Risks Level Assessments for Automotive Application

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Abstract: The article presents a modelization and assessment of automotive risk accidents taking into account the interactions between environment, driver and vehicle. The evaluated risk is composed of two parts: one concerns the impending risk (i.e. risk of a clearly identified danger and which is present in a short time horizon) and the other one, the latent risk (i.e. risky behavior of the driver which can lead to an accident). The developed tool uses information present in the CAN bus, additional sensors and car communication for shared sensing. With the collected information and estimated variables (e.g. grip and reaction time), it infers a probability of risk with a Bayesian Network. The tool can also be used for evaluating autonomous car driving and driver decisions.

Keywords: Risks, Bayesian Network, ADAS, collision warning, VANET.

1. INTRODUCTION

Driver inattention and unconsciousness are the most important causes of road accidents. As a response, over the years, French governments imposed rules (see ONISR (2014)) such as speed limitation, speed limit control, blood alcohol limit, alcohol test on road, etc. In the same time, vehicles manufacturers have developed passive and active safety, for example: crumble zone, airbag, anti-lock braking system and electronic stability control.

Thanks to those actions between 1970 and 2013 road deaths have gone down from 20'000 to 4'000 deaths per year. Advanced driver assistance systems (ADAS) and road infrastructure contribute to ensure improvement in road safety. However, nowadays, road death decreases only slowly. So to continue the enhancements, one idea is to take into account interactions between the environment, driver and vehicle.

Vehicle and environment states predictions can be easier handled than prediction of driver reactions. Hence, one solution is to replace the driver by developing autonomous car. Nowadays few companies already propose marketable cars such as Google and Tesla, but those vehicles do not communicate. To obtain the same results, the first step is to develop ADAS. For example, Otto et al. (2012) track pedestrian in the blind spot. For their work, they use several cameras and a radar, fuse their measures and run it with an extended Kalman filter. Another active safety system developed by Milanés et al. (2012) has the objective to avoid a rear-end collision in congested traffic situations. Authors have developed a collision warning system and a collision avoidance system.

Furthermore, Anderson et al. (2012) work on navigation for semi-autonomous vehicle taking into account road's geometry and vehicle's limits to get the reachable path avoiding collision while keeping comfort and control of the car. In the same field of research, Pérez et al. (2012) present an autonomous vehicle guidance system based on fuzzy logic with the intention to construct a path without any disturbance such as traffic jam, road closure, etc. Other teams focus on car intelligence, i.e., control agent for longitudinal and lateral dynamic based on fuzzy logic, see Rastelli Pérez et al. (2013)

Another topic of research focus on driver intention see Liebner et al. (2012) and driver fatigue see Yang et al. (2010). The last research team collects information (EEC i.e. electroencephalogram, ECG i.e. electrocardiograph and electromyogram) and with a Bayesian Network recognizes driver fatigue. But this system is intrusive and is not dedicated to be on board implemented.

At the same time, Vehicular Ad-hoc NETwork (VANET) is coming up and allows communication between vehicles (V2V) and between vehicle and infrastructure (V2I), so we take into account other road users, see Hartenstein and Laberteaux (2009). For example, Firl et al. (2012) introduce V2V, V2I and navigation information coupled with an hidden Markov model to recognize and classify situations. V2V can also be used for shared sensing see Caveney and Dunbar (2012). This possibility of low-cost communication opens up new opportunities in the safety management. For that reason, considering semi/full autonomous car or smart vehicle, it is necessary that the car is capable of communicating. Moreover, those cars need communication to send warning messages, for platooning, to shared sensing, for safety and comfort control, etc.

Some research teams work on risk estimation where in general risk is related to time to collision. The principle is to predict trajectory in absence of intersections and to estimate probability of front-collision and rear-collision such as Houenou et al. (2014). They predict the trajectories of the ego vehicle and of the other cars detected on the scene, and then compute a Monte Carlo simulation by taking into account the propagation of uncertainty to obtain risk probability. In Lefèvre et al. (2012) a method to estimate intersection collision risk is presented using a Dynamic Bayesian Network. The probability is based on position,

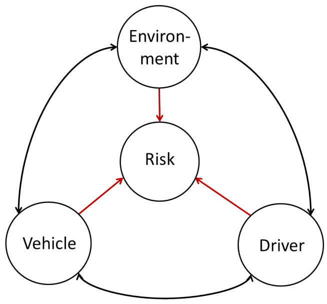

Fig. 1. Scheme of risk formation

speed and orientation of each vehicle (with information gathered by V2V). Then, it compares the estimated driver maneuvers and the driver intention.

