International Journal of Automotive Technology, Vol. 19, No. 1, pp. 167−177 (2018)
DOI 10.1007/s12239−018−0016−1

pISSN 1229−9138/ eISSN 1976−3832

BELIEF AND FUZZY THEORIES FOR DRIVING BEHAVIOR ASSESSMENT IN CASE OF ACCIDENT SCENARIOS

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(Received 29 September 2016; Revised 26 April 2017; Accepted 23 June 2017)

ABSTRACT−The estimation of the overspeed risk before the accident is among the main goals of this paper. The proposed method uses the Energy Equivalent Speed (EES) to assess the severity of an eventual accident. However, the driver behavior evaluation should take into account the parameters related to the Driver, the Vehicle and the Environment (DVE) system. For this purpose, this paper considers a two-level strategy to predict the global risk of an event using the Dempster-Shafer Theory (DST) and the Fuzzy Theory (FT). This paper presents two methods to develop the Expert Model-based Basic Probability Assignment (EM based BPA), which is the most important task in the DST. The first one is based on the accident statistics and the second method deals with the relationship between the Fuzzy and Belief measurements. The experimental data is collected by one driver using our test vehicle and a Micro-intelligent Black Box (Micro-iBB) to collect the driving data. The sensitivity of the developed models is analysed. Our main evaluation concerns the Usage Based Insurance (UBI) applications based on the driving behavior. So, the obtained masses over the defined referential subsets in the DST are used as a score to compute the driver's insurance premium.

KEY WORDS : Advanced driver assistance system, Driver-vehicle-environment system, Fuzzy inference systems, Belief theory, Driver behavior

1. INTRODUCTION

Driver safety has been always the main focus of automotive manufactuers as well as researchers. Different systems have been designed to improve the driver safety and prevent him from dangerous scenarios. For example, Wang *et al*. (2016) investigated the temporal window size used to detect drowsy behavior based on the accelation, velocity and steering angle. Yang *et al*. (2017) have extended their works by developping a new algorithm called Extended Support Vector Data Description (E-SVDD) to predict the collision. Nevertheless, the driving behaviour recognition still remains a challenge since it involves different factors of distinctive types: static (e.g. driver age) and variable (e.g. speed). Different researchers have used the Hidden Markov Model (HMM) as Meng *et al*. (2006), Neural Network (NN) or Gaussian Mixture Model (GMM) as Angkititrakul *et al*. (2011) to classify the driver behaviour as "Aggressive" or "Not Aggressive". In these cited reference, authors have not taken into account neither the driving environment nor the driver characteristicvs (e.g. age, gender) simultaneously. Therefore, the driving assessment remains incomplete, especially in case of Usage Based Insurance (UBI) applications based on the driver behavior such as the Pay How You Drive (PHYD) and Pay Where You Drive (PWYD) concepts.

The heterogeneity of the driving parameters raises the question on how to take them into account simultaneously and considering the data incertainties since we have a MEMS based sensors (for example, the higher cost of a sensor is less than one dollar). There are three theories to deal with such problems. The first one is the probability theory which requires a rigorous mathematical basis and *a-priori* knowledge of the situation. The second one is the possibility theory which can model the imprecision and the inaccuracy of data. Nevertheless, a wise choice of the combination operator is required. The third one is the evidence or Belief Theory (or Dempster-Shafer Theory (DST)) which can model the imprecision and the inaccuracy of the data and manage the conflict between sources through various methods of combination. Nevertheless, the DST has the disadvantage of the high correlation between the complexity of the problem and the cardinal of the frame of discriminant used to classify the driving behavior in our application. This paper considers this problem by proposing a two-level fusion architecture as shown in Figure 1. Here, the first level in our fusion architecture is composed of three local fusion algorithms related to the Vehicle, the Driver and the Environment entities. The second level is dedicated to fuse the local risks from each entity of the DVE system using the DST. Here, the output of the DST algorithm represents the driving scores, which are also the masses over the defined referential subset in the DST.

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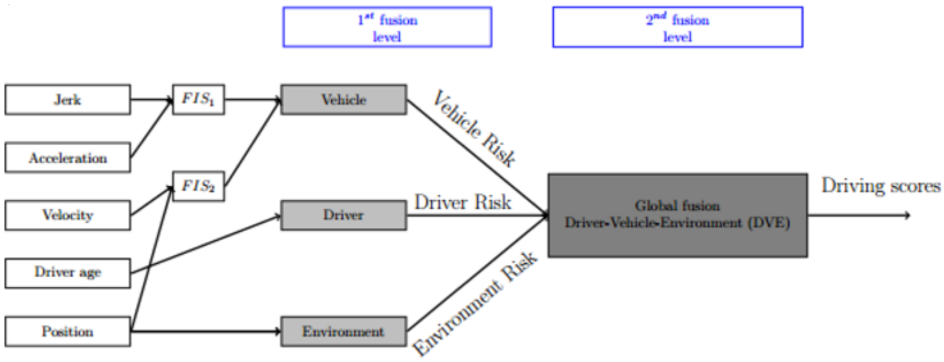

Figure 1. Fusion architecture.

To reduce the complexity of the fusion problem, a Fuzzy Inference Systems (FISs) have been developed. The first one has the acceleration and the jerk as inputs and the driver aggressiveness as output. The second FIS is related to the accident severity, which is more detailed later.

