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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,

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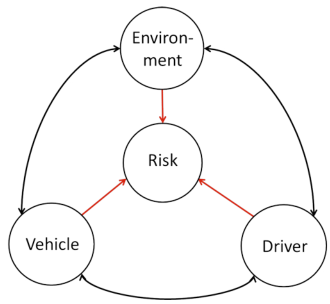

Fig. 1. Scheme of risk formation

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, crossroad), 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.