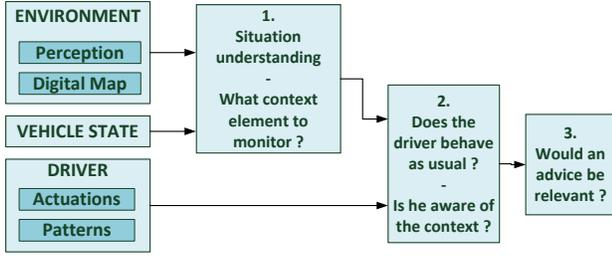
Fig. 2. Block Diagram of the proposed framework

Fig. 3. Graphical Representation of the Bayesian Network

(habits, in other words) have to be previously learnt. For example, [2] proposes a method to learn approaches to stop intersections.

The first step is to fuse environment data and vehicle state data to clearly understand the context, and the influence of every contextual object on the subject vehicle. Usually, one object has more influence than the others on the vehicle, and this influence leads to a particular vehicle parameter to monitor (speed, etc.). This step is not the object of this paper. In the rest of the paper, the most important contextual object is manually set. Some works propose methods for scene understanding, such as [15] and [18] which may be used within the framework.

The second step is to estimate if the behaviour of the driver matches with the behaviour expected in similar contexts. Driver patterns are compared with the current behaviour of the driver to estimate the awareness regarding the main contextual element. This step will be described in the rest of this paper.

C. Detection of unusual behaviours and awareness estimation

This section aims at describing the box number 2 introduced in Figure 2 which allows detection of unusual behaviours and thus estimation of awareness. For this task, a Bayesian Network (BN) [14] has been developed. BNs offer a way to fuse different sources of information, taking uncertainties into consideration.

It is assumed that the context has been understood (box number 1) and that the parameter to monitor has been identified.

1) Variables: Variables are separated into two categories, depending on their observability:

a) Observable variables: These variables can be measured by the embedded sensors on a subject vehicle. They are defined as follows:

- $P_t \in \mathbb{R}$, the parameter to be monitored, with regard to the contextual object considered by the box 1 (c.f. Figure 2). It may be the vehicle speed, interdistance, lateral position, etc.
- $R_t \in \{0, 1\}$, the reaction of the driver. The driver can give an indication that he finally perceived/ took into consideration the most important contextual object. This variable is considered as a way to reduce the risk
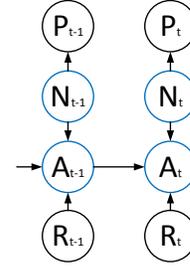
of non-relevant advice. It is related to the parameter to monitor, and may be an action on the brake pedal, or for instance an information provided by vision (c.f. [17]).

b) Hidden variables: These variables cannot be directly measured. However the DBN enables to estimate their values.

- $N_t \in \{0, 1\}$, the estimation of the "Normality" of the driver's behaviour. By "Normal behaviour", it is understood a behaviour that matches with the behaviour that the driver usually has in a similar context.
- $A_t \in \{0, 1\}$, the estimation of the awareness of the driver with regard to the contextual object taken into consideration by the box number 1 (c.f. Figure 2).

2) Graphical Representation: The structure of the proposed BN is shown in Figure 3; its corresponding joint distribution is given by Eq.(1).

$$P(P_t, N_t, A_t, R_t) = P(N_t) \times P(R_t) \times P(P_t|N_t) \\ \times P(A_t|R_t, N_t, A_{t-1}) \quad (1)$$

The relationship between all the nodes has to be understood as follows:

- A behaviour considered as Normal means that the observed Parameter matches with the driver's patterns, and that the driver seems Aware of the main contextual object.
- The Awareness of the driver (with regard to the main contextual object) is inferred by the estimation of the Normality of the driver's behaviour, and also by a Reaction of the driver.

