Adaptive Fuzzy Classifier to detect Driving Events from the Inertial Sensors of a Smartphone

César Arroyo, Luis M. Bergasa, Eduardo Romera

Abstract— **In the last years there has been a rising interest in monitoring driver behaviors by using smartphones, due to their increasing market penetration. Inertial sensors embedded in these devices are key to carry out this task. Most of the state-of-the-art apps use fix thresholds to detect driving events from the inertial sensors. However, sensors output values can differ depending on many parameters. In this paper we present an Adaptive Fuzzy Classifier to identify sudden driving events (acceleration, steering, braking) and road bumps from the inertial and GPS sensors. An on-line calibration method is proposed to adjust the decision thresholds of the Membership Functions (MFs) to the specific phone pose and vehicle dynamics. To validate our method, we use the UAH-Driveset database [1], which includes more than 500 minutes of naturalistic driving, and we compare results with our previous DriveSafe [2] app version, based on fix thresholds. Results show a notable improvement in the events detection regarding our previous version.**

I. Introduction

In the last years, there has been an increasing interest in utilizing smartphones as distributed sensing platforms because they have a great amount of embedded sensors that facilitates the cost-effective capturing and processing of data from the real world. In addition, they are small, cheap, and ubiquitous. On the other hand, profiling driving behavior has become a relevant aspect in fleet management, automotive insurance and eco-driving.

Inertial sensors are a good option to monitor driver behavior [3]. A review about publications and commercial applications toward developing systems that make driving safer confirms this hypothesis [4]. The premise of many of these approaches is that providing feedback of recorded driving actions to drivers, they are encouraged to change their behavior and reduce their individual risk. In addition, these works propose solutions for diver problems as: driver assistance [5], drowsiness detection [6], eco-driving [7], fleet management [8], road condition monitoring [9], accident detection [10] and insurance information (Pay-As-You-Drive) [11][12] among others.

Using smartphones inertial sensors to detect driving events and maneuvers, in a general way, have to overcome some important issues: 1) Diversity of the inertial sensors (measures and noise level can differ among different devices). 2) Smartphone pose (position inside the vehicle can be different for each user in each trip). 3) Vehicle dynamics (parameters involve the vehicle dynamics are different among vehicles and can change over the time.

Most of the state-of-the-art proposals for detecting acceleration, braking or steering events from inertial sensors are based on fix thresholds [13][14]. In the previous version of DriveSafe [2], used as baseline in this work, these events are triggered when the sensing values overpasses some predefined thresholds (e.g. 0.1 g for acceleration, braking and steering) set empirically. Only a few applications propose calibration techniques to adjust the thresholds for events detection. In [15], a Support Vector Machine (SVM) method is used to recognize driving events and the results of applying a Gaussian Radial Basis Function (RBF) kernel as opposed to K-Mean clustering are evaluated. The achieved optimal recognition rate was 60%, and it was observed that acceleration event data did not meet expectations. SenseFleet includes a calibration phase consisting in the collection of a fixed number of input samples segmented by speed ranges and the computation of their cumulative distribution function [16], but this is a priori calibration phase, it takes around 17 minutes long, and is not adaptive. If the vehicle dynamic parameters or the phone pose changes during the trip, the thresholds are not updated, which can compromise the correct events detection. In addition, the extra time needed to perform this calibration process makes drivers perceive these systems as tedious and complex.

To overcome all these limitations, we propose an Adaptive Fuzzy Classifier where the decision thresholds of the MFs bellowing to the inertial sensor inputs are adjusting in an on-line calibration process. Measures collected in some trip sections (constant turns, uniform acceleration maneuvers) are cumulated to obtain its cumulative distribution function in different ranges. Thresholds are adjusting in order to fit the real and the theoretical distributions during the trip.

II. DRIVESAFE AND UAH-DRIVESET

DriveSafe [2] is a smartphone app that collects driving manoeuvers data to evaluate and profile driver behaviors. During driving, it assists the driver to improve his safety. At the end of each trip, it scores driving and records information trip in order the driver analyzes his skills and how to improve them. DriveSafe is strictly not designed to replace any onboard

This work has been funded in part from the Spanish MINECO through the SmartElderlyCar project (TRA2015-70501-C2-1-R) and from the RoboCity2030-III-CM project (Robótica aplicada a la mejora de la calidad de vida de los ciudadanos. fase III; S2013/MIT-2748), funded by Programas de Actividades I+D en la Comunidad de Madrid and cofunded by Structural Funds of the EU."