This paper deals with a new tool called RIsk Level Assessment Tool (RILAT) which estimates a risk level by using a Bayesian Network (BN). This BN takes into account simultaneously estimates of driver attention, vehicle motion, environmental parameters such as road infrastructures, weather and information coming from other cars. In a first step, presented in this paper, RILAT evaluates the probability that an accident occurs, and it is tested only in simulation. Further works will focus on the evaluation of damages, implementation in our test car and human-machine interface. Some examples of other works in this field are Lefèvre et al. (2012) or Houenou et al. (2014). RILAT uses sensors already mounted on standard vehicles (e.g. available on CAN bus), a few additional low cost sensors and shared information by V2V. For instance, neither directly measured human physiological data (e.g. EEC and ECG), nor specialized RaDAR / LiDAR systems are used to estimate risk. Evidently, if these measurements are available, risk estimation can be enhanced.

In a more general way, risk estimation can be implemented on ADAS or autonomous cars. Indeed, even for autonomous cars, risk can not be zero, due to the uncertainty of environment such as the evolution of the road surface (i.e. adherence), motion and intention of the pedestrians, cyclists, etc. Another application could be monitoring used by insurers or the police to collect and evaluate driver behavior and in the case of an accident, driver responsibility.

This paper is organized as follows: section 2 presents the risk definition, and a short introduction to VANETs and Bayesian Networks. In section 3, variables used for the prediction of risky situations are defined. With these variables we construct a causal network modeling the interactions between variables and two risky situations which are rear-end collision and lane departure crash. Subsequently, the causal network is completed with probabilities to make the BN. In section 4, the simulation results are presented and analyzed for the rear-end collision case. Finally, conclusions are given in section 5.

2. DEFINITIONS AND PRINCIPLES

2.1 Risk

One definition of risk is given by the International Organisation for Standardization (ISO 31'000): risk is expressed in terms of a combination of gravity, i.e. the consequences of an event (including changes in circumstances) and the associated likelihood of occurrence. On actual state of our work, the paper focuses on the probability of an accident i.e. a collision with a mobile obstacle (e.g. pedestrians, cyclists, vehicles) or with a fixed one (e.g. road infrastructure). The event consequences will be developed in further studies. For simplicity of notation, the probability of occurrence of the risk will be called risk level.

We distinguish two kinds of risk: the impending risk and the latent risk. The impending risk is associated to a clearly identified danger which can cause an accident in a temporal horizon of several seconds. For instance, when approaching a curve, the tool analyzes the risk of losing control by taking into account vehicle speed, road adherence estimation and road curvature. The latent risk expresses the possibility of a driver-related danger due to reckless behavior (e.g. non-respect of safety distances, speeding, zigzagging), or increased reaction time (e.g. tiredness, distraction). This risk is present even without any clearly identified danger in a short time horizon.

2.2 Car Communication

Autonomous car use integrated sensors to sense the local environment (GPS, LiDAR, vehicle internal sensors, drivers state, etc.), communication with other vehicles will enlarge the sensing range and situation awareness. As discussed in introduction, information may come from different objects (vehicle, infrastructure, smartphone, etc.). In this paper, we will consider only V2V and will integrate more objects in future works. RILAT needs information about the environment such as weather, kind of road, road infrastructure, drivers state, vehicles dynamic (i.e. of ego car and others). VANET has a high signal range compare to a RaDAR or LiDAR. It is used to communicate with surrounding cars and to exchange information like speed, acceleration, driver intention (e.g. overtake a car, cross-road), safety messages, shared sensing, to confirm or deny the own knowledge of environment states and individual estimated risk level.

Crucial point in VANET is the quality of service especially in such kind of security application. Information should arrive without exceeding a fixed delay. In different study about VANET, it is shown that the arrival of a message is not guaranteed and the delay of delivered message may vary depending on environment conditions as shown in Ledy et al. (2015). The VANET research teams work on the improvement of message spread and management i.e. to chose the best path to reach receivers, to secure the communication and to get a high rate of message received. Another advantage of communication is the correlation between information from the own sensors and communicated information that will attenuate data lost in case of sensor failure.