3) Conditional probabilities: A description of the parametric form of the conditional probabilities is presented in this section.

a) The Parameter to monitor, P_t: It is considered that P_t follows the normal law such as:

$$P(P_t|N_t) = \mathcal{N}(p_{mean}, \sigma_s)$$

It means that whatever method can be used to provide the usual driver's behaviour, the only constraint is that the provided value has to be composed by mean and variance.

Table I gives the value of P_t given the Normality of the behaviour N_t:

N_t	P_t
0	$\mathcal{N}(p_{Abnormal}, \sigma_{Abnormal})$
1	$\mathcal{N}(p_{Normal}, \sigma_{Normal})$

TABLE I

CONDITIONAL PROBABILITY OF THE PARAMETER P_t

	Cond.			Prob.
#	N_t	A_{t-1}	R_t	$P(A_t = 1 \mid N_t, A_{t-1}, R_t)$
1	0	0	0	α
2	1	0	0	α
3	0	1	0	α
4	1	1	0	β
5	0	0	1	β
6	1	0	1	β
7	0	1	1	β
8	1	1	1	β

TABLE II

CONDITIONAL PROBABILITIES OF THE AWARENESS A_t

b) The Normality of the behaviour, N_t: The probability that abnormal behaviours occur is low, it is defined as follows:

$$P(N_t = 0) = \gamma$$

c) The Reaction of the driver, R_t: The probability that the driver reacts because of the presence of a contextual object is set as follows:

$$P(R_t = 1) = 0.5$$

d) The Awareness, A_t: It is assumed that there is continuity in the driver awareness. The conditional probabilities of the Awareness node are defined in Table II.

It is considered that the driver may be not aware of the main contextual object (i.e. α is small) if:

- At time $t-1$, the driver is not considered as aware of the context, and does not show any reaction at time t.
- Even if at time $t-1$ the driver was considered as aware of the context, if the behaviour turns abnormal and no reaction is perceived.

On the contrary, it is considered that the driver seems aware of the main contextual object (i.e. β is high) if:

- A reaction is perceived at time t.
- At time $t-1$ it was estimated that the driver was aware of the context, and his behaviour seems normal at time t.

4) Behaviour Normality and Context awareness estimation: The model is used to estimate the behaviour normality and the degree of awareness regarding the contextual object that is supposed to have the biggest influence on the subject vehicle. This awareness is estimated by Eq. 2:

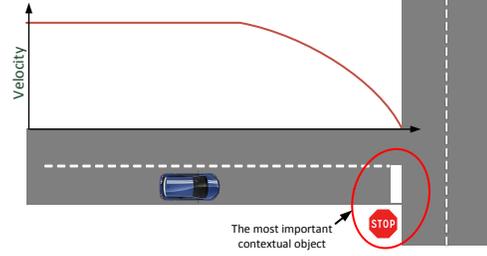$$P([N_t = 0], [A_t = 0] \mid P_t, R_t, A_{t-1}) \qquad (2)$$

Fig. 4. The use case: a typical stop intersection vs expected velocity profile

IV. PRELIMINARY EVALUATION AND DISCUSSION

A. Use Case

A simple use case has been chosen to run a first evaluation of the framework proposed in the previous section. A subject vehicle is moving on a road that leads to a stop intersection. There is no lead vehicle moving in front of the subject vehicle, no pedestrian and no infrastructure such as speed bumpers or crossing. Thus the intersection is the only contextual object that has influence on the vehicle, and the only vehicle parameter to monitor is the velocity. Figure 4 illustrates the use case.

B. Bayesian Network adaptation

The observable nodes of the DBN described in Section III-C have to be adapted to the given use case:

1) The parameter P_t : This parameter to monitor is the vehicle velocity. This velocity depends on the distance to the stop intersection, as illustrated in Figure 4.

It is considered that a driver has an unusual behaviour when he does not decelerate before the intersection.

The usual behaviour of the driver while he is approaching to a stop intersection has to be learnt. In [2], it is proposed to learn the customized velocity profile of a driver at the approach to stop intersections. Gaussian Processes are used. It has been shown that this method is well adapted for this task, since it allows to model accurately the driver patterns taking into account uncertainties which might exist due to the driver and the quality of the on-board sensors. In addition, the outputs follow the normal law and are composed by mean and variance.