The choice of the parameters is an important issue in case of incurance application based on the driver behavior. The jerk is usually used to measure the comfort of movements. Since the driving comfort is highly related to the driving aggressiveness, the jerk remains an important parameter to assess the driver behaviour. In addition, the jerk is always available even in case of GPS outages. Of course the acceleration is widely used but its variation is also important when it concerns the driving behavior evaluation. In previous studies such us those done by Angkititrakul *et al*. (2011) and Ly *et al*. (2013), this parameter has been neglected in case of insurance application and was used only for vehicle control applications. The other used parameters in this paper, which are acceleration, velocity, position and driver age, were allways evaluated separately by insurers. For example, the insurance cost depends on the driver's address and not on the driver's driving environment. So, the evaluation was static in contrary to our approach of driving assessment dedicated to UBI concepts (Pay How You Drive and Pay Where You Drive).

According to the National Highway Traffic Safety Administration's traffic safety facts report of 2012, the overspeed causes 30 % of the fatalities in the USA (NHTSA, 2014). In this paper, a new approach is developed to model the risk of the overspeed based on the probability and the severity of the eventual accident. This proposed model can be integrated in an advanced driver assistance system to prevent the driver from the accident in case of car following driving situation.

This paper illustrates in Section 2 some basic concepts of the DST which is used for risk information fusion. Section 3 details the proposed approaches to determine the basic probability assignment in each of the Driver-Vehicle-Environment (DVE) system's entities. The sensitivity of the developed models and the experimental results presented in Section 4 are followed by conclusions and future works.

2. DEMPSTER-SHAFER THEORY OF EVIDENCE

The Dempster-Shafer Theory (DST) has been developed for the first time by Dempster and Shafer (Smarandache and Dezert, 2009). This theory represents an extension of the probability theory since it can represent an incomplete knowledge. The DST has been applied to various applications such as the human action recognition in videos by Ramasso *et al*. (2008), target detection by Ristic and Smets (2005) and ground water vulnerability assessment by Al-Abadi (2015). Nevertheless, it has never been used in case of insurance application based on the driver behavior. This paper apply this theory to the UBI applications.

The DST is based on four steps: 1) Modelling which aims to define the frame of discriminant, 2) Estimation which is designed to choose the mass functions from information sources, 3) Combination using algorithms such as the one of (Deng *et al*., 2004) and 4) Decision step which based on credibility, plausibility and pianistic probability functions.

2.1. Modeling and Estimation Steps

The DST is based on the definition of the frame of discriminant composed by all the possible sets. Let θ the set of the hypotheses defined as $\theta = \{\theta_1, \theta_2, \dots \theta_p)$ where θ_p is a possible solution. In our framework, the frame of discriminant is composed by Low Risk (LR), Medium Risk (MR) and High Risk (HR), which qualify the risk related to each parameter. The relative referential subset 2^p (power set) is defined as $2^\theta = \{\varnothing, \theta_1, \theta_2, \dots \theta_p, \theta_1 \cup \theta_2, \dots, \theta\}$ where $\varnothing$ is the impossible hypothesis (conflict between sources) and θ the ignorance (the union of all hypotheses). The conflict between sources characterizes the non-exhaustiveness of the fixed frame of discriminant.

The belief in each hypothesis is represented by the Basic Probability Assignment (BPA), which is called also the mass that verify the following criteria:

$$\begin{cases} m : 2^{\theta} \rightarrow [0 \quad 1] \\ \sum_{A \in 2^{\theta}} m(A) = 1 \end{cases} \tag{1}$$

The determination of the BPA depends on the problem's constraints. There is no common method in the literature. In this paper we propose a new method that could be generalized for problems that deal with the DST. It consists in developing the Fuzzy Inference System (FIS) models then converting the fuzzy measurements to BPAs.

2.2. Combination Step

The Dempster-Shafer (DS) rule is the first rule of combination appeared in the DST. The mass of a focal element X is given by the following expression:

$$m_c(X) = \frac{1}{1 - \sum_{A \cap B = \varnothing} m_1(A) m_2(B)} \sum_{A \cap B = X} m_1(A) m_2(B) \tag{2}$$

Where A and B are focal elements. The normalization term $k = \frac{1}{1 - \sum_{A \cap B = \varnothing} m_1(A) m_2(B)}$ is called the conflict term since it represents the degree of conflict between two sources. $K = 1$ means that there is no intersection between two propositions. This conflict describes the non-exhaustiveness of the defined discriminant frame. The limitation of the DS's rule of combination is the equal redistribution of the conflict by means of the normalization term. To reduce the conflict, the Proportional Conflict Redistribution (PCR) operator has been developed by Smarandache and Dezert (2005). Martin and Osswald (2006) has improved the PCR and presented its sixth version (PCR6), which is used in our framework since it has shown good performances in our previous studies.

2.3. Decision Step

According to Martin (2008), generally one of the following functions are considered:

− The credibility *Bel* function is defined as follows:

$$Bel(X) = \sum_{Y \subseteq X \neq \varnothing} m(Y) \tag{3}$$

Where m(Y) is the mass over the proposition Y

− The plausibility *Pl* is given by the following expression:

$$Pl(X) = \sum_{Y \cap X \neq \varnothing} m(Y) \tag{4}$$

3. BASIC PROBABILITY ASSIGNMENT OF THE DVE ENTITIES

The first and important step in the DST is the determination of the Basic Probability Assignment (BPA) which is still an open issue. A good modelling leads to a precise results with minimum of conflict between sources. However, researchers have addressed this issue using different techniques. For example, Jiang *et al*. (2015) use the similarity measures of membership functions to determine the BPA in a fuzzy environment. In the same framework, another method has been proposed by Dutta and Ali (2011) who use the parameter $\alpha \in [0 \quad 1]$ to divide the interval of a set. For each α-cut the belief and plausibility measures are computed.

Denœux (2006) uses the multinomial confidences regions to build the belief functions from the realization of a discrete random variable with unknown probability distribution.