2.3 Bayesian Network

Neapolitan (2003) defines briefly Bayesian Networks as a graphical structure coding causal bond between variables, associated to a probabilistic model. This last model is obtained using statistical data, expert knowledge.

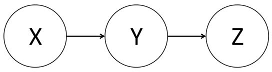

Fig. 2. Example of a Bayesian Network scheme

Fig. 2 shows the dependency between three nodes. A node represents a variable and can eventually be observed. Node X which is the parent of Y, is defined by a prior probability, while Y is defined by a conditional probability i.e. probability depending on X. Node Z only depends on his parent Y and his conditional probability. Hence each node is characterized by a conditional probability table (CPT). Action can only go in arrow direction which means Y will never act on X. But information can go from X to Z and vice versa. Additionally, we can get information about the node Y (supposed not measured in this example) thanks to the observation of the node X, or Z or both simultaneously. For more details see Pearl (1988) and Korb and Nicholson (2010).

The advantage of choosing BN is that it facilitates modeling of highly non linear and uncertain interactions between environment, driver and vehicle. Furthermore it provides directly the probability of a risk situation and not measured nodes can be estimated when information from other variables is available. At last, it provides a clear graphical structure with a causal interpretation.

3. RISK LEVEL ASSESSMENT TOOL

3.1 Feature of the instantaneous risk level assessment tool

As mentioned in section 2 we distinguish two kinds of risk, impending risk and latent risk, but in this paper we only focus on the impending risk tool.

For RILAT, considered accidents are collisions with fixed or mobile objects i.e. cars, pedestrians, road infrastructures, etc. Accidents can be explained by the maladjustment of the coupled triplet: inter distance (i.e. distance between ego car and road users, or road infrastructure), speed, and driver behavior. An illustration is given by a car running quickly, so the driver has to compensate by increasing the inter distance and his level attention compared to normal one. The tool is composed of four blocks (see Fig. 3) which are the driver behavior block, environment and car features block (i.e. influence of the weather on the road, the road surface, etc.), the inter distance block which includes car velocity, and finally, the risk block. These blocks are a model which represents a causal relation between the variables.

Behavior block To caracterize the safety distance we evaluate the minimum stopping distance. For that we

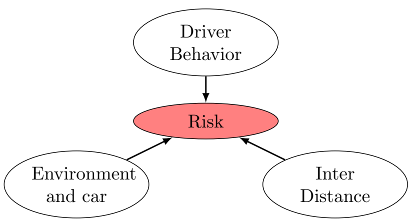

Fig. 3. Interactions between the triplet and risk

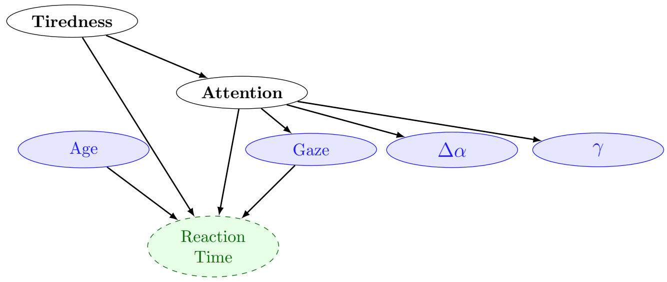

Fig. 4. Causal network of reaction time

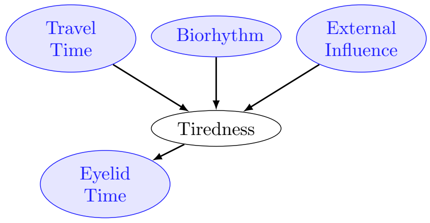

Fig. 5. Causal network of tiredness

suppose that the ego car applies an emergency braking. The greater the distance between the two cars is compared to the stopping distance, the bigger the margin of safety is. But if the ego car brakes weaker, margin will be less important. Therefore the risk level will raise and we warn the driver to brake stronger. By this procedure, safety distance depends on the initial speed of the ego car, the maximum deceleration (depends only on environmental states and car features) and the reaction time.