The authors are with the Department of Electronics, University of Alcalá. Alcalá de Henares, Madrid, Spain.email: cesar.arroyo@uah.es, luism.bergasa@uah.es, eduardo.romera@depeca.uah.es

vehicle control system nor assistant system. Its goal is alert and assess driving behaviors to encourage safe driving.

In order to investigate the most suitable techniques to calibrate sensors for detecting driving events, a large and heterogeneous database which provides naturalistic driving data is required. A database that fulfills these requirements is UAH-DriveSet [1]. No less important than having access to a proper database is to have a tool to exploit the information contained in it.

This dataset has been recorded using the application DriveSafe. The app uses all the available sensors on the smartphone, such as accelerometers, GPS and the frontal camera, to analyze driving parameters and behaviors.

DriveSet Reader is a tool available with DriveSet. This tool allows to select each of the routes in order to simultaneously reproduce the associated video and plot a selection of variables synced in real-time within a user interface. We use this tool to find patterns in the driving behaviors by reviewing all the available variables in the dataset together with the videos that show what actually happened during the trips, thus facilitating analysis of the available variables in the database.

III. Adaptive Fuzzy Classifier Proposal

In this section, we describe our Fuzzy Classifier designed to detect driving events and the calibration process carried out to adjust its decision thresholds. As shown in Fig.2 the event detector uses as inputs the inertial sensors and GPS sensor. Acceleration, steering and braking indicators are detected by using Fuzzy Logic. In addition a new indicator related with the bumps detection is added.

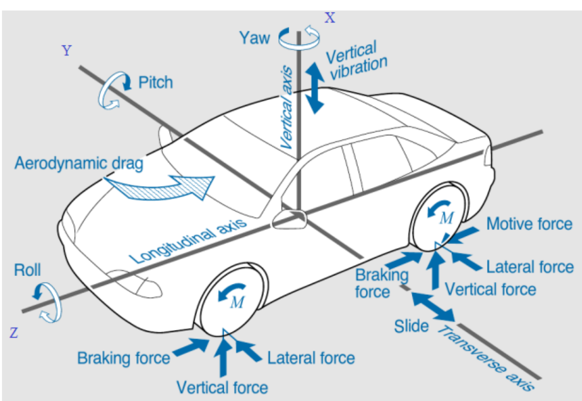


Fig. 1. Scheme forces

A. Vehicle dynamics foundations

When the driver performs some maneuvers related to the indicators under study, the vehicle is put under forces that modify its dynamic [17], as it is shown in Fig.1. When the brakes are activated the vehicle decelerate. If the accelerator is pressed the vehicle increases its speed. When the vehicle is performing a curve, launched by a steering maneuver, the faster we go the higher will be centrifugal force over it. When the vehicles pass through a bump or an area with irregularities in the asphalt, some abrupt peaks appear in the accelerometers, especially in the vertical axis.

Some parameters involve in the vehicle dynamic can change over the time (i.e. the pressure of the tires, the vehicle weight, the ability to dissipate energy from the brakes). In consequence the energy that our vehicle is able to absorb is changing.

B. Fuzzy classifier

To detect inertial events we use a zero-order Sugeno Fuzzy Inference System (FIS) as classifier due its computational efficiency. The input variables of our FIS are shown in Fig. 2:

- Linear velocity (v_L) is obtained from the GPS and is given in kilometers per hour. It is used to: 1) Avoid the detection of false steering events on curve sections. 2) Disable the detection of events when the speed is lower than 14 kilometers per hour. 3) Classifier the level of steering events.

- Acceleration in “Z” axis (a_z) is obtained from the inertial sensor (accelerometer), and measures the longitudinal acceleration in the vehicle progress direction. A sudden positive increase in Z indicates an acceleration, where abrupt peaks may indicate aggressive increases of velocity. A decrease in the same accelerometer represents a sudden deceleration, which may be an indicative of harsh braking. The samples are normalized by the gravity.

- Absolute acceleration value in “Y” axis ($|a_y|$) is obtained from the inertial sensor (accelerometer) and it evaluates the behavior of the vehicle in the curves because a high increase or decrease in Y axis are indicatives of excessive velocity in left or right turns, provoking a sharp turn. The samples are normalized by gravity.

-Axis with the higher acceleration value ($|AXIS|$) is calculated from motion sensors (accelerometers), to avoid false events detections. Also is essential to detect bumps and irregularities in the asphalt. When the vehicle pass through a bump, some abrupt peaks appear in all accelerometer axis. These samples are “0” when the dominant acceleration is in Z or Y axis, or take the acceleration absolute value in X axis, when this is the dominant.