This section presents the methodology to develop the Expert-Model-based BPA (EM-BPA) of each entity of the DVE system. It uses the relatioship between the fuzzy theory and the DST.

3.1. From Fuzzy Theory to Belief Theory

The determination of the BPA remains a complex problem when the application is based on uncertain and imprecise parameters. In this paper, fuzzy modelling is used as bridge between data from sensors and BPAs.

For example, the BPA could be derived from probabilities. Boudraa *et al*. (2004) defined a method to compute the BPA in case of image segmentation. For each number of cluster or membership function there is a method of BPA computation. In our case of three membership functions ("Good", "Normal" and "Aggressive"), this model can adapted as follows:

$$\alpha = \max_{1 \le i \le N} \mu_i(x) - \min_{1 \le i \le N} \mu_i(x) \tag{5}$$

Where $\Sigma_{i=1}^{N} \mu_i(x) = 1$ and μ_i the degree of the membership function.

The mass functions are defined as follows:

$$\begin{aligned} m_{H_k \cup H_i}(x) &= \alpha[\mu_k(x) + \mu_i(x)] \\ m_{\left(\bigcup_{i=1}^{N} H_i\right)}(x) &= 1 \\ m_{H_i}(x) &= [1 - m_{H_k \cup H_i}(x)]\mu_i(x) \end{aligned} \tag{6}$$

Where H_i the the membership function and N its number.

3.2. Vehicle Entity's EM-based BPAs

3.2.1. Acceleration-Jerk FIS model

The Acceleration-Jerk FIS has the acceleration and jerk as inputs to compute the driver aggressiveness through the fixed output membership functions ("Good", "Normal" and "Aggressive").

The membership functions of the Forced Acceleration (FA) and Sharp Deceleration (SD) fuzzy sets are trapezoidal functions with the following parameters [0 4 10 10] and [−10 −10 −3 0], respectively. A "Good" acceleration is represented in Figure 2 (a) by a triangular membership function with the parameters [−4 0 3] as mentioned by Ge *et al*. (2008).

In Figure 2 (b), the jerk is “Low” (respectively “High”) when it is equal or less than -4 m/s^3 (respectively equal or greater than 3 m/s^3). The two fuzzy sets are represented by a trapezoidal membership functions. The “Low” jerk is qualified as dangerous because it corresponds to an emergency braking scenario. When it is close to zero, it is considered as “Good” (Figure 2 (b)). The choice of the interval of the jerk is based on the work done by Molina (2005). The output membership function is given by Figure 2 (c). The driver aggressiveness varies from 0 to 100 %. We assume that a “Good” (respectively “Aggressive”) driver is qualified by aggressiveness less than 20 % (respectively greater than 80 %). Figure 2 (d) presents the relationship between the driver aggressiveness, the acceleration and the jerk. Here, as the sudden change in acceleration (jerk) gets more important, the driving behaviour shifts to an uncomfortable state and the driver is considered “aggressive” (high risk driving).

The type of the applied FIS is Mamdani, the “OR” method is the maximum, the implication method is minimum, the aggregation method is the sum and the defuzzification method is the Middle Of Maximum (MOM).

3.2.2. Overspeed and severity models

The risk R of an event is defined by the product of the severity S of this event and its probability of occurrence P. Then, the analysis of an accident requires the study of these two parameters P and S simultaneously.

Usually the probability of the accident can be estimated based on statistical data but the estimation of the crash severity between two vehicles is still an open issue. In the literature as well as in practice, the severity is estimated after the accident accoding to the measurement of deformation of the car and the vehicle’s observable braking distance. So, there is no *a-priori* estimation of the eventual crash severity, especially in case of overspeed which is our case of study.

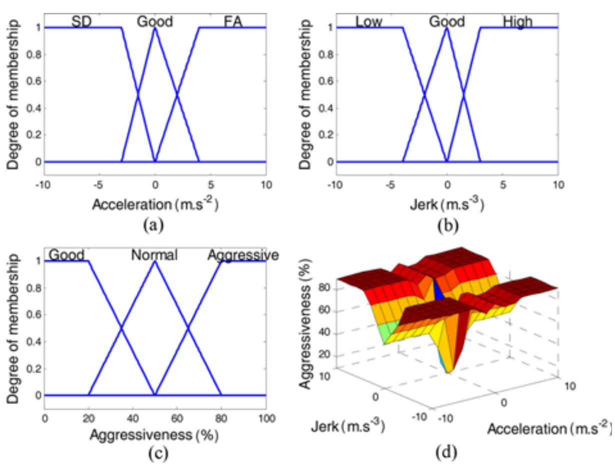

Figure 2. Fuzzy Inference System relative to the longitudinal acceleration and jerk parameters.

The impact of overspeed on traffic safety has long been an important topic for research. The speed is recognised as the most important contributor to the crashes and its severity. Most of research studies in the literature were conducted to evaluate the impact of speed difference between the traffic’s average speed and the single vehicle speed on the crash rate for different type of traffic road or speed limits. Solomon (1964) and Cirillo (1968) studied this relationship in the cases of rural roads and highways, respectively. The same curve shape has been found by these two authors as shown in the Figure 3. Their relationship can be used in our framework if we suppose that the average mean speed is equal to the speed limit. We note that if there is no surrounding vehicle in the traffic, there is a virtual vehicle traveling with the speed limit. So, a positive deviation with respect to the speed limit represents the overspeed.

Figure 3 shows that the low speed environment are subject to high risk more than high speed environment. In fact, rural road are more complex than highway, then it has more accidents. In this paper, the driving place is taken into account when assessing the driving behavior.