Hence all driver states (e.g. fatigue, distraction) and driver behavior (e.g. prudent or risky driving) are linked to accident probability only via the reaction time. This variable depends on tiredness, attention, the gaze tracking and the driver age (e.g. an elderly has his reflex and movement speed slow) see Fig. 4. The blue nodes are observed variables, green dashed nodes are variables that are communicated by VANET, and bold variables will be developed in a further graph. Nodes $\Delta\alpha$ and γ are symptoms of attention. $\Delta\alpha$ compares the steering angle to the normal trajectory (i.e. if the car zigzags one explanation can be that the driver is inattentive). γ is the longitudinal and lateral accelerations, which can be used to analyze driver behavior abruptness. Finally the reaction time is communicated to other road users. Indeed, the probability that an inattentive driver has to make an emergency stop is augmented compares to an attentive and anticipating driver. Consequently informing following cars allow drivers to reduce risk level by increasing the inter distance.

The tiredness node in Fig. 5 depends on travel time, external influences such as ambient temperature, and biorhythm i.e. biological cycles depending on driver habit. For example, a driver used to drive by night, is probably less tired than someone who is not accustomed. Tiredness can partially be observed by eyelid time.

In Fig. 6 attention depends on road monotony and the distraction in the cabin, e.g. talking, radio and telephone call. For example if the driver is not tired and he is talking to the passenger, so he is likely to be distracted. On the contrary, if he is tired, talking help him to stay awake, see

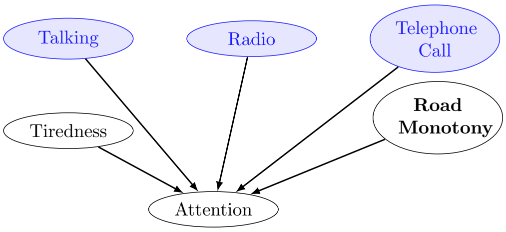

Fig. 6. Causal network of attention

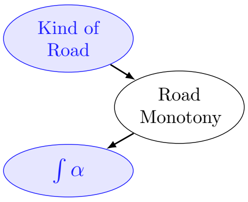

Fig. 7. Causal network of monotony

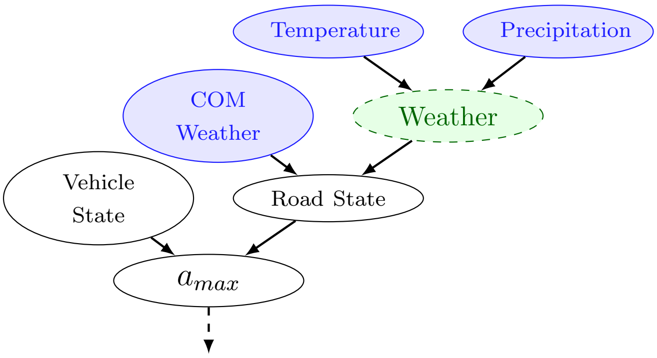

Fig. 8. Causal network of maximum deceleration a_{max}

also Canadian Centre for Occupational Health and Safety Government of Canada (2015).

Monotony occurs mainly on highway, when traffic is less important, and on straight roads. Hence road monotony depends on where the vehicle is in or out of town. $\int \alpha$ gives the evolution of steering angle during a time window (see Fig. 7). A low value means that the road is straight.

Environment and car features block All car and environment states are linked to accident probability via the maximum deceleration a_{max} see Fig. 8. a_{max} is the physical limit of the brakes, whether or not the driver goes up until this limit.

Vehicle state gathers car features such as brakes, tires and dampers status. The road state represents the environment effect on the road, i.e. the road is dry, wet or icy. Road state is the combination between information coming by VANET and our knowledge about the weather. In fact, temperature and precipitation sensors give only uncertain information about the weather. That is why communication allows to decrease or increase the uncertainty. We communicate only the measured weather to avoid an auto-validation of our knowledge by repeated communication.

