

Driver behavior assessment based on the G-G diagram in the DVE system

Oussama Derbel and René Jr. Landry

*University of Québec, École de technologie supérieure,
Montreal, Canada*

e-mail: first-name.last-name@lassena.etsmtl.ca

Abstract: This paper proposes a driving risk model based on the information given from the Driver-Vehicle-Environment (DVE) entities. It develops a two-level strategy to evaluate the driving risk. The first level aims to assess the risk locally in each entity and the second one concludes the global risk. The advantage of this approach is the simultaneous consideration of the parameters related to the DVE system regardless of information type (dynamic and static). It uses the Dempster-Shafer Theory (DST) for information fusion at each level. The approach uses Fuzzy Theory (FT) to design Basic Probability Assignment (BPA) functions, which is the significant part of the belief theory. The drivers' information for the driver risk evaluation the age and gender. Two parameters in the Vehicle entity are used in the cases of lane keeping and a left/right turn scenarios with utilizing two different developed Fuzzy Inference Systems (FIS). The first system uses an Euclidean acceleration-norm and the velocity of the vehicle; while, the second one, uses lateral/longitudinal acceleration based on G-G diagram and a proposed risk indicator.

The results of different scenarios validate the developed risk models using the sixth version of the Proportional Conflict Redistribution (PCR6) combination algorithm.

© 2016, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved.

Keywords: Fuzzy theory, risk assessment, G-G diagram, belief theory, Pay How You Drive, Pay Where You Drive

1. INTRODUCTION

Nowadays, inappropriate speed and acceleration are the major causes of drivers death in road accidents. According to Road Safety Canada Consulting (2011), 27% of casualties in 2011 are caused by speeding where 81% of them occur in highways. In addition, 30% of accidents take place at intersections according to Rocha et al. (2013). This leads to take into account not only the vehicle parameter's but also the environment aspects such as where you drive and as you drive. For example, the night driving is considered riskier than the day driving, according to the accident number, due mainly to the visibility.

In the last two decades, there are numerous research works that focus on the risk assessment in some particular driving situations such as lane keeping and braking. There are different autonomous vehicle-follower control systems such as ACC with co-operative vehicle-follower control was designed to reduce the rear-end crashes by adjusting the vehicle speed and the inter-distance with the follower vehicle. However, the acceptance of these systems by people depends on its intuitiveness, unobtrusiveness, and performances as discussed by Zhang et al. (2010). So, the design of such systems has to be based on a good framework that links the parameters related to the Driver, Vehicle and Environment to have a better risk estimation. Especially, the case of insurance application, the accuracy of the estimated risk is very important, because it is directly linked to the insurance charge according to the Pay How You Drive (PHYD) and Pay Where You Drive

(PWYD) models. Several works use the Hidden Markov Model (HMM) and the Gaussian Mixture Model (GMM) to estimate the driver skills as done by Meng et al. (2006) and Angkititrakul et al. (2011), respectively. However, these references were only concentrated on the vehicle parameters to assess the driving behavior and it is more judicious to consider the Driver and Environment entities.

This paper deals with the risk estimation based on the parameters of the DVE system using the Dempster-Shafer Theory (DST) and the sixth version of the Proportional Conflict Redistribution (PCR6) methods of Belief theory in the case of insurance applications. The developed risk models are designed to assess the driving risk in the case of lane keeping situation as well as the turning scenario using the G-G diagram. This latter was used in the literature to define the driving safety area based on the longitudinal and lateral accelerations. Based on this diagram a risk indicator is developed and integrated in a Fuzzy Inference System (FIS). Two developed FIS are used in the Vehicle entity to compute the driving risk level.

After the presentation of the problematic and our methodology to assess the driving risk in Section 2, Section 3 introduces the DST used for risk information fusion. Section 4, develops the risk models for each entity of the DVE system. Before the conclusion in Section 6, Section 5 presents the results of the proposed scenarios used to validate the proposed risk models.

2. PROBLEM STATEMENT AND METHODOLOGY

The evaluation of the driver safety remains a complex task due to the heterogeneity of the parameters in terms of time variation (e.g. driver age and vehicle velocity). Moreover, vehicle's parameters are measured using low-cost sensors, and therefore are noisy. The noise affects the driver safety indicators accuracy and makes the risk assessment more difficult, especially in the case of insurance applications, where the driver is charged according to his driving behaviors (PWYD and PHYD).

To take into account the heterogeneity of the parameters, Figure 1 presents the adopted fusion architecture. In this one, the noise is spread from the vehicle sensors level to the global decision level using the Dempster-Shafer theory of evidence. This theory allows taking into account the noise of the parameters by computing the belief and plausibility parameters. The difference between these two parameters is the uncertainty of the output given the errors of the inputs. Figure 1 shows two fusion levels while the first one is designed to fuse locally the risk of each entity of the DVE system, and the second one computes the global driving risk.

In this paper, the risk in Driver entity depends on the driver age and gender. In fact, analysis of accident statistic reveals that the driver's gender is an important factor that affects the traffic safety as shown in Figure 4a. In this figure, male drivers are less involved in accidents than female drivers for all ages. Therefore, the risks related to the age and gender are fused to obtain the local risk related to the Driver entity.