From a dozen of approaches recorded on real roads, the framework described in [2] allows to provide learnt patterns as the one shown in Figure 5. At any position before the intersection, Gaussian Processes allow to compute the velocity (mean and variance) at which the vehicle is usually moving at the same position, in similar contexts.

2) The Reaction R_t: Usually, when approaching to a road intersection, a driver decelerates or brakes. In the case of stop intersections, a sign that the driver understood the presence of the contextual object is that he pushes (more or less) the brake pedal. For the proposed use case, the framework uses the brake pedal state (0 or 1) as a reaction of the driver.
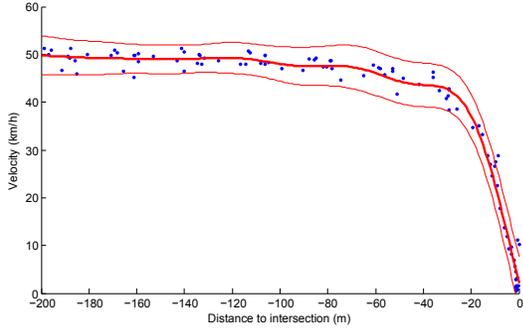
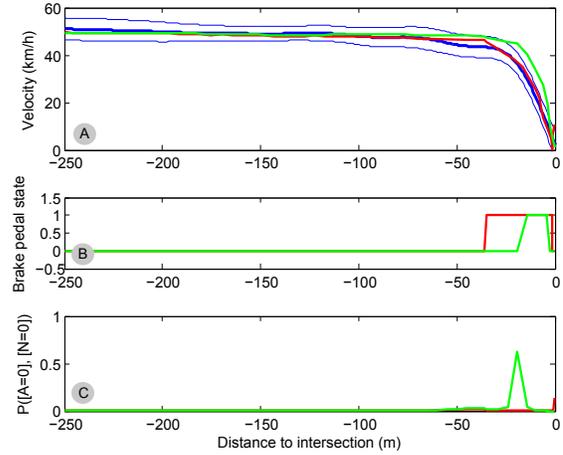Fig. 5. Customized velocity profile provided by Gaussian Processes

Fig. 6. Scenarios 1&2 : Normal behaviour and late reaction. In red, data related to normal behaviour, in green data related to late reaction. In windows A, the learnt pattern is in blue (mean and 95% confidence).

3) Parameters α, β and γ : The value of these Bayesian Network parameters are set manually such as $\alpha = \gamma = 0.1$ and $\beta = 0.9$.

C. Results

Preliminary evaluations of the framework have been realized, using real data recorded on open roads. Acquisitions were accomplished with the same protocol as the one described in [2].

Three scenarios have been chosen for the evaluation:

1) Scenario 1: Normal behaviour.
2) Scenario 2: Unusual late deceleration.
3) Scenario 3: No reaction, comparison with the use of a generic profile.

1) Scenario 1: In this scenario, the driver behaves as he usually behaves while approaching to a stop intersection. The Figure 6 illustrates the behaviour of the DBN for this normal behaviour (red curves). It is noticeable that:

- The velocity stays inside the individual envelope defined by the customized driver pattern, and thus seems to be adapted to the context.
- Since the velocity of the vehicle matches with the driver pattern, the action of the driver on the brake pedal does not have influence on the model.
- The model considers that the driver is aware of the stop intersection.

2) Scenario 2: In this scenario, the driver does not approach to the intersection with an usual behaviour, and reacts lately. The Figure 6 illustrates the behaviour of the DNB for this abnormal behaviour (green curves). It is noticeable that:

- The velocity leaves the envelope defined by the personalized speed profile.
- As soon as the behaviour (i.e. the velocity) turns unusual, the risk that the driver did not consider the stop intersection starts increasing.
- When the driver starts pushing the brake pedal, the system considers that he took the stop intersection into consideration, and thus that he is aware of this contextual object. The risk decreases close to 0.