Inter distance block The inter distance is the most important part of the risk assessment. Because if the car inter distance is adapted whatever the situation, then the

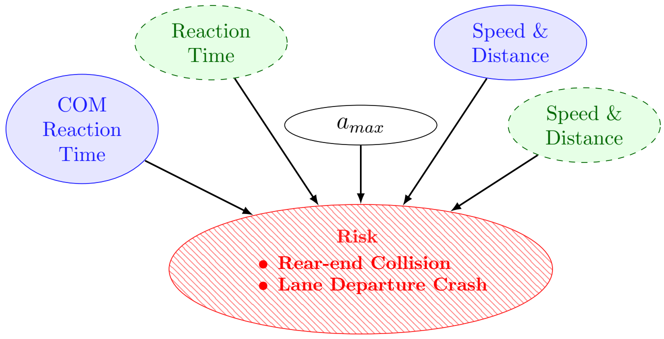

Fig. 9. Causal network of risk assessment

accident can be avoided. The inter distance is a function of speeds and positions. These two variables are accessible thanks to information already present in the car, to car communication and GPS. Car mapping combined with shared sensing give the positions and speeds of road users, and thus their inter distance.

Risk block Risk block depends on the reaction time, maximum deceleration, speed, and inter distance see Fig. 9. The impending risk can be split in two parts: rear-end collision with mobile objects (actually only vehicle) and lane departure crashes (e.g. front-end collision, collision with roadside object and road-leaving in curve).

3.2 Translation into BN

The causal network has to be completed with a probabilistic model. This is done by associating to all nodes a probability distribution table: for not measured root nodes (e.g. age or travel time) this table contains prior probability and for all other nodes their conditional probability.

Standard BN deals with discrete nodes which is adapted for some nodes like weather or telephone call (i.e. discret by nature). The continuous variables have to be discretized. The number of states depends on several parameters. For instance in the case of temperature even if the sensor precision would allow a fine discretization, two or three states are sufficient. In fact that what we want to know is whether or not a wet road surface turns icy. Additionally knowing that computation time depends exponentially on the number of nodes and states, uselessly granularity has to be avoided. On the other side, for some variables like the reaction time, it would be advantageous to discretize finely. But we do not have precise measurement but only a rough estimation. Therefore more than three states for the reaction time would show a precision which does not exist.

The above BN is described by twenty six tables (one for each node). Due to the limited page number we present only one table as an example see Table 1. The BN is coded with the Matlab Bayes Net Toolbox created by Murphy (2001). Tables are filled with experts knowledge, data from statistical documents, official accident reports (ONISR (2014)), and personal knowledges of the situation. Therefore, further discussions with experts can enhance estimation quality.

Situations							Result		
Temperature (°C)				Precipitation			Weather		
$T < -3$	$-3 \le T < 1$	$1 \le T < 4$	$T \ge 4$	True	$< 1h$	False	Sun	Rain	Snow
X				X			0	0.1	0.9
	X			X			0	0.3	0.7
		X		X			0	0.85	0.15
			X	X			0	0.99	0.01
X					X		0	0.05	0.95
	X				X		0.05	0.1	0.85
		X			X		0.05	0.9	0.05
			X		X		0.05	0.95	0
X						X	0.9	0	0.1
	X					X	0.95	0	0.05
		X				X	0.99	0	0.01
			X			X	1	0	0

Table 1. Conditional probability of weather

3.3 Computation of risk

As already mentioned, RILAT assess vehicle rear-end collision risk and lane departure crashes. As an example, risk assessment between a car B following directly a car A is described in this section.

A potential dangerous situation appears when car A brakes and when the inter distance, with regard of the vehicle speed and reaction time of driver B, is small. Hence the following classification of inter distance, as in Wardzinski (2008), is adopted see Fig. 10: the low risk zone is characterized by a low collision probability. Driver B is able to stop without having to make an emergency stop in order to avoid collision. This zone corresponds to the French highway code which specifies that a driver has to keep at least the distance he covers in two seconds, called d_{margin}.

In the high risk zone, there is a high probability that emergency braking by driver B avoids collision. In the very high risk zone, even if the driver B makes an emergency braking, there is low probability for avoiding collision. The risk estimation for each zone corresponds to maximum risk because it is supposed that driver A makes an emergency stop. In fact, actual risk can be lower, because driver A is not necessarily applying emergency braking and possibly not even braking at all. A solution to improve risk assessment could be achieved by taking into account road infrastructure as approaching highway entrance, crossroads, traffic lights, etc. (object of further works).

To determine these three areas (states of safety distance node), RILAT makes the difference between the stopping distance of car A (i.e. braking at the maximum deceleration a_{max} which is the worst case) and the stopping distance of car B augmented by the distance covered during the estimated reaction time of B. This distance is called d_{min} which, in absence of correction term, provides no safety margin. Thus a correction term X is chosen depending on road surface state (dry, wet, icy) $X = 10\%, 15\%$ and 25%. Also d_{margin} is augmented by a correction term Y ($Y = 5\%, 5\%$ and 5%). With these definitions, zone classification is shown in Table 2.