- Absolute value of Angular velocity ($|\omega|$) is calculated from the gyroscope sensor (yaw). It is used to avoid false detections of sharp turns in curves. The samples are given in degrees per second.

The input variables are obtained at different sampling rates. In the case of inertial sensors, the sampling rate provided by the dataset is 10 Hz and the GPS frequency is 1 Hz. We implemented a Sensor Fusion layer to synchronize inertial and GPS samples (Fig. 2). As GPS samples are received at 1 Hz, we consider constant speed until the next sample and we use this speed to detect events each 0.1 seconds in the next second.

The MFs of the fuzzy sets defined for the inputs are shown in Fig. 3.

For the $|a_y|$ input we define 4 trapezoidal MFs named as VLY, LY, MY and HY (Fig. 3.a). The decision thresholds for this input are Th_{Y1}, Th_{Y2} and Th_{Y3}. The default value for them are 0.1g, 0.2g and 0.4g, obtained in a heuristic way and they are adjusted in a calibration process.

For the a_z input we define 7 trapezoidal MFs named as NH, NM, NL, Zero, PL, PM and PH (Fig. 3.b). The decision thresholds for this input are Th_{Z1}, Th_{Z2}, Th_{Z3}, Th_{Z4}, Th_{Z5} and

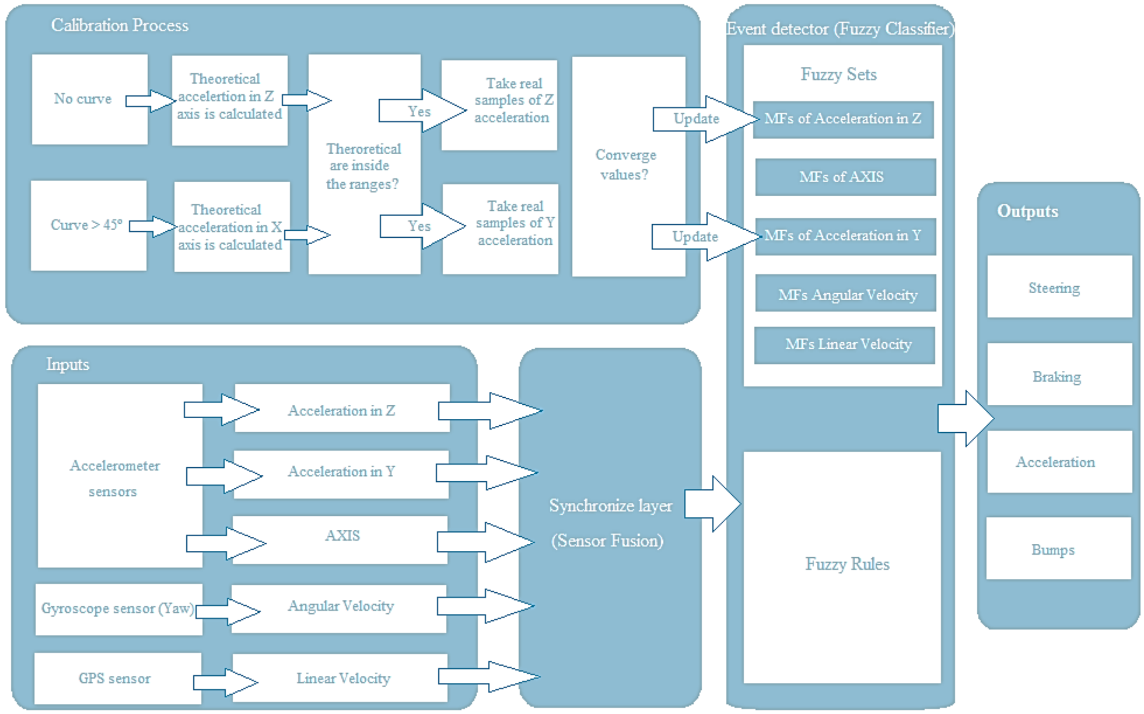


Fig. 2. Calibration method of fuzzy classifier architecture

Th_{Z6}. The default value for they are -0.4g, -0.2g, -0.1g, 0.1g, 0.2g and 0.4g, obtained in a heuristic way and they are adjusted in a calibration process.