3) Scenario 3: In this scenario, it is simulated that the driver does not decelerate and does not react at all while approaching to a stop intersection. Figure 7 illustrates the behaviour of the system for this scenario. The behaviour of the DBN is tested using a profile customized for a rather relaxed driver (in blue), and with an average generic profile (in green). The generic profile shows a $2.4m/s^2$ deceleration rate which is an average rate at $50km/h$, as indicated in [19]. In addition, a $-9m/s^2$ deceleration curve is drawn. This curve represents an average maximum deceleration rate for emergency braking. It is noticeable that:

- As soon as the velocity leaves the envelopes (learnt and generic envelopes) without any reaction (on the brake pedal), the probability that the driver did not take the stop intersection into account increases up to 0.9.
- This example highlights the advantage of using customized patterns. For a relaxed driver (in blue), the system detects a risk of context unawareness about $19m$ before the estimation of a risk with the generic profile. Moving at $50km/h$, $19m$ are travelled in $1.35s$ which may represent a high average reaction time for a driver.
- With the learnt pattern, the estimated probability that the driver is not aware of the stop intersection reaches a value of 0.9 $34m$ before the maximum emergency deceleration curve. Moving at $50km/h$, this distance is travelled in $2.42s$. This is more than enough for the driver to react to an advice (for example: "Have you seen the stop intersection ?") and to brake much smoother than an emergency braking.

D. Discussion

According to the preliminary evaluation presented, the proposed framework provides a coherent estimation of the risk that a driver does not take into account the main contextual object. However, a quantitative evaluation of the system have to be done with a significant amount of data recorded in real conditions.
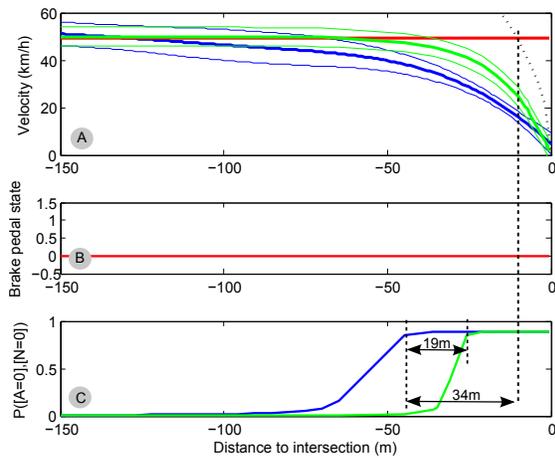
Fig. 7. Scenario 3. 1 run (in red) tested with 1 customized profile (in blue) and with a generic profile (in green). The black dot curve is the 9m/s² deceleration curve.

In addition, the use of customized driver patterns enhances the integrity of the generated information. Whilst uncertainties are taken into account by the personalized driver model, small uncertainties on measurements will lead to better estimation of risk.

For drivers used to drive sportingly, the framework allows also an estimation of unawareness. Nevertheless, this information can come too late to have time to generate an advice. In this case, it is better to generate warnings instead of advices. Further works have to be done to estimate when time is no longer sufficient to give an advice.

Finally, the simplicity of the use case enables to know in a straightforward manner that the stop intersection had to be monitored (c.f. Box 1 in Figure 2). In more complex contexts, it is not that simple. Thus, further works have to be done to automatically interpret the road context, and to detect contextual objects which interfere with the subject vehicle.

V. CONCLUSION

An underlying framework for the estimation of driver awareness with regard to a particular contextual object has been presented. It takes into account that all drivers have different driver patterns, thus it learns how drivers behave under different contextual situations. Then, it infers if drivers are behaving differently as they approach similar situations. The model has been used within a simple use case (stop road intersection) to evaluate its relevance using a single observed variable, the vehicle velocity profile as it approaches the stop line. For this task, real data and customized driver patterns have been used. This preliminary evaluation has shown that the model provides a coherent estimation of context awareness (with regard to the focus object), and would make it possible to produce early advices to the driver.