4. SIMULATION RESULTS

As examples, five scenari are discussed in Table 3. In all these scenari, two cars are moving in town, where car A runs at 11.11 m/s (40 km/h) and car B is getting closer to A at 11.94 m/s (43 km/h) with different reaction time, weather condition, road state and inter distance. On Table 4 we show the results of risk level assessment. As already mentioned, the estimated values concern maximum risk, as for we suppose that driver A is performing emergency braking. In reality, driver A, when braking, does not necessarily go up until maximum deceleration, and even, in most of time, he will not brake at all. Because of the uncertainty of the probability values used in the BN, the major signification of the estimated risk level lies not in its absolute value but in its evolution in time.

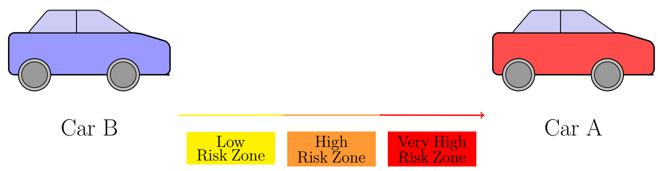

Fig. 10. Three zones of safety distance

Comparison	Result
$d_{A,B} > d_{margin} \cdot Y\%$	Low risk zone
$d_{margin} \cdot Y\% \ge d_{A,B} > d_{min} \cdot X\%$	High risk zone
$d_{A,B} \le d_{min} \cdot X\%$	Very high risk zone

Table 2. Safety distance states depending the inter distance

Scenario Number	Reaction time	Road state	Inter distance (m)
1	Normal	Dry	15
2	Normal	Wet	15
3	Normal	Slippery	20
4	Normal	Dry	13
5	Average	Dry	15

Table 3. Five scenari

Scenario	Risk level (%)		
Number	Low risk	High risk	Very high risk
1	0	89	11
2	0	46	54
3	0	37	63
4	0	40	60
5	0	0	100

Table 4. Risk level of the five scenari

As shown in Table 4, the legal distance d_{margin} is not respected by drivers, in fact for car running at 11.94 m/s, $d_{margin} = 23.9$ m. This is an often observed driver behavior when traveling in town. Hence, for scenario 1 and $d_{A,B} > d_{min} \simeq 13.5$ m, 11 % are in very high risk of an accident. Almost all drivers are safe as long as car A is not making an emergency braking. In scenario 2, car accident level increases which is due to the lower a_{max}. For scenario 3, even if the driver increases the inter distance (i.e. he is more careful) the risk level is in a very high risk of collision that means the driver overestimates his a_{max}. In scenario 4, $d_{A,B} < d_{min}$, car B is under the limit of safety. Thus if car A brakes the risk of collision is important, that is why the probability of high risk zone is increasing in comparison to the first scenario. The last scenario reveals for a bad reaction time (e.g. a tired driver) a 100 % risk level when driver A makes an emergency braking. Hence, beyond of 2 s reaction time, car accident could be unavoidable.

5. CONCLUSION AND FUTURE WORK

In this paper we describe a new tool, called RIsk Level Assessment Tool. It deals with impending risk (i.e. it can occur in a short time horizon) and latent risk (not presented in this paper). Information needed for assessment are obtained by several sources: sensors already present in standard cars, some additional low cost sensors and information exchange via VANET covering interactions between drivers, vehicles and environment such as signal panels, traffic light which will be added to our model in future works. Naturally, RILAT allows sensors to be added such as RaDAR or LiDAR, cameras etc.

The causal representation of the Bayesian Network allows an easy interpretation of the situation. Moreover risk level corresponds to the computed probability of the three defined risk levels. Then for rear-end collision, we evaluate the minimum distance to stop the car for all the possible situations and classify the inter distance. However, the assess risk is the maximal risk because we are not taking into account the probability that driver A is not necessarily applying emergency braking. Therefore driver braking intention will be the object of future works, as well as risk estimation of lane departure crashes, uncertainty in car communication and test in realistic environments.