Solomon (1964) has studied the impact of the driving time on the crash involvment rate for different deviation from the traffic’s average speed. The day time in rural road represented by blue curve in the Figure 3 is above the night driving time’s curve. It means that the night driving time is more risky than the day driving time. The curves of Solomon (1964) and Cirillo (1968) can be used for the positive and negative speed deviations but there is no analytic expression of the relationship between the crash involvment rate and the speed deviation. We note that the curves in Figure 3 are taken point by point from the works of Solomon (1964) and Cirillo (1968), and then fitted by polynom approximation.

To synthetise the EM-based BPA related to the risk of accident, the data used by Solomon (1964) and Cirillo

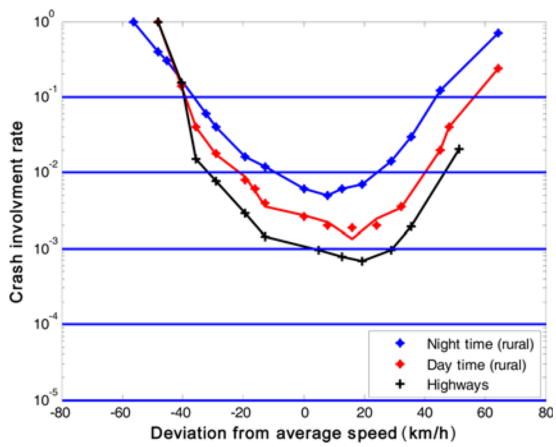

Figure 3. Crash involvment rate according to the deviation from the average speed (interpreted from Solomon (1964) and Cirillo (1968)).

(1968) are normalized to define the thresholds between the different elements of the power set as shown in the Figure 3. According to the subsection 2.1, the referential subset in our application is defined as:

$$2^{\theta} = \{\varnothing, LR, MR, HR, LR \cup MR, LR \cup HR, LR \cup HR, \theta\}$$

Figure 4 presents the EM-based BPA related to the probability of crash involvement in case of overspeed in highways. The choice of the triangular and rectangular shapes has the advantage of simplicity and fast computation, so they should be start functions for our problem.

The estimation of a collision severity is a basic requirement in accident analysis. There are three parameters to evluate the collision severity according to Burdzik *et al.* (2012). The most frequently used parameter is the relative velocity between the two collided vehicles just before the collision.

The second parameter is the Energy Equivalent Speed (EES), which is a measure of the speed that is converted into energy of deformation during the collision. The last one is the Equivalent Barrier Speed (EBS), which is the speed at which a vehicle had crashed into a solid motionless block, causing similar damage in case of a moving object.

In this paper, the EES is modeled through the application of the conservation of momentum theorem on a system composed by the vehicle and its follower. We suppose that a followed vehicle is travelling with the speed limit of the road section. Therefore, the relative velocity $\Delta v = v_n - v_{n+1}$ represents the over-speed of the follower vehicle.

Considering a system of two vehicles (n and $n+1$) where the vehicle $n+1$ is the followed and the vehicle n is the follower. The Momentum Conservation Principle (MCP) applied to this system in case of inelastic collision is given by:

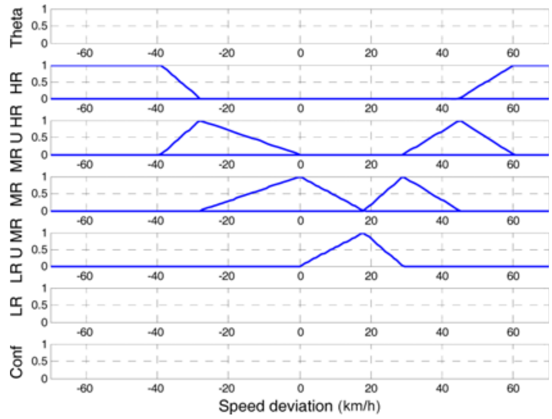

Figure 4. EM-based BPA related to probability of crash involvment in highways.

$$m_{n+1} v_{n+1} + m_n v_n = m_a v_a$$

where the index "*a*" means the system composed of the two damaged vehicles that formed the agglomerate.

Assuming that there is no loss of material during the impact, then $m_{n+1} + m_n = m_a$. Consequently, the velocity of the agglomerate is given by

$$ees_n = (v_n - v_{n+1}) \frac{m_{n+1}}{m_n + m_{n+1}} \tag{7}$$

where ees_n is the velocity variation of the vehicle $n+1$ (followed vehicle) wrecked by the follower vehicle n.

The advantage of the use of the EES in Equation (7) to quantify the severity is the use of the masses and the relative speed which are the most sensitive parameters to

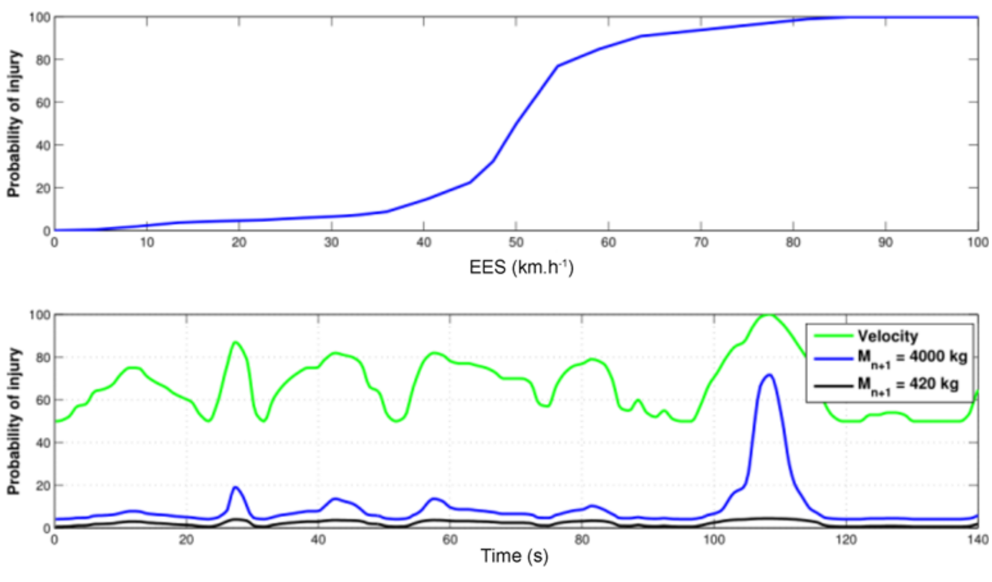

Figure 5. EES and MAIS probability for a moderate injury (Glaser *et al.*, 2010).