The proposed framework will be extended by including other contextual objects, namely the presence of a lead vehicle between the subject vehicle and the next road intersection. This use case requires the use of other observation variables.

REFERENCES

[1] G.S. Aoude, V.R. Desaraju, L.H. Stephens, and J.P. How. Driver behavior classification at intersections and validation on large naturalistic data set. *in Proceedings of the IEEE Intelligent Transportation Systems Conference*, 13(2):724 –736, june 2012.

[2] A. Armand, D. Filliat, and J. Ibanez-Guzman. Modelling stop intersection approaches using gaussian processes. *Accepted for IEEE Intelligent Transport Systems Conference 2013*, 2013.

[3] H. Berndt, J. Emmert, and K. Dietmayer. Continuous driver intention recognition with hidden markov models. *in Proceedings of the IEEE Intelligent Transportation Systems Conf.*, pages 1189 –1194, oct. 2008.

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

[5] K. Hayashi, Y. Kojima, K. Abe, and K. Oguri. Prediction of stopping maneuver considering driver s state. *in Proceedings of the IEEE Intelligent Transportation Systems Conf.*, pages 1191 –1196, sept. 2006.

[6] J. Ibanez-Guzman, S. Lefevre, A. Mokkadem, and S. Rodhaim. Vehicle to vehicle communications applied to road intersection safety, field results. *in Proceedings of Intelligent Transportation Systems (ITSC)*, pages 192–197, 2010.

[7] R. Labayrade, C. Royere, and D. Aubert. A collision mitigation system using laser scanner and stereovision fusion and its assessment. pages 441–446, 2005.

[8] S. Lefevre, C. Laugier, and J. Ibanez-Guzman. Risk assessment at road intersections: Comparing intention and expectation. *in Proceedings of the IEEE Intelligent Vehicles Symp.*, pages 165 –171, june 2012.

[9] M. Liebner, M. Baumann, F. Klanner, and C. Stiller. Driver intent inference at urban intersections using the intelligent driver model. *in Proceedings of the IEEE Intelligent Vehicles Symposium*, pages 1162 –1167, june 2012.

[10] A. Lindgren and F. Chen. State of the art analysis: An overview of advanced driver assistance systems (adas) and possible human factors issues. *Human Factors and Economic Aspects on Safety*, page 38, 2006.

[11] C. Maag, D. Muhlbacher, C. Mark, and H-P Kruger. Studying effects of advanced driver assistance systems (adas) on individual and group level using multi-driver simulation. *Intelligent Transportation Systems Magazine, IEEE*, 4(3):45–54, 2012.

[12] European Road Safety Observatory. Traffic safety basic facts 2010 junctions. *SafetyNet, Project co-financed by the European Commission*, 2010.

[13] M.G. Ortiz, J. Fritsch, F. Kummert, and A. Gepperth. Behavior prediction at multiple time-scales in inner-city scenarios. *in Proceedings of the IEEE Intelligent Vehicles Symposium*, pages 1068 –1073, june 2011.

[14] J. Pearl. Bayesian networks: a model of self-activated: memory for evidential reasoning. 1985.

[15] M. Platho, H-M Groß, and J. Eggert. Traffic situation assessment by recognizing interrelated road users. *Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on*, pages 1339–1344, 2012.

[16] TRACE. Analyzing human factors in road accidents. Technical report, 2008.

[17] C. Tran and M.M. Trivedi. Vision for driver assistance: Looking at people in a vehicle. *Visual Analysis of Humans*, pages 597–614, 2011.

[18] S. Vacek, T. Gindele, JM Zollner, and R. Dillmann. Situation classification for cognitive automobiles using case-based reasoning. *Intelligent Vehicles Symposium, 2007 IEEE*, pages 704–709, 2007.

[19] J. Wang, K. Dixon, H. Li, and J. Ogle. Normal deceleration behaviour of passenger vehicles starting from rest at all way stop controlled intersections. *Transportation Research Record*, pages 158–166, 2005.