For the v_L input we define 4 trapezoidal MFs and 3 fix thresholds due to its samples are obtained from GPS (Fig. 3.c).

For the AXIS input we define 2 trapezoidal MF´s named NoX and X (to detect bumps and avoid false detections) (Fig. 3.d). We define only a fix threshold to optimize the general working.

For the |ω| input we define 5 trapezoidal MFs named VL, L, MHV, MMV and H (Fig. 3.e). The decision thresholds are fix due the yaw gives an absolute angular value with high precision. The default values are 1.2º/s, 5.3º/s, 6.8º/s and 8.5º/s, obtained in a heuristic way.

TABLE I. OUTPUT VALUESOF FUZZY CLASSIFIER

Outputs	**MF´s**
Steering	NoSt, High, Medium, Low
Braking & Acceleration	A_Low, A_Medium, A_High, No_Event, B_Low, B_Medium, B_High
Bumps	Yes, No

For the output variables, we select crisp set for each MF to allow a defuzzification based on weighted sums. The output MFs are shown in table I.

Fuzzy rules design is a straightforward way of knowledge that is subjective and ambiguous. Given the large number of member functions that we have, a complete fuzzy rules set is not optimum. A reduced number of 28 rules have been designed in an experimental way where each rule indicates a specific conditions for each event detection. For example, in order to detect a "low braking" event, the classifier applies the following rule:

IF ($Acel_Y$ IS NL) AND (Axis IS NoX) AND (Linear Velocity IS NOT VLV) THEN (event IS B_Low)

The detection of steering events are controlled by the rules indicated in the table II.

TABLE II. RULES SET FOR A STEERING EVENTS DETECTION

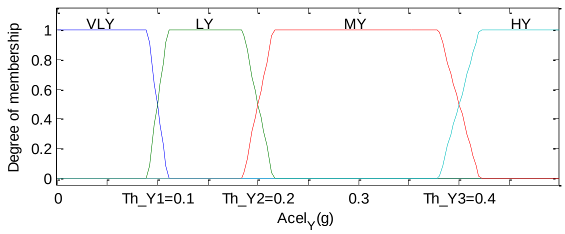
		Angular velocity				
	MFs	***VL***	***L***	***MHV***	***MMV***	***H***
Linear Velocity	***VLV***	No St	NoSt	NoSt	NoSt	NoSt
	LV	No St	High/ Medium /Low *	High/ Medium /Low *	High/ Medium /Low *	NoSt
	MV	No St	High/ Medium /Low *	High/ Medium /Low *	NoSt	NoSt
	HV	No St	High/ Medium /Low *	NoSt	NoSt	NoSt

*The specific activated MF is defined by the a_z input

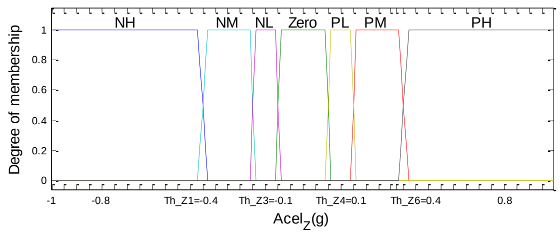
When a new threshold is proposed by the calibration process for an input of our fuzzy classifier, this is sent to the update process in order to adjust the involved MFs (Fig.2), changing their shape.

C. Calibration of accelerometer Y

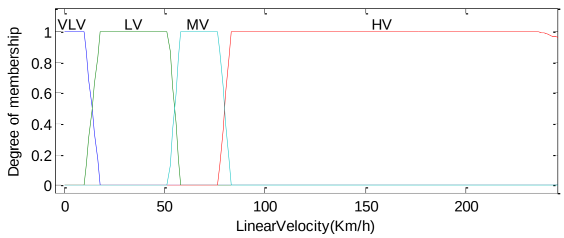
The a_y input is used together with |ω|, v_L and AXIS inputs to determine the sharp level of the turns. We have to calibrate three decision thresholds (Th_{Y1}, Th_{Y2}, Th_{Y3}) for this inertial sensor.