the collision severity. In addition, the model in Equation (9) can be integrated in an Advanced Driver Assistance System (ADAS) and gives an *a-priori* evaluation of the risk severity.

Figure 5 top plot represents the likelihood of a moderate injury (Maximum Abbreviated Injury Scale (MAIS) > 2) with respect to the EES taken from Glaser *et al*. (2010). Figure 5 bottom plot represents an example of the probability of injury in case of two different masses of the followed vehicle (v_{n+1} = 420 kg and m_{n+1} = 4000 kg). The speed profile of the follower vehicle is given by the green line in that figure and the speed limit is equal to 30 km/h. Here, for the same current vehicle speed, the probability of injury increases as the mass of the followed vehicle increases also as expected when regarding the Equation (7). As the overspeed and the estimated severity get more important, the driving behaviour shifts to an important aggressive state (high risk driving).

Figure 6 presents the membership functions related to the severity of an accident. The choice of the shape is made for simplicity and cost computation. In addition, the use of the triangular and trapezoid functions facilitate the implementation of the model, and then it could be useful for real time risk assessment. So, with the Figure 6, the fuzzy measurement are computed, and then converted to belief measurement using the Equations (5) and (6).

3.3. Driver Entity's EM-based BPAs

In this paper, the Driver entity's risk depends on the driver's age. Figure 7 top plot presents the number of drivers in Canada per age group given from TC (2011). This figure shows that the number of drivers having more than 65 years-old is greater than those having less than 19 years-old. Then, the risk of the drivers having more than 65 years-old is intended to be greater than the risk of drivers with less than 19 years-old. This conclusion is not valid when regarding the statistics of killed driver per vehicle kilometer per age group presented in the Figure 7 bottom plot. Therefore, the number of killed driver per vehicle kilometer is normalized by the number of driver to avoid the over-representation or under-representation of the risk per each age group. The obtained risk is normalized by its maximum to have the relative risk, which is presented in the Figure 8. According to this Figure, it is clear that young drivers having less that 19 years old are the most riskiest ones due to the highest number of killed drivers per billion vehicle kilometers. These results reflect the impact of the driver experience and his reaction time on the driving risk. In fact, young drivers are less experienced than older drivers, and then they are more riskier. But, driver with more 65 years old are more risker than those having between 25 and 64 years old due to their age and reaction time compared to younger drivers.

3.4. Environment Entity's EM-based BPAs

The development of the EM-based BPA for the Environment entity uses the same methodology of the last Section. Accident rate in Montreal per district is given by Gilbert and Halsey-Watkins (2013). Figure 10 defines the

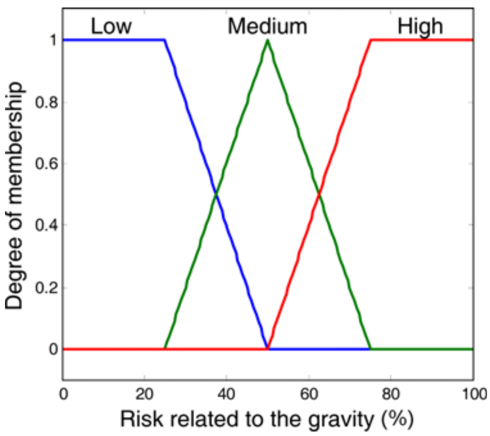

Figure 6. Fuzzy Inference System according to the over-speed and its severity in case of accident.

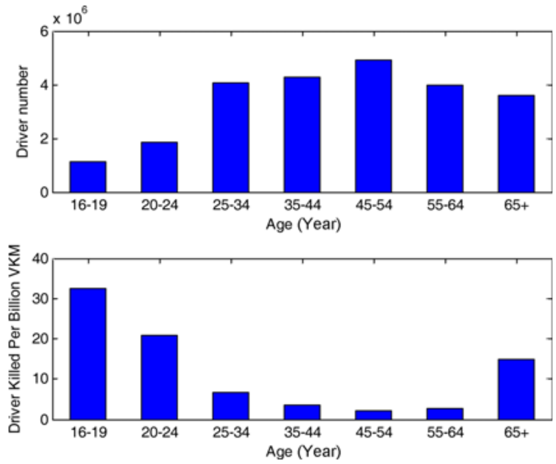

Figure 7. Accident statisctics by age group.

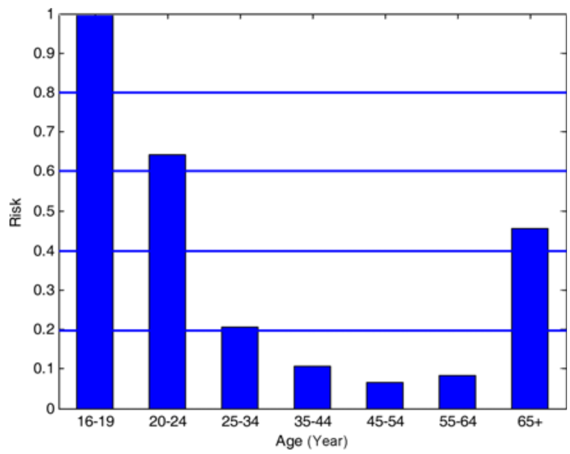

Figure 8. Driver risk by age group.