In the Vehicle entity, the longitudinal and lateral accelerations as well as the acceleration norm and the velocity are taken into account. The lateral and the longitudinal acceleration are evaluated together by means of the G-G diagram (more explanation is given in Section 4.3). The diagram is divided into different zones that characterizes the driving behavior, especially in the case of a curved road (e.g., right/left turns). Since the vehicle parameters are noisy, the fuzzy logic theory is applied in our framework to ensure the fuzzy passage between the different zones of the G-G diagram. From the insurance point of view, the Vehicle safety level serves to evaluate the insurance policy based on the PHYD model. Here, as the Vehicle risk level gets more important as the driver is considered aggressive and the insurance charge gets important.

According to the accident statistical analysis done by Gilbert and Halsey-Watkins (2013), the driving place, the time of the day, and the day of the week are of great importance. Figure 2 presents the normalized risk level related to the time of driving during the day which is considered in this paper.

3. DEMPSTER-SHAFFER THEORY OF EVIDENCE

The Dempster-Shafer Theory (DST) has been developed by Dempster (1968) and later on by Shafer (1976). The DST theory is based on the definition of the frame of discriminant composed by all the possible sets (or hypotheses). Let Θ be the set of the hypotheses defined as $\Theta = \{\theta_1, \theta_2, \dots, \theta_p\}$, where θ_p is a possible solution. The relative referential subset 2^Θ (power set) is then defined as

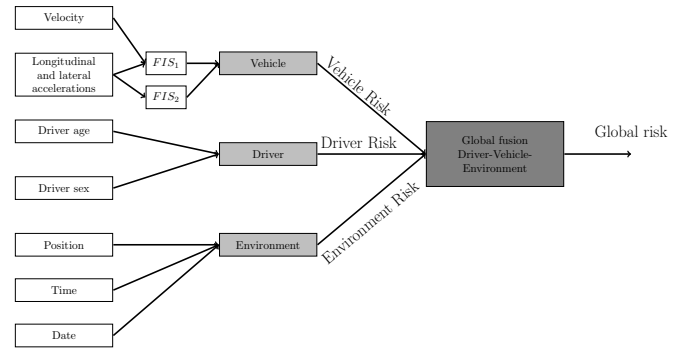


Fig. 1. Diagram for driving risk assessment

$$2^\Theta = \{\emptyset, \theta_1, \theta_2, \dots, \theta_p, \theta_1 \cup \theta_2, \dots, \Theta\}, \quad (1)$$

where \emptyset represents the conflict between sources and Θ the ignorance (the union of all hypotheses). The belief in each hypothesis is represented by the mass, the Basic Belief Assignment (BBA) or the Basic Probability Assignment (BPA) defined as:

$$m : 2^\Theta \rightarrow [0, 1], \quad (2)$$

where $\sum_{A \in 2^\Theta} m(A) = 1$ and $m(\emptyset) = 0$.

So, the DS structure is not a fuzzy measure since it is not required to have $m(\Theta) = 1$. Yager (1999) studied the difference between the Fuzzy and the DS theories and concludes that the DST allows representing an additional information to the fuzzy measure about the uncertainty in the parameter. In our framework, the algorithm developed by Boudraa et al. (2004) is used in the case of fuzzy measure.

The combination step is the third step of this theory. There are a variety of fusion algorithms in this part and the choice among them depends on the application. Daniel et al. (2013) suggest the use of the Proportional Conflict Redistribution (PCR) algorithm, which is developed by Smarandache and Dezert (2005), in the case of risk fusion. However, Daniel et al. (2013) used the fifth version of this algorithm that Martin and Osswald (2006) has demonstrated some drawbacks and propose the sixth version of the PCR given for N sources as follows:

$$m_{PCR6}(X) = \sum_{\theta_1 \cap \dots \cap \theta_p = X} \prod_{i=1}^N m_i(\theta_i) + \sum_{k=1}^N m_k(X)^2 \sum_{\substack{\bigcap_{k=1}^{N-1} \theta_{\gamma_k(k)} \cap X = \emptyset \\ \theta_{\gamma_k(1)}, \dots, \theta_{\gamma_k(N-1)} \in (2^\Theta)^{N-1}}} \frac{\prod_{j=1}^{N-1} m_{\gamma_k(j)} \theta_{\gamma_k(j)}}{m_k(X) + \sum_{j=1}^{N-1} m_{\gamma_k(j)} \theta_{\gamma_k(j)}} \quad (3)$$

where γ_k is given by:

$$\begin{cases} \gamma_k(j) = j & \text{if } j < k \\ \gamma_k(j) = j + 1 & \text{if } j \geq k \end{cases} \quad (4)$$

The decision step is used to assign the output masses over the reference subset given by (1). In this paper, the Belief function is used to decide the risk output. More information about the decision function can be found in the reference of Martin and Osswald (2006).

Download English Version:

<https://daneshyari.com/en/article/714011>

Download Persian Version:

<https://daneshyari.com/article/714011>

[Daneshyari.com](https://daneshyari.com)