REFERENCES

Anderson, S., Karumanchi, S., and Iagnemma, K. (2012). Constraint-based planning and control for safe, semi-autonomous operation of vehicles. In *2012 IEEE Intelligent Vehicles Symposium (IV)*, 383–388. doi:10.1109/IVS.2012.6232153.

Canadian Centre for Occupational Health and Safety Government of Canada (2015). Fatigue : OSH Answers. URL `http://www.ccohs.ca/oshanswers/psychosocial/fatigue.html`.

Caveney, D. and Dunbar, W. (2012). Cooperative driving: Beyond V2v as an ADAS sensor. In *2012 IEEE Intelligent Vehicles Symposium (IV)*, 529–534. doi:10.1109/IVS.2012.6232210.

Firl, J., Stubing, H., Huss, S., and Stiller, C. (2012). Predictive maneuver evaluation for enhancement of Car-to-X mobility data. In *2012 IEEE Intelligent Vehicles Symposium (IV)*, 558–564. doi:10.1109/IVS.2012.6232217.

Hartenstein, H. and Laberteaux, K.P. (2009). *VANET Vehicular Applications and Inter-Networking Technologies.* Wiley.

Houenou, A., Bonnifait, P., and Cherfaoui, V. (2014). Risk assessment for Collision Avoidance Systems. 386–391. IEEE. doi:10.1109/ITSC.2014.6957721.

Korb, K.B. and Nicholson, A.E. (2010). *Bayesian Artificial Intelligence, Second Edition.* Chapman & Hall, second edition.

Ledy, J., Hilt, B., Boeglen, H., Poussard, A., Drouhin, F., Vauzelle, R., and Lorenz, P. (2015). Impact of Realistic Simulation on the Evaluation of Mobile Ad Hoc Routing Protocols. *IEEE Transactions on Emerging Topics in Computing*, 3(3), 317–334. doi:10.1109/TETC.2015.2405478.

Lefèvre, S., Laugier, C., and Ibanez-Guzman, J. (2012). Risk assessment at road intersections: Comparing intention and expectation. In *2012 IEEE Intelligent Vehicles Symposium (IV)*, 165–171. doi:10.1109/IVS.2012.6232198.

Liebner, M., Baumann, M., Klanner, F., and Stiller, C. (2012). Driver intent inference at urban intersections using the intelligent driver model. In *2012 IEEE Intelligent Vehicles Symposium (IV)*, 1162–1167. doi:10.1109/IVS.2012.6232131.

Milanés, V., Pérez, J., Godoy, J., and Onieva, E. (2012). A fuzzy aid rear-end collision warning/avoidance system. *Expert Systems with Applications*, 39(10), 9097–9107. doi:10.1016/j.eswa.2012.02.054.

Murphy, K.P. (2001). The Bayes Net Toolbox for MATLAB.

Neapolitan, R.E. (2003). *Learning Bayesian Networks.* Prentice-Hall, Inc.

ONISR (2014). L'accidentalite routiere en 2013. Technical report, Observatoire national interministeriel de la securite routiere.

Otto, C., Gerber, W., Leon, F., and Wirnitzer, J. (2012). A Joint Integrated Probabilistic Data Association Filter for pedestrian tracking across blind regions using monocular camera and radar. In *2012 IEEE Intelligent Vehicles Symposium (IV)*, 636–641. doi:10.1109/IVS.2012.6232228.

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: networks of plausible inference.* Morgan Kaufmann Publishers Inc.

Pérez, J., Godoy, J., Milanés, V., Villagra, J., and Onieva, E. (2012). Path following with backtracking based on fuzzy controllers for forward and reverse driving. In *2012 IEEE Intelligent Vehicles Symposium (IV)*, 1108–1113. doi:10.1109/IVS.2012.6232191.

Rastelli Pérez, J., Milanés, V., and Santos Peñas, M. (2013). Control Agents for Autonomous Vehicles in Urban and Highways Scenarios. 120–125. doi:10.3182/20130626-3-AU-2035.00023.

Wardzinski, A. (2008). Dynamic risk assessment in autonomous vehicles motion planning. 1–4. IEEE. doi:10.1109/INFTECH.2008.4621607.

Yang, G., Lin, Y., and Bhattacharya, P. (2010). A driver fatigue recognition model based on information fusion and dynamic Bayesian network. *Information Sciences*, 180(10), 1942–1954. doi:10.1016/j.ins.2010.01.011.