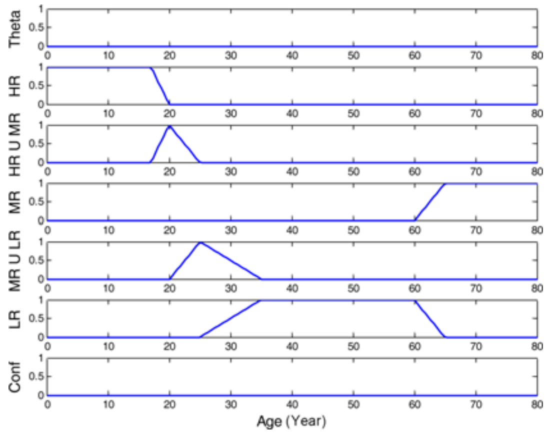

Figure 9. EM-based BPA related to the driver.

normalized risk level using the accident statistics, which is normalized by the demography of the following distrincts: Anjou, Lachine, LaSalle, Mont-Royal, Sud-Ouest, Montreal Nord, Outremont, Saint Laurent, Ville Marie and Verdun. The normalization of the risk level helps us to define the thresholds, and thus develop the Expert-model-based BPA.

Figure 10 shows that the Outremont district is characterized by a Low risk since the accident number is very small relatively to the maximum number of accident in Montreal. At the opposite, the Montreal's Sud-Ouest district is the most risky one relative to the other districts. Based on the developed Expert model, the BPA for each district is computed and used at the high level of information fusion. For simplicity, we do not consider the spatial continuity between districts. So, every district has one non null mass over time and over the referential subset defined in the subsection 2.1. For example, according to the Figure 10, the district "Outremont" has a total mass assigned to the risk level "LR" ($m_{\mathrm{LR}} = 1$) and the masses

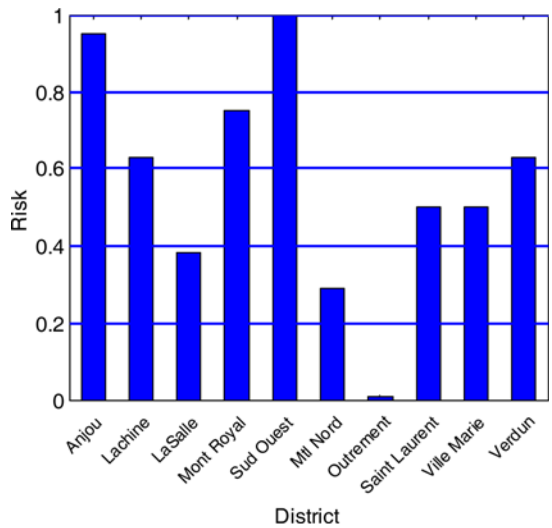

Figure 10. Risk for each district in Montreal.

assigned to the other propositions are null.

4. EXPERIMENTAL RESULTS

4.1. Introduction

This section is designed to test the developed DVE models. Two types of scenario are presented. The first one is composed by a samples of data and the second type is designed to evaluate a driving mission composed by a set of data (Figure 12) recorded by the Micro-iBB (Figure 11). The final masses are the mean of the obtained instantenous masses over the mission time.

The designed Micro-iBB is equipped by an Inertial Navigation System (INS), a Global Positionning System (GPS) receiver and an LTE module for communicating and wiressely sending the recorded data. A GPS/INS integration algorithm is implemented to obtain an accurate real time position even in harsh environments such as tunnel and urban canyons where there is GPS outage. The Micro-iBB can be placed anywhere in the vehicle in contrary to some commercial products that must be connected to the OBD II port.

4.2. Description

To test the developed DVE models, Table 1 presents the sample test scenarios. The base case is the first scenario, which considers a 50 years old driver in Outremont district with a speed equals to 100 km/h in a traffic section with 100 km/h as speed limit. In these tests, we don't take into account the following parameters: driver experience (number of driven kilometer travelled per years, number of years with driving license), driving time, traffic congestion and road format. Then, this configuration presents a low risk environment conditions.

The scenario #2 is designed to test the overspeed models. That's why the vehicle speed is higher than the traffic section's speed limit.

The configuration of the third scenario assumes a slightly older driver than the one of the first scenario (70 years old) to analyse the impact of the driver age on the global driving risk.

In the fourth scenario, only the Environment of driving is changed compared to the first scenario. Now the driving district is Sud-Ouest instead of Outrement.

To evaluate a driver through a whole driving mission, the experimental test is done in Montreal city using a Dodge 2012 car of the LASSENA laboratory and the Micro-iBB (Figure 11) to record the driving data. The trajectory of the mission includes residential area in the district Outremont and the highway 30 in Montreal. In each driving place, the mean of BPAs of each entity is computed. In this mission, only one driver, with 17 years old, drives during the entire mission. Then, the BPA of the Driver entity remains constant. At the end of the mission, the mean of all BPAs of each proposition in the referential subset is computed, and this represents the driving scores

Table 1. Test cases.