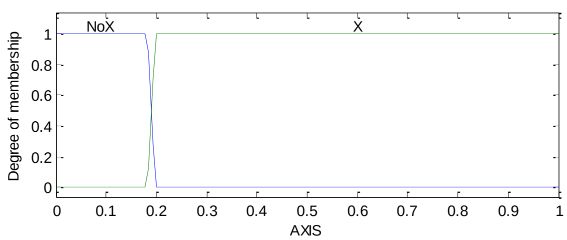
(a)



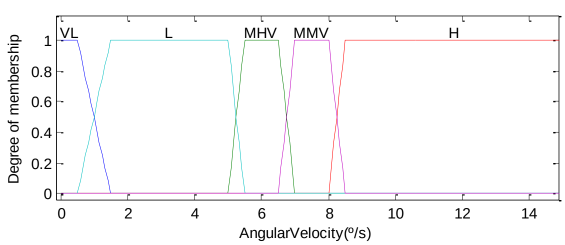
(b)



(c)



(d)



(e)

Fig. 3. Membership functions defined for the inputs

A rigorous method to calibrate the inertial sensor consist on the vehicle performs a series of sharp turns to obtain some master patterns to adjust the thresholds. However, these maneuvers carries great risk and are carried out in a previous setup [16]. We choose a different approach based on an online calibration method over sections of curve where the centrifugal forces (see Fig. 4) are similar to those suffered in the sudden turns but with lower range values and performing safer manoeuvers. We studied the trips of the UAH-Driveset [1], taking only data in curves to find out correlations between a_y, $|\omega|$ and v_L. The a_y gives the acceleration experienced by the driver in the vehicle in this axis, although this acceleration value does not match the value that suffer a solid-rigid to make the same trajectory (a_y^{Theo}) as the current vehicles are provided with energy absorbing systems (a_y^{Abs}).

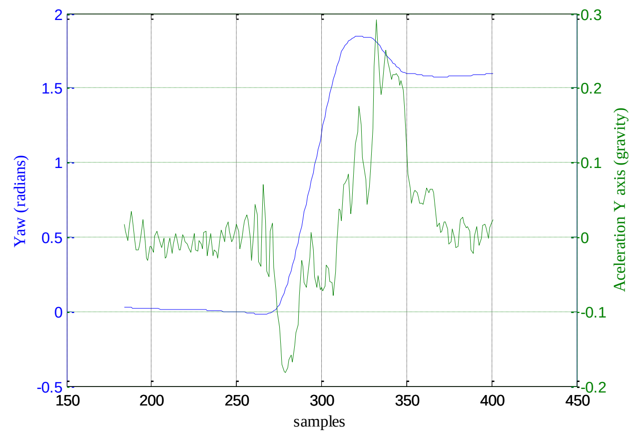


Fig.4. Centrifugal force in curve sections

$$a_y^{Theo} = a_y + a_y^{Abs} \rightarrow a_y = a_y^{Theo} - a_y^{Abs} \quad (1)$$

For calibration we choose those curve sections where we detect continuous course change in the same direction of at least 45º without any event (Fig.2). We calculate the angular velocity (ω) from the gyroscope (yaw) and the linear velocity from GPS in these sections (2). Then, a_y^{Theo} is calculated as the product of ω and v_L (3).

$$\omega = \frac{\Delta yaw}{\Delta time} \quad (2)$$

$$a_y^{Theo} = v_L \cdot \omega \quad (3)$$

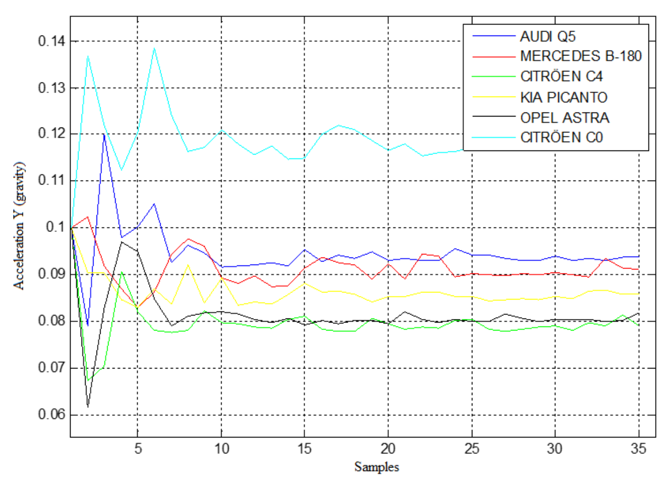


Fig. 5 Evolution of Th_{Y1} for each vehicle

Our calibration method consist on estimating the decision thresholds taking a_y samples in the moments when a_y^{Theo} falls within a specific range for each threshold (Fig. 2). To do that, a study with a master vehicle to decide which a_y values determine the level of the sharp turns was made. In this way, we correlate values given by the accelerometers with the theoretically calculated. After finding the theoretical acceleration ranges, these can be used in the calibration of other vehicles and thus their decision thresholds will be adjusted regarding the master vehicle. Among all vehicles available in the database (UAH-DriveSet), the Audi Q5 was selected to be the master vehicle. The range of theoretical acceleration (a_y^{Theo}) for Th_{Y1} was [0.12g - 0.14g]. Extending this analysis to other vehicles, we show the adapted values of the decision thresholds for each vehicle in table III.