Data		Scenario #1	Scenario #2	Scenario #3	Scenario #4
Driver	Age	50 years	50 years	70 years	50 years
Vehicle	Velocity	100 km/h	150 km/h	100 km/h	100 km/h
	Acceleration	0	0	0	0
	Jerk	0	0	0	0
Environment	Velocity limit	100 km/h	100 km/h	100 km/h	100 km/h
	District	Outremont (highway)	Outremont (highway)	Outremont (highway)	Sud-Ouest (highway)

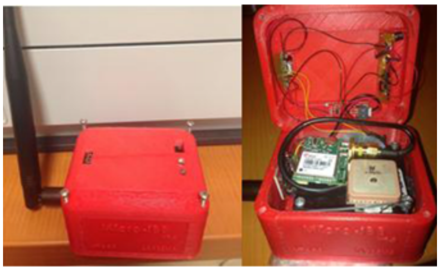

Figure 11. Data collector (Micro-iBB).

of the mission.

4.3. Results and Discussion

4.3.1. Results related to the static data

The results of the local and global fusions related to the first scenario are given in the Figure 13. The Driver entity's masses are given to the proposition LR (m_{LR} = 1) since the driver has 50 years old. These masses are computed according to the Expert-model related to Canadian drivers given in Figure 9.

In the Vehicle entity, the acceleration and the jerk are twice zero, therefore the aggressiveness given by the developed Acceleration-Jerk FIS is null. Since the speed limit in the district Outremont is 100 km/h and the vehicle speed is equal to 100 km/h, there are two consequences. The first one is deduced when regarding the Figure 4, so the risk level is medium according to the developed model in that Figure. The second consequence is given when regarding the severity of a prospective collision. In fact, the relative speed is null, therefore the severity is also null. Accordingly, the total mass given from the gavity FIS is assigned to the low risk level. The local fusion at the Vehicle entity level assigns the masses to the propositions LR (m_{LR} = 0.6667) and MR (m_{MR} = 0.3333). These results validate our choice of the combination algorithm in terms of conflict managment since there are two sources of information which indicate two distinctive risk levels (LR and MR). In case of Payment Telematics System (PTS) application, the robustness of the fusion algorithm remains very important since the driver or the automobile insurance client will be charged according to the results of that algorithm.

At the Environment entity, the total mass is assigned to LR (m_{LR} = 1.0) since the district Outremont is characterized by a low risk as shown in Figure 10.

The results of global fusion assign the masses over the propositions LR (m_{LR} = 0.9524) and MR (m_{MR} = 0.0476).

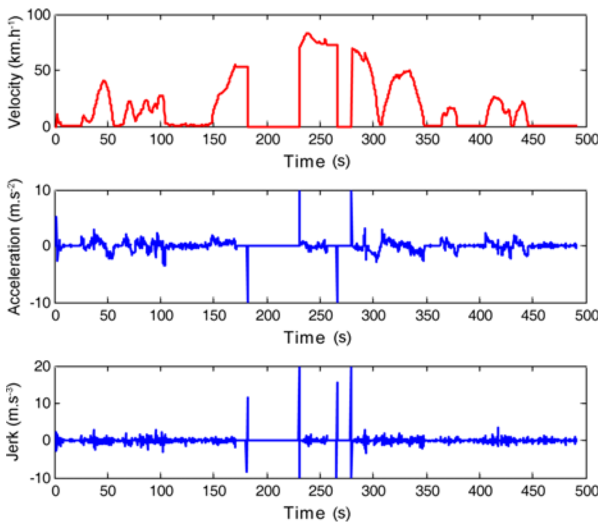

Figure 12. Experimental test data.

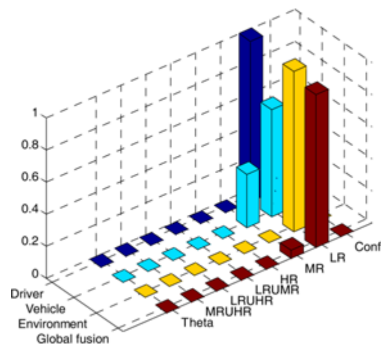

Figure 13. Results related to the scenario #1.

We note that the small mass given to the proposition MR comes from the Vehicle entity thanks to the PCR6 combination algorithm which reporoduces all the risks level obtained at the local fusion levels.

The second scenario's local fusion level is changed only at the Vehicle entity compared to the first scenario's local fusion level since the difference consists in the increase of the vehicle speed from 100 km/h to 150 km/h. So this scenario focuses mainly on the masses related to the overspeed and the severity of accident in case of an eventual frontal collision. In this scenario, the masses related to the probabitlity of collision are assigned to the propositions HR (m_{HR} = 0.3333) and MRuHR (m_{MRuHR} = 0.6667). The total mass related to the gravity of an eventual collision is assigned to the HR proposition since the EES is equal to 50 km/h. According to the Figure 5 (a), the probability of human injury is 80 %. Although the vehicles travel at very high speed, the total mass related to the acceleration-jerk FIS is assigned to the LR proposition. This mass affects the result of local fusion related to the Vehicle entity. They are assigned to the propositions LR (m_{LR} = 0.3929), MRuHR (m_{MRuHR} = 0.1667) and HR (m_{HR} = 0.4405), which is the largest value between them due to the higher masses of the HR proposition from two sources of information (accident probability and severity).

The masses related to the global fusion results are distributed to the propositions LR (m_{LR} = 0.9077), HR (m_{HR} = 0.0795) and MRuHR (m_{MRuHR} = 0.0128). So, the mass over the proposition LR is close to 1 and the other propositions masses are very small that could not qualify the real driving risk. One possible solution to this problem is to ignore the masses given from the FIS_1 when the acceleration and jerk are twice zero. Another solution consists in designing another FIS using the vehicle acceleration and speed.

Compared to the first scenario, the third one considers the same parameters related to the Vehicle and Environment entities and changes the age of the driver to a 70 years old. The total masses of the Driver entity are assigned to the proposition MR (m_{MR} = 1). So, the global fusion level's masses are changed and shared between the propositions LR (m_{LR} = 0.5595) and MR (m_{MR} = 0.4405). These results proves the global risk of driving is sensitive to driver age.

In the fourth scenario, only the driving district is changed to the "Sud-Ouest" compared to the driving district of the first scenario, which is "Outrement". So, the Driver and Vehicle entities's local risk results of the first scenario remain unchanged. The "Sud-Ouest" district is characterised by a high risk since the number of accident is also high. The results of the global fusion distribute the masses over the propositions LR (m_{LR} = 0.0.5595), MR (m_{MR} = 0.0476), HR (m_{HR} = 0.3929). The largest mass is given to the LR and HR propositions due the risk involved by the Environment entity. This study shows the sensitivity of our models towards the driving place.

4.3.2. Results related to the experimental test

As previously mentioned, the PCR6 is used at this level to combine the risks of the DVE system entities and conclude about the global driving score which is divided through the different elements of the referential subset. Figure 14 presents the local and global mean masses related to the experimental test.

As mentioned in paragraph 4.1, the Driver entity is characterized by a static BPAs since only one driver made the test. Here, the driver has 17 years old, then the total mass is assigned to the porsposition HR (m_{HR} = 1.0).

The Vehicle entity's mean BPAs of the entire test is distributed over four propositions. The big mass is assigned to the proposition LR (m_{LR} = 0.9638). The other masses are assigned to MR (m_{MR} = 0.0178), HR (m_{HR} = 0.0095) and LR ∪MR ($m_{LR\cup MR}$ = 0.0089). The Environment risk is low since the Outremont district and the highway 30 are characterized by a low risk.

The fusion of these risk levels assigns a large mass to the proposition LR (m_{LR} = 0.6558) due to the Environment and Vehicle entities risks and, to the proposition HR (m_{HR} = 0.3420) due to the Driver entity risk.

The masses presented in this paragraph gives an overview of the average risk of driving during a period of driving time.

From the insurance point of view, these global masses (or scores) of the mission can be used to compute the insured's insurance charge. In this context, a web interface has been developed to display the scores of every driver and give him feedback about his driving behavior.

In case of Advanced Driver Assistance System, the instantaneous scores could help and prevent the driver to mitigate dangerous situations by changing the driving trajectory or adjusting the vehicle parameters.

5. CONCLUSION AND FUTURE WORKS

This paper has presented a two-level strategy based on the

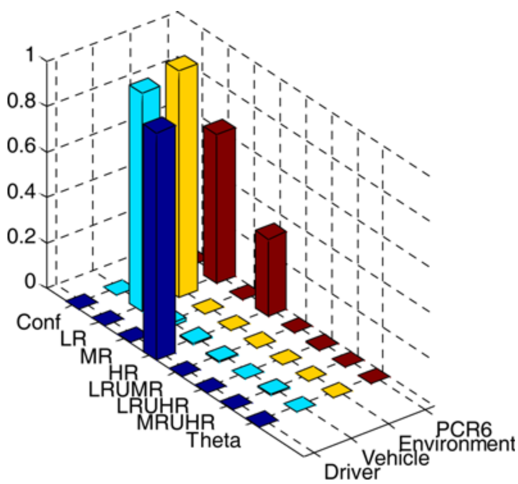

Figure 14. Results related to the experimental test.

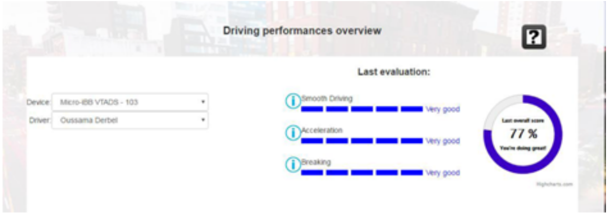

Figure 15. Web interface related to the driving performance overview.

belief and fuzzy theories to evaluate globally and locally the driving behaviour in the DVE system. The determination of the Vehicle entity's BPA is based on the fuzzy theory. The Driver's Expert-model-based BPA is defined using the relationship between the Driver age and the accident statistics. In the Environment entity, the development of the Expert-model-based BPA is based on the number of collisions in each district. The advantages of this methodology are as follows: 1) Attribution of a non- binary score (i.e between 0 and 100 %) to each class of drivers through the use of the DST. 2) The driver behavior can be assessed according to his driving places (i.e locally) 3) Reduce the complexity of the problem through the use of fuzzy theory by fixing the same output membership functions to the developed FIS. In fact, in the literature the use of the belief theory was not aided by another one to reduce the complexity when the cardinal of the referential subset is greater than 2.

Montreal city has been the case of study in this paper. Results have demonstrated the relevance of the proposed risk models and methodology. We note that there are no masses affected to the union of all hypotheses and/or the empty set in case of static scenario and experimental test and this conclusion validates the proposed models and approaches. In addition, a sensitivity analysis has been made to test these risk models of the DVE system.

The developed risk model of the Environment entity allows us defining the Pay Where You Drive (PWYD) model in case of UBI. When Environment risk is fused with the Vehicle entity (Pay How You Drive), motor vehicle insurance can charge the driver according to the PWYD and PHYD models using data from the Micro-iBB or equivalent device.

Future work consists taking into account more risk parameters related to the DVE to develop more UBI models.

ACKNOWLEDGMENT–This research is part of the project entitled Vehicle Tracking and accident diagnostic system (VTADS). This research is partially supported by the Natural Sciences and Engineering Researcj Concil of Canada (NSERC), Ecole de Technology Superieure (ETS) within the LASSENA laboratory in collaboration with two industrial partners namely iMetriK global Inc and Future Electronics.

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