As we mentioned before, the vehicle weight, width and tire pressure determine the vehicle behaviour in curves. The wider the tire are the higher the surface friction is and as consequence the higher energy absorption will be (centrifugal acceleration).

The energy is absorbed by the damping system which increases with the mass of the vehicle. Heavy vehicles absorb more energy than light vehicles. Energy not absorbed by the damping system makes the vehicle suffers a great centripetal acceleration.

If the pressure of the tires is low, the vehicle will lose grip and its control can be compromised. If the tires are over pressured, they will not absorb uneven ground properly. With a correct tires pressure we have maximum tire surface in contact with the ground, and also supporting the same effort over the whole surface.

Figure 5 shows the evolution of Th_{Y1} for each vehicle on a trip around 16 Km long. Initially the threshold is 0.1g and according to the acquired samples the threshold is adapted to vehicle conditions. The calibration method takes only few seconds if the acceleration conditions are met (curve sections in roundabouts, in roads input and exits, etc).

Opel Astra and Citroen C4 have similar performance and they converge to a similar threshold (0.08g). However, in the Mercedes B-180, despite having the same width tires, it has more mass and then the threshold is higher (0.091g). Despite Kia Picanto has lower performance than the Mercedes, it presents lower threshold because it has lower weight. The Audi Q5 was selected as master car and its threshold is 0.094g, greater than Mercedes, because it has more mass and it has the highest centre of gravity. Finally, the Citroën C0 (electric car) is heavy in relation to the width of its tires in comparison with the other vehicles of the database, thus the threshold get 0.117g.

TABLE III. CALIBRATED VALUES FOR THE Y ACCELEROMETER THRESHOLDS IN EACH VEHICLE

Threshold			Adapted threshold			
Initial value		*Range values for calibration*	*Opel Astra*	*Citroën C0*	*Audi Q5*	*Mercedes B180*
Th$_{Y1}$	0.1 g	[0.12g 0.14g]	0.08	0.117	0.094	0.091
Th$_{Y2}$	0.2 g	[0.21 g 0.25 g]	0.165	0.21	0.169	0.155
Th$_{Y3}$	0.4 g	[0.4 g 0.5 g]	0.313	0.38	0.315	0.34

D. Calibration of accelerometer Z

The a_z is used together with v_L and AXIS inputs to detect acceleration and breaking indicators. We have to calibrate six decision thresholds (Th_{Z1}, Th_{Z2}, Th_{Z3}, Th_{Z4}, Th_{Z5}, Th_{Z6}) for this inertial sensor. Extending to Z axis the calibration method for the accelerometer in Y axis, we perform the calibration of the accelerometer Z on straight sections of the road where the vehicle is only affected by longitudinal forces.

The foundation of our calibration method for this sensor is based on uniform acceleration. The GPS gives the linear velocity of the vehicle each second. This frequency is sufficient to consider that the acceleration is constant, so the second derivative of the position of the vehicle is then constant:

$$a_z^{Theo} = \frac{V_t - V_{t-1}}{t-1} \tag{4}$$

$$a_z = a_z^{Theo} - a_z^{Abs} \tag{5}$$

The calibration method is based on estimating the decision thresholds taking a_z samples in the moments when a_z^{Theo} falls within a specific range for each threshold. A study with a master vehicle was carried out to decide the values a_z that determine the intensity degree for the sudden acceleration or braking events. We have correlated acceleration given by the accelerometer and the theoretically calculated. After finding the theoretical acceleration ranges, these are used in the calibration of other vehicles, being able to adjust their thresholds decision regarding the master vehicle. Audi Q5 was selected to be the master vehicle. The range of theoretical acceleration for Th_{Z3} is [-0.11g -0.14g] and for Th_{Z4} is [0.115g 0.145g]. Extending this analysis to other vehicles, we show the adapted values of the decision thresholds for each vehicle in table IV.

The method to calibrate (Th_{Z1}, Th_{Z2}, Th_{Z5}, Th_{Z6}) is similar although it should be noted that the range values for these theoretical acceleration thresholds is higher and we get fewer samples unless driver performs aggressive accelerations and braking. To solve this problem we estimate these thresholds as a function of the first ones (Th_{Z3}, Th_{Z4}) due to the linearity among the calibrated values, as it can be observed in table IV. Calibration of these thresholds are not as relevant as already mentioned because these events occasionally occur.

TABLE IV. CALIBRATED VALUES FOR Z ACCELEROMETER THRESHOLDS IN EACH VEHICLE

Threshold			Adapted Threshold		
Initial value		*Range values for calibration*	*Opel Astra*	*Citroën C0*	*Audi Q5*
Th$_{Z1}$	-0.4g	[-0.4g -0.5g]	-0.36	NES	NES
Th$_{Z2}$	-0.2g	[-0.22g -0.26 g]	-0.18	-0.185	-0.165
Th$_{Z3}$	-0.1g	[-0.115g -0.145g]	-0.104	-0.110	-0.096
Th$_{Z4}$	0.1g	[0.115g 0.145g]	0.088	0.112	0.088
Th$_{Z5}$	0.2g	[0.22g 0.26 g]	0.157	0.196	0.16
Th$_{Z6}$	0.4g	[0.4 g 0.5g)]	NES	NES	NES

**NES= No enough samples*

IV. EXPERIMENTAL RESULTS

We perform experimental evaluation of our proposal comparing events detected between our previous DriveSafe version (based on fix thresholds) and the improved one (based on fuzzy classification and adaptive decision thresholds) over the sequences recorded in the UAH-Driveset database [1], which includes 18 trips performing by 6 different drivers and vehicles. In order to measure the accuracy of the events, we use precision (PR) and recall (RC) performance indicators.

TABLE V. COMPARATIVE OF DETECTED EVENTS

Vehicle	Events by DriveSafe					
	Acceleration		*Braking*		*Steering*	
	PR	*RC*	*PR*	*RC*	*PR*	*RC*
Audi Q5	0	0	0.86	0.73	0.9	0.76
Mercedes B180	0.69	0.67	0.56	0.67	0.86	0.72
Citroën C4	0.74	0.55	0.72	0.74	1	0.44
Kia Picanto	0.79	0.64	1	0.36	0.97	0.66
Opel Astra	0.83	0.72	0.76	0.78	0.88	0.69
Citroën C0	0.54	0.8	0.62	0.97	0.19	1
TOTAL	**0.67**	**0.59**	**0.71**	**0.71**	**0.59**	**0.69**
Vehicle	**Events by Improved DriveSafe**					
	Acceleration		*Braking*		*Steering*	
	PR	*RC*	*PR*	*RC*	*PR*	*RC*
Audi Q5	0.94	0.76	0.87	0.93	0.88	0.92
Mercedes B180	0.71	0.81	0.87	0.97	0.89	0.91
Citroën C4	0.85	0.87	0.83	0.94	0.89	0.92
Kia Picanto	0.89	0.87	0.86	0.84	0.9	0.93
Opel Astra	0.82	0.85	0.89	0.97	0.9	0.9
Citroën C0	0.72	0.88	0.84	1	0.87	0.91
TOTAL	**0.81**	**0.85**	**0.86**	**0.94**	**0.89**	**0.91**

The results obtained in the Table V for Total Precision in the revised version improves between 14% and 30% regarding the previous one. Total Recall improves between 23% and 30% depending on the events. Using the last version the number of false detections is significantly reduced and the number of real detections is considerably incremented.

We apply a similar method to evaluate the bumps detection obtained in Table VI.

TABLE VI. BUMPS DETECTED IN EACH VEHICLE

Vehicle	*Bumps*	
	Precision	*Recall*
Audi Q5	0.98	0.8
Mercedes B180	0.93	0.96
Citroën C4	0.94	0.93
Kia Picanto	0.86	1
Opel Astra	0.98	0.85
Citroën C0	0.77	1
TOTAL	**0.87**	**0.91**

V. CONCLUSIONS AND FUTURE WORKS

Experimental results show that our online calibration method based on adjusting our fuzzy classifier decision thresholds using data obtained in certain route sections (concentrated turns and uniform accelerations) performs better than our previous version based on fix thresholds.

The previous Drivesafe version only worked for velocities higher than 50 km/h. This version detect events at velocities lower than this threshold. At low velocities fuzzy classifier works quite better than using fix threshold.

When the vehicle speed is over 80 km/h, a small bump causes acceleration changes in all the axis (x, y, z). The new fuzzy classifier only detect sudden braking/acceleration or steering events when the $|a_Z|$ or the a_y is the highest. This control condition saves a lot of false detections.

A new functionality as the detection of bumps or irregularities of the asphalt, has been included. Using this data we can identify the type of the road and adjust the detection thresholds if the quality of the road changes.

For future work, we intend to design a high level layer in order to find out new events (overtaking attempts, abrupt gear shifts or sudden swerves) performed by drivers, which are also interesting to evaluate the driving behaviour.

REFERENCES

[1] Eduardo Romera, Luis M. Bergasa, Roberto Arroyo, "Need Data for Driver Behaviour Analysis?" in IEEE Int. Conf. on Intelligent Transportation Systems (ITSC), *accepted for presentation*. 2016. http://www.robesafe.uah.es/personal/eduardo.romera/uah-driveset/.

[2] Luis M. Bergasa, Daniel Almeria, Javier Almazán, J. Javier Yebes, Roberto Arroyo, "DriveSafe: An App for Alerting Inattentive Drivers and Scoring Driving Behaviors", in IEEE Intelligent Vehicles Symp. (IV), 2014, pp. 240–245.

[3] G. Castignani, R. Frank, and T. Engel, "An evaluation study of driver profiling fuzzy algorithms using smartphones," in Proc. IEEE Workshop Vehicular Communications Applications, 2013

[4] "Mobileye applications," http://www.mobileye.com/en/manufacturerroducts/applications/.

[5] Smartphone App. iOnRoad, http://www.ionroad.com/.

[6] You, C. -W., et al." Carsafe app: Alerting drowsy and distracted drivers using dual cameras on smartphones". In Proceeding of the 11th annual international conference on Mobile systems, applications, and services. 2013. ACM

[7] R. Araujo, A. Igreja, R. de Castro, and R. Araujo, "Driving coach: A smartphone application to evaluate driving efficient patterns," in Proc. IEEE Intelligent Vehicles Symp. (IV), June 2012, pp. 1005–1010.

[8] Greenroad, http://greenroad.com/.

[9] M. Perttunen, O. Mazhelis, F. Cong, M. Kauppila, T. Leppänen, J. Kantola, J. Collin, S. Pirttikangas, J. Haverinen and T. Ristaniemi, "Distributed Road Surface Condition Monitoring Using Mobile Phones. In Ubiquitous Intelligence and Computing—8th International Conference, UIC 2011, Banff, Canada, September 2–4, 2011. Proceedings; Springer Berlin Heidelberg: Berlin, Germany, 2011; Volume".

[10] J. Zaldivar, C. Calafate, J. Cano and P. Manzoni, "Providing accident detection in vehicular networks through OBD-II devices and Android-based smartphones. In Proceedings of the 2011 IEEE 36th Conference on Local Computer Networks, Bonn, Germany, 4–7 October 2011; pp. 813–819".

[11] Gys A.M. Meiring and Hermanus C. Myburngh, "A Review of Intelligent Driving Style Analysis Systems and Related Artificial Intelligence Algorithms", in Sensors 2015, 15, pp: 30653-30682.

[12] Usage Based Insurance Global Study, PTOLEMUS Consulting Group, Brussels, Belgium, 2012

[13] H. Eren, S. Makinist, E. Akin, and A. Yilmaz, "Estimating driving behavior by a smartphone," in Proc. IEEE Intelligent Vehicles Symp. (IV), June 2012, pp. 234–239.

[14] Daza, I.G.; Bergasa, L.M.; Bronte, S.; Yebes, J.J.; Almazán, J.; Arroyo, R. "Fusion of Optimized Indicators from Advanced Driver Assistance Systems (ADAS) for Driver Drowsiness Detection". Sensors 2014, 14, 1106-1131.

[15] M. Van Ly, S. Martin and M. Trivedi, "Driver classification and driving style recognition using inertial sensors" in Proceedings of the 2013 IEEE Intelligent Vehicles Symposium, Gold Coast, Australia, 23–26 June 2013; pp. 1040–1045.

[16] German Castignani, Thierry Derrmann, Raphaël Frank, and Thomas Engel, "Driver Behavior Profiling using smartphones: A low-Cost Platform for driver monitoring", in IEEE intelligent transportation system mazine, Spring 2015; pp. 91-101.

[17] Konrad Reif, "Brakes, Brake control and driver Assistance Systems: Function, Regulation and Components", Ed. Springer, 2014; pp. 